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Corporate technological patent and financing accessibility - An empirical analysis based on startups

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- An Empirical Analysis Based on Startups

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I hereby declare that this PhD dissertation is my original work and it has been written by me in its entirety.
I have duly acknowledged all the sources of information which have been used in this dissertation.
This PhD dissertation has also not been submitted for any degree in any university previously.

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XU Tao

30 May 2024

Abstract

Technological innovation is not only central to competition among firms but also a crucial driver of economic growth. The process of corporate technological innovation often demands substantial financial support. However, due to information asymmetry and capital constraints, tech startups encounter numerous obstacles in sustaining innovation. Venture capital is instrumental in fostering continuous corporate innovation, providing essential financial support for innovative activities, and playing a key role in achieving core technological breakthroughs. As a significant manifestation of corporate innovative technology, patents can mitigate the information asymmetry between startups and investors by creating a positive patent signal from diverse perspectives. Therefore, investigating the influence of different types of patent signals on the financing accessibility of tech startups holds substantial practical significance. This exploration not only has deep implications for enhancing the integration of technology and finance but also supports the development of small and medium-sized technology enterprises.

This paper compiles a comprehensive database of financing events for tech startups specializing in advanced manufacturing and healthcare, integrating a complete sample of patent data for these firms. The study collects 28,610 financing events and 1,897,517 patent records from January 1992 to March 2024. It constructs patent signals based on quantity, quality, legal status, and business relevance from the perspectives of the company's independence and its associations. Subsequently, we develop regression models to examine the effects of these variables on tech startups' financing accessibility. The moderating role of venture capital's reputation and focus on the influence of patent signals is further analyzed. Additionally, this paper investigates the variations in the impact of patent signals on financing accessibility across companies with different technological attributes and financing stages. Finally, the paper employs a survival analysis model to address potential endogeneity issues by assessing the impact of patent signals on the likelihood of securing financing in subsequent rounds.

The findings of this study are as follows: (1) From an independent perspective, the quantity, quality, and legal signals generally aid startups in securing larger financing

volumes, with patent quantity and quality signals having a more pronounced impact on financing volume. In contrast, the business and legal signals of patents exert a comparatively smaller influence on the cumulative number of investment rounds than on financing volume. (2) From an associative perspective, the business signal significantly enhances the likelihood of startups obtaining financing, surpassing the effect of independent company-level patent signals. (3) The analysis of moderating mechanisms reveals that the reputation of venture capitals notably diminishes the positive impact of patent signals on financing accessibility, while limited attention from investors significantly bolsters the effect of technological similarity signals on financing accessibility. (4) Heterogeneity tests indicate that different technological attributes and financing stages of companies influence the impact of patent signals on financing accessibility, although the variations in impact magnitude are minimal. (5) The survival analysis in the robustness tests demonstrates that the influence of various patent signals on financing accessibility remains consistent even after addressing endogeneity concerns.

The contributions of this paper are threefold: Firstly, at the theoretical level, it expands the study of the relationship between patent signals and financing accessibility across multiple dimensions such as quantity, quality, business, legal, and technological similarity, refining the application of signaling theory in the venture capital domain. Secondly, from a methodological standpoint, this paper employs advanced deep learning algorithms and textual analysis to construct a corporate-patent-technology topic graph. Utilizing patent text data, this paper innovatively develops a technological similarity index among startups and extends the measurement of technological association and similarity indicators into the Chinese startup financing market. Lastly, on the practical front, this paper provides strategic decision-making references for R&D investment and patent deployment for tech startups. It offers insights for government policy on patent information management and disclosure and promotes venture capital involvement in tech startups, suggesting avenues to accelerate the integration of technology and finance.

Keywords: Patent Signals, Technological Similarity, Financing Accessibility, Venture Capital's Reputation, Venture Capital's Attention

Contents

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I aspire to lead my team toward collective growth and the creation of a remarkable enterprise. I hope this endeavor will enhance the lives of their families and enable each team member to become a source of pride for their parents and children.

Starting from humble beginnings, I embarked on the path of entrepreneurship. Though I have not yet achieved great success, I deeply understand the challenges it entails. Throughout this journey, I have witnessed the resilience of the Chinese people and the strength of small and micro enterprises. This phase of study and exploration has clarified my future mission. I aim to help Chinese small and micro enterprises connect with financial resources. By enabling finance to support and nourish enterprises like ours, we can ultimately showcase the strength of China's small and micro enterprises to the world.

Although graduation marks an end for our DBA study, it is also the start of the new chapter for our life's journey. The mountains remain unchanged, and the rivers flow ever on, until we meet again on life's journey!

I. Introduction

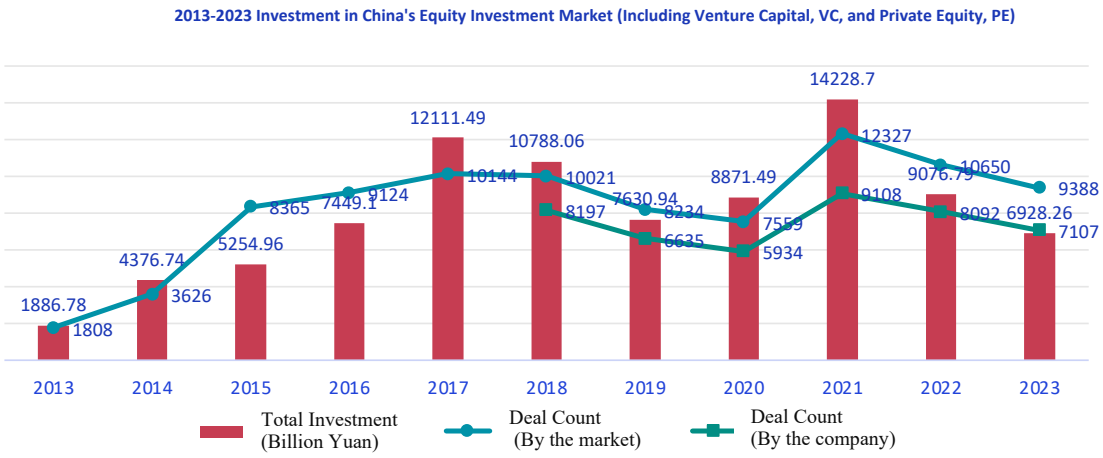
1.1 Research Background and Significance

(1)Research Background

As of the end of 2022, there were over 52 million small and micro enterprises in China, including more than 450,000 technology-based small and medium-sized enterprises (SMEs). These enterprises are becoming the backbone of high-quality economic development in China. In the era of the knowledge economy, technological innovation is not only a crucial driver of international economic growth but also the cornerstone of business competition. However, technology-based SMEs often face substantial funding challenges due to the significant financial support required for technological innovation. The "14th Five-Year Plan" addresses this issue by outlining enhancements to investment-loan linkages and intellectual property pledge financing, aiming to foster the integration of technology and finance and support the development of technology-based SMEs. Thus, examining the operational conditions of financing methods for technological innovation in SMEs and offering solutions to strengthen the technology finance support system is of practical significance for alleviating financing difficulties.

Venture capital, as a form of equity capital, can effectively mitigate external financing constraints for enterprises and offer value-added services that aid business growth and development. It is regarded as an effective financing method and a vital

catalyst for technological innovation. However, due to the high uncertainty associated with entrepreneurship and the information asymmetry between investors and investees, venture capital institutions often struggle to identify high-quality businesses. Moreover, many promising startups also find it difficult to attract venture capital support. As depicted in Figure 1-1, the overall venture capital market in China experienced a decline in 2023, with an 11.8% year-on-year decrease in the number of cases and a 23.7% reduction in investment amounts. Consequently, both investors and investees are highly motivated to discover evidence supporting the innovative development prospects of startups.



Data source: Zero2IPO Research Center

Figure 1-1: Overview of the Venture Capital Market in China from 2013 to 2023

Within the startup ecosystem, patents are not just legal protections but also vital commercial assets and strategic tools. As indicators of a startup's level of innovation, patents are intricately linked to a company's technological innovation capabilities. Particularly, once a patent is granted legal effectiveness by the national intellectual

property office, it not only holds high innovative value but also facilitates the dissemination of patent-related information. This enables the creation of outward patent signals, which assist venture capital firms in evaluating the technological innovation capabilities and investment potential of tech startups, thus reducing the information asymmetry between enterprises and investors.

In China, as the intellectual property protection laws continue to be refined, the activity of corporate patent applications has become increasingly proactive, achieving notable results. From the perspective of a company's independence, existing studies have indicated that a company's patent information can transmit various investment and financing signals. Researchers such as Hsu and Ziedonis (2015), Conti (2006), and Mann and Sager (2008) suggest that the granting of patents to startups can signal a company's innovation capabilities and potential market value to venture capital firms, thereby creating a competitive advantage and attracting investors. Additionally, some studies have found that patents can reflect national and legal recognition and protection of a company's innovative achievements, thus safeguarding the company's technological innovations.

From the perspective of corporate associations, innovation models have evolved from the traditional model of independent and large corporations working alone to a new ecosystem involving the government. In this ecosystem, universities, capital markets, and collaborations among enterprises of various sizes cooperate with each other. Although the products developed by different companies for consumers may vary significantly, there are numerous connections at the technological level. This connectivity is further enhanced

by the advancement of general technologies such as the Internet of Things, big data, and artificial intelligence. These technologies have broadened the impact of high-tech companies from products and technologies to the entire industrial level, thus creating a high-tech product ecosystem, a global value chain, and a globalized industrial competitive-cooperation system that embodies the concept of "you are part of me, and I am part of you."

From the perspective of technological similarity among companies, some researchers, like Lee et al. (2019), have begun to explore the effects of technological proximity among companies. Therefore, investigating whether a company's patent information assists startups in obtaining venture capital and identifying the channels through which this occurs remains a critical research topic. However, existing studies have yielded inconsistent and even contradictory conclusions, highlighting the need for further in-depth exploration.

The impact of patent signals on financing accessibility and venture capital has been a contentious academic research topic. On one hand, some scholars assert that the investment decisions of venture capital institutions are indeed influenced by the patent signals of startups. As mentioned earlier, patents can act as indicators of a company's innovative capacity and research level, transmitting value-added information. Since patents not only reflect the future monetization potential of a company's technology but also demonstrate the company's learning and management capabilities, they can represent the market value of the company and help reduce the information asymmetry faced by startups in seeking venture capital. Many empirical results support a positive correlation

between the number of patent applications and the amount of venture capital obtained by companies (Baum and Silverman, 2004; Mann and Sager, 2007). On the other hand, some studies indicate that patents can negatively affect startups' ability to obtain venture capital (Heeley et al., 2007). Since patent applications and inventions are time-consuming and costly activities that represent a company's R&D outcomes rather than its capacity to monetize, investors may not always see direct benefits. In complex situations, patents may even convey potential technological, financial, and evaluative risks associated with a company, thereby hindering the company's ability to attract external investment. Higgins and Gulati (2006) also found that the facilitative effect of patents on venture capital diminishes over time.

Given the inconsistent conclusions between technical patents and venture capital, our study aims to investigate whether technical patents emit a positive signal for startups. Thus, utilizing venture capital and patent data from startups, this paper examines the influence of various types of patent signals on the accessibility of risk financing from the perspective of signal theory. Our goal is to gain a deeper understanding of the factors that affect corporate financing accessibility. Specifically, this paper seeks to address the following questions:

（1）From the perspective of company independence, can the quantity, quality, business, and legal signals of patents influence a company's financing accessibility?

（2）From the perspective of company associations, can the technological similarity of startups and the business signals of patents impact a company's financing accessibility?

(2)Research Significance

From a theoretical perspective, on one hand, existing research on the relationship between enterprises and venture capital primarily focuses on the impact of venture capital on enterprise R&D investment, technological innovation capabilities, and investment performance. There is a notable gap in in-depth studies regarding whether patent signals prior to venture capital involvement guide these investments. This article not only considers signal transmission from the perspective of corporate patent characteristics but also integrates the heterogeneous features of venture capital into the research framework. It examines how the reputation and attention of venture capital institutions influence the relationship between patent signals and venture capital, thus broadening the scope for understanding the impact of patent signals and offering theoretical insights for enhancing the venture capital engagement of technology-based startups. On the other hand, while many scholars have explored corporate patents, most have focused solely on the quantity of corporate patents or the patent development characteristics of individual enterprises. Less attention has been paid to the cumulative effects of multiple signals such as quantity, quality, legal, and business signals. Furthermore, in terms of measuring technological similarity among startups, existing studies often rely on coarse IPC classification, which does not adequately reflect the technological nuances of startups. This study pioneers a measurement method for technological similarity that better aligns with the characteristics of startups and empirically tests its effect on financing accessibility, enriching the discourse on how business signals from patents impact venture capital.

From an application and practice perspective, in the context of enterprise

transformation and high-quality economic development, accelerating technological innovation and enhancing independent innovation capabilities are imperative for technology-based SMEs. Thus, continuous increases in R&D investments are essential for technology companies to maintain their innovative status and core competitive advantages within the industry. The conclusions of this paper hold significant real-world relevance for technology-based SMEs, venture capital institutions, and government regulatory agencies. Firstly, since the quantity, quality, legal, and business signals of patents showcase a company's technological innovation capabilities and investment appeal, they can increase the scale of venture capital investment. This offers new insights for technology-based SMEs seeking to expand external financing. Such SMEs should enhance the disclosure of their patent information and the transmission of business signals. This will help technology companies effectively manage and utilize their patents, release positive core business signals, and improve their financing capabilities. Secondly, this paper enhances the measurement of technological similarity among SMEs using machine learning methods, providing a new approach for assessing patent similarity. This method can serve as a reference for startups in identifying potential competitive relationships and partners. Thirdly, it is crucial to explore which signals can heighten the sensitivity of venture capital institutions to optimize investment decisions and improve the match rate of investment and financing. The proposed method for measuring technological similarity also offers new solutions for investors to identify relevant enterprises. Finally, the policy recommendations derived from the research results will aid China's patent management departments in enhancing the patent system and assessing patent value, thus promoting

the healthy development and beneficial cycle of technological innovation and venture capital.

1.2 Research Content and Methods

Part One: Introduction. This section introduces the research background, objectives, and significance of the thesis. It discusses the impact of corporate patent signals on financing and underscores the importance and necessity of measuring and testing the various signals from patents on the financing of startups.

Part Two: Theoretical Foundation and Literature Review. Initially, the theoretical foundations applied in this research are elucidated, including an introduction to signal theory. Subsequently, the literature on venture capital operations and financing availability is reviewed, providing objective and concrete evaluations of representative viewpoints. This is followed by a summary of the literature concerning the impact of technology patents on venture capital and the evidence of the existence of technology similarity effects. Finally, the differences between domestic and international research are compared, critiques of existing research are provided.

Part Three: Theoretical Analysis and Hypotheses. This section is composed of five parts: (i) analysis of the impact of patent quantity signals on financing availability; (ii) analysis of the impact of patent quality signals on financing availability; (iii) analysis of the impact of patent legal signals on financing availability; (iv) analysis of the impact of patent business signals on financing availability.

Part Four: Data Sources and Empirical Testing Strategy. This section is organized

into four subsections: (i) an introduction to the data sources utilized in this paper; (ii) a detailed explanation of the variables employed in the empirical analysis, including the primary variables (four types of patent signals) and additional control variables; (iii) an overview of the econometric models and testing methodologies applied to evaluate various hypotheses, featuring classic panel regression analysis and survival analysis; (iv) a presentation of the descriptive statistics for these variables.

Part Five: Empirical Analysis. Drawing from the financing and patent data of startups, and referencing existing literature on constructs such as firm technological similarity, patent signals, and firm financing size, this paper employs the distribution of patents granted to firms to formulate variables for startups' technological linkages and multiple patent signals. These variables serve to test the following hypotheses: (i) the patents of a firm generate a cumulative signal effect on its financing availability; (ii) the financing conditions of technologically similar associated enterprises can forecast the financing situations of the target enterprise; (iii) additional analysis on how the characteristics of venture capital institutions themselves (such as the reputation and attention they command) influence the market performance of multiple patent signals.

Part Six: Conclusions and Implications. This section synthesizes the research findings and, in conjunction with the theoretical and empirical analysis, offers policy recommendations to improve the financing framework for startups and increase the efficiency of financial markets. Additionally, it outlines the limitations or deficiencies of this thesis and suggests directions for future research.

1.3 Research Contributions

The most significant contribution of this paper is the construction of a technological similarity measure for startups by integrating cutting-edge deep learning methods to perform word-level analysis. Existing studies primarily use the International Patent Classification (IPC) to measure technological similarity, which presents several limitations. Firstly, the traditional IPC classification method, adhering primarily to an application-first and function-secondary principle, fails to accurately reflect the technical themes of patents within startups. Additionally, different IPC classes and subclasses may overlap significantly yet are categorized distinctly, which is more pronounced in patent similarity among startups. Therefore, the technology similarity measurements used for listed companies are not appropriate for the objectives of this study. This paper innovatively combines deep learning and machine learning to construct a technology similarity measure specifically tailored for China's startup financing market.

Secondly, the paper employs panel regression and survival analysis to test the varied impact effects of multiple patent signals on financing availability. Previous research has often focused on a single patent signal and has not fully analyzed the different types of patent signals from a systemic, integrated perspective.

Finally, this paper demonstrates the presence of business signals in the startup market, where technologically related startups exhibit a certain "lead-lag" effect in terms of financing scale, investment rounds, and the duration of securing financing. This influence effect is attributed to investors' limited attention, which subsequently leads to irrational pricing in the investment and financing market.

II. Theoretical Foundation and Literature Review

This chapter initially defines and elucidates the concepts and characteristics of venture capital and patents, then discusses and analyzes the theories pertinent to this paper's research. It comprises four sections: enterprise technology patent signals, venture capital operations and financing availability, the impact and mechanisms of technology patents on venture capital, and the influence of technological similarity on investment value.

2.1 Enterprise Technology Patents and Their Signal Function

Patents are a reflection and legal safeguard of innovation entities' research and development outcomes. Their ultimate value realization must transition into the main sphere of economic activities and be converted into actual productivity, that is, the market value conversion of patents. As an output of corporate innovation, patents extend beyond merely securing market returns through intellectual property protection; they also function as an active signaling mechanism to reduce information asymmetry with investors. Since patents showcase a company's R&D strength, technological innovation capabilities, and investment appeal, venture capital can utilize patent signals to assess whether an enterprise merits investment. Furthermore, these signals help optimize investment decisions and maximize returns. Existing research has theoretically confirmed the viability of corporate patents in transmitting signals to venture capital and has further empirically validated the utility of patents as crucial indicators of startups' technological innovation capabilities and corporate value in three main aspects.

(i) As a critical component of innovative output, patents demonstrate a company's R&D strength, technological accumulation, and future market potential and value. They also highlight the company's innovation team's strength, its ability to attract top talent, and receive national recognition and subsidies, thus reducing information asymmetry with investors and bolstering their investment confidence (Edward and Ann, 2009).

(ii) Once a patent is filed and approved by the national intellectual property office, relevant information about the company's patents can be promptly accessed from the official website. This official information can alleviate information asymmetry during corporate financing and readily create patent signals (Chen Zonghan et al., 2017).

(iii) The granting of a patent provides legal assurance of the validity of the number of patents a company can leverage, offering legal protection and embodying high innovation values such as novelty, creativity, practicality, and difficulty in imitation (Long, 2002).

From an empirical standpoint, current studies indicate that patent signals significantly mitigate information asymmetry between companies and investors. Long (2002) notes that corporate patents reflect the current status of a company's R&D projects, aiding investment institutions in evaluating the company's future development. Hsu and Ziedonis (2013), Conti (2013), and Mann and Sager (2007) assert that patents are the most direct and effective means of gauging a company's innovation capability and can serve as benchmarks to evaluate a company's technological innovation capacity. Caldera (2010) observes that patent quality can more accurately depict the quality of innovative outputs, propel a company's innovative progress, and boost its profitability. Chen

Zonghan (2017) points out that venture capital firms often use corporate patent metrics to assess their innovation capacity when investing in startups, thereby adjusting the company's value assessment. Zheng Ying (2018), Xu Xiangyang (2018), and others believe that patents play a crucial signaling role in companies securing financing from venture capital institutions. In summary, both theoretically and empirically, patents aid investors in evaluating a company's innovation capability and corporate value and are effective in reducing information asymmetry between companies and investors.

2.2 Venture Capital Operations and Financing Accessibility

Venture capital (VC) is a form of equity investment focused on providing capital support to unlisted startups and actively engaging in their management, with the aim of achieving capital appreciation and exiting the investment as the startups mature. The operations of venture capital typically consist of two main aspects: the capital operation and growth process of the venture capital firms themselves, and the investment and management process alongside the startups.

Firstly, before making an investment, venture capital firms usually undertake project screening, selecting potential startups based on criteria such as founder background, team quality, technical level, and business model. Startups must also proactively showcase their development potential to attract investment. Once an investment is secured, venture capital firms generally engage actively in the management of the companies they invest in and provide value-added services to support the startups' growth. According to the theory of information asymmetry, venture capital firms and startups often encounter

information imbalances, prompting venture capital firms to engage actively in the management of the invested companies to mitigate potential moral hazards.

Secondly, based on the enterprise life cycle theory, the phases of startups can typically be segmented into seed, startup, growth, and maturity stages. From the standpoint of technology transfer, these stages correspond to the R&D, commercialization, industrialization, and so forth, of high-tech enterprises. Technological development occurs across all these stages.

Research in China on venture capital and financing accessibility primarily examines the effects of venture capital on enterprise innovation (Chen Si et al., 2017; Wen Jun and Feng Genfu, 2018), IPO performance (Zhang Xueyong and Liao Li, 2011; Zhang Xueyong and Zhang Yeqing, 2016), and corporate value (Wu Chaopeng et al., 2012; Zhao Jingmei et al., 2015; Cai Ning and He Xing, 2015; Dong Jing et al., 2017), with fewer studies focusing on the factors influencing venture capital. A persistent debate exists regarding whether "innovation priority" or "venture capital priority" prevails, that is, whether it is the innovation of startups that draws venture capital, or if the involvement of venture capital fosters innovation in startups, or perhaps both aspects mutually reinforce each other. Most extant research supports the "venture capital priority" argument, suggesting that venture capital fosters startup innovation, while often overlooking how startup innovation might also attract venture capital. Chen Si et al. (2017) demonstrate that venture capital facilitates business innovation through a sample of A-share listed companies from 2006-2011. Wang Lanfang and Hu Yue (2017), using data from CVsource's startups, empirically confirm that venture capital promotes business

innovation. Furthermore, some studies suggest a nonlinear relationship between venture capital participation and business innovation. Wen Jun and Feng Genfu (2018) find that the impact of venture capital on business innovation exhibits a U-shaped relationship, initially decreasing then increasing. Wadhwa et al. (2016), using pre-IPO data from 2004-2013 for companies on the Shenzhen SME Board and ChiNext, discover an inverted U-shaped relationship. Wen et al. (2018) indicate that the relationship between venture capital involvement and the level of enterprise innovation is nonlinear. Tang Manping et al. (2019) find that only state-backed venture capital fosters business innovation, while foreign and mixed-capital venture capital does not impact innovation.

The main reasons for the lack of consensus in the debate between "innovation priority" and "venture capital priority" include: firstly, the absence of robust means to assess the innovation capability of startups, as data on startup innovation prior to receiving venture capital (e.g., patent data for unlisted startups) is needed, and the development of this database in China has been relatively slow. Secondly, most existing studies fail to address potential endogeneity problems because empirical research methods have inherent limitations.

2.3 The Impact and Mechanism of Technology Patents on Financing Accessibility

Corporate patents play a pivotal role in fostering investment in enterprises (Pan Yanan, 2020) and represent an important intellectual property asset. As manifestations of a company’s innovative achievements, they are essential for startups. Current research on technology patents and venture capital financing accessibility falls into two categories:

The first examines the impact of corporate technology patents on startup venture capital financing, both theoretically and empirically. The second explores the mechanisms of patents on startup venture capital financing accessibility, considering the various types and stages of venture capital development.

From the perspective of impact effects, the influence of technology patents on venture capital financing accessibility is multifaceted. On one hand, patents may enable startups to capture market share and enhance their investment scale (Cohen et al., 2000; Graham and Sichelman, 2009), thereby facilitating external financing. Mann and Sager (2007), analyzing data from startups in the software industry, discovered that patents maintain a significant and robust positive relationship with the rounds of venture capital financing, total investment received, equity exits, and subsequent venture capital funding. Levitas (2009) and colleagues, using a sample of 108 American biotechnology firms, affirm that patents serve as an important signaling mechanism to the capital market, reducing information asymmetry between companies and venture capital firms, and consequently decreasing the companies' need to maintain liquid assets. Domestic studies also verify the positive effect of patents on the scale of venture capital. Xu Liang (2016) suggests that patents help diminish the level of information asymmetry between startups and venture capital firms, aiding startups in securing venture capital. Xu Xiangyang and others (2018), from the standpoint of "venture capital-patent signal sensitivity," analyze the impact mechanism of patents on venture capital using all financing events of A-share listed companies as the research sample, finding that corporate patents significantly enhance the likelihood and amount of investment in the first round of financing. Fu Haojie

(2019), using data from companies listed on the Growth Enterprise Market, finds that while the number of patents is not directly related to venture capital, the quality of patents and their industrial heterogeneity significantly influence the financing of startups by venture capital. Meng Tao and Xu Guanglin (2020), analyzing data from 117 unicorn companies in China from 2016-2018, determine that the number of patent applications is a primary driver of the increasing valuation levels and speed of unicorn companies.

On the other hand, some studies reveal that patents can negatively impact startups' ability to obtain venture capital. Heeley et al. (2007) observe that in the high-tech industry, patent applications and inventions are time-consuming and costly activities, merely representing the R&D results of companies and not their capacity to monetize, thus not appealing to investors. In complex scenarios, patents may even signal future technological, financial, and evaluative risks to the company, thus hindering the company's ability to secure external investment. Chen Jin and others (2016), integrating signal theory and prospect theory, contend that patents transmit both value-added and risk information, and venture capital firms weigh these signals differently depending on the context. They find, using data from 255 information technology companies that received venture capital from 2004 to 2013, that both breakthrough and incremental innovation patents significantly increase company valuation, but the influence of breakthrough patents decreases with successive financing rounds while the impact of incremental patents diminishes with the rising status of venture capital institutions.

From the perspective of mechanisms, scholars who assert that patents facilitate startups in obtaining venture capital generally subscribe to two viewpoints: the quality

signal view and the property protection view. The quality signal view posits that patents act as indicators of a startup's innovative capabilities, conveying quality information to venture capitalists, helping to alleviate information asymmetry between startups and venture capitalists, and thus more effectively attracting venture capital. Meng Dabin and Li Yang (2019), within the framework of signal transmission theory proposed by Spence (1973), utilize a sample of 178 startups listed on the New Third Board in Tianjin and employ the Tobit model to demonstrate that patents attract venture capital and that invention-type patents have a stronger financing signal function than utility-type patents. The positive impact of patents on venture capital financing diminishes with subsequent financing rounds, being significant in Series A but less so in rounds B and C, thus supporting the quality signal viewpoint. Qi Su and Liu Lichun (2020), using data from 427 companies listed on the Growth Enterprise Board, find that patents enhance the valuation of investee companies by venture capital institutions, and this effect is more pronounced in the early stages of financing and with more influential venture capital institutions. As financing rounds progress, the correlation between patents and the valuation of investee companies by venture capital gradually diminishes, supporting the quality signal viewpoint.

The property protection view asserts that patents serve a protective function, safeguarding the company’s products, warding off competitors, and expanding market share, thereby more readily attracting the interest of venture capitalists. Vo (2019), analyzing a sample of 468 early-stage startups in Canada, acknowledges that patents positively influence the acquisition of venture financing. He argues that the impact of

patents on venture capital decisions is predominantly through their property protection function rather than the technical quality signals they provide.

2.4 Impact of Technological Similarity on Investment Value

Corporate technological innovation not only yields private benefits for the company itself but also imparts social benefits such as value, productivity, and innovation to other firms that are technologically similar. Hence, companies may forge strong technological ties within specific niche technology areas, even if they have little overlap in product markets. These affiliations can confer a technological premium on related companies (Lee et al., 2019), influencing various aspects of the target company. The mutual influences among technologically affiliated companies have emerged as a significant driver of economic growth, offering new avenues for investors.

Concerning whether corporate innovative R&D leads to substantial spillovers and similar effects, existing research has predominantly concentrated on the stock market. Owing to the spillover nature of knowledge, valuable technological information or knowledge can be inadvertently leaked, and companies that invest in R&D cannot prevent others from freely benefiting from their R&D endeavors. Companies that reap benefits from R&D investments do not compensate for the use of the knowledge generated by these activities, which reduces their production costs (Reinganum, 1981; Spence, 1984; Bernstein and Nadiri, 1989). This, in turn, fosters productivity growth, impacting the profits and market value of the companies.

In terms of the mechanisms of technological similarity effects, most scholars

typically interpret it from the perspective of investors' underreaction to information. Chan et al. (2001) contend that companies with high R&D expenditure yield higher returns because investors underreact to information about the company's operations. Despite past performances that are average or even poor, companies continue to invest in R&D, signaling that these stocks are undervalued and investors are likely unaware of this, underestimating these stocks' potential returns. They also demonstrated that companies with high R&D spending and mediocre past performance tend to perform well in subsequent years. Hirshleifer et al. (2013) showed that investors' underreaction to related information stems from their limited attention. However, the question of whether investors' limited attention leads to technological similarity effects in startups remains a relatively unexplored area in the literature.

From the perspective of signal theory, due to the complexity of patent information processing (Qi Su and Liu Lichun, 2020), certain business signals from technology-based startups are not promptly captured by investors. For instance, in the healthcare industry, some biopharmaceutical companies involved in the R&D process may appear unrelated, such as those primarily focused on new drug development versus those engaged in pharmaceutical engineering. Nevertheless, because they may involve some core steps in pharmaceutical production, they might share the same upstream companies. Traditional industry classifications or patent IPC classifications may not categorize them as the same type of business, leading to investors possibly overlooking these companies and failing to analyze them in a timely manner due to limited attention. This results in mutual influence effects of technological similarity signals among these companies.

2.5 Literature Review

This section highlights that the majority of existing studies contend that patents play a beneficial role in enabling startups to secure venture capital investment and enhance financing accessibility. The main mechanisms of this influence are twofold: Firstly, patents signify the innovative capacity of startups and convey high-quality information to venture capital institutions, which helps to mitigate the information asymmetry between startups and venture capitalists, thereby increasing the scale of venture capital investment. Secondly, as a form of intellectual property, patents protect the products of startups, ward off competitors, and expand market share, thus aiding in attracting venture capital. However, the literature presents controversy over these mechanisms, with little attention given to the heterogeneity issues of signal theory. Additionally, some studies suggest that patents can transmit technology-related signals, leading to the transfer of investment value among associated companies.

Existing research has empirically tested the influence of patents on venture capital, producing a wealth of conclusions, yet there remains scope for further investigation. Firstly, the impact of patent signals on venture capital has rarely been studied from a systematic perspective. While some scholars have explored the impact of a single patent signal on corporate risk financing, a comprehensive analysis of how different types of patent signals affect venture capital is lacking. Secondly, the findings regarding whether patents facilitate startups in obtaining venture capital financing and the mechanisms involved are inconsistent and warrant further exploration. Currently, domestic scholars primarily focus on the impact of patent signals of listed companies on the scale of venture

capital, with a lack of in-depth research on the guiding role of patent signals of pre-IPO tech startups on venture capital. Thirdly, concerning the measurement of business signals and technological similarity and their effects on financing accessibility, most existing studies concentrate on the stock market, with limited focus on startups. Fourth, the measurement methods for technological similarity are predominantly based on the IPC main classification of patents; however, due to the concentrated business scope of startups, using the IPC classification numbers to measure technological similarity among startups often leads to the issue of low distinctiveness between companies. Lastly, few scholars have integrated the technological similarity of patents among startups from different sub-industries, financing stages, and technological attributes into the research framework of the relationship between patent signals and venture capital.

III. Theoretical analysis and hypothesis development

This chapter examines the relationship between the number and quality of patents, legal aspects, and business signal effects, and the availability of financing. It conducts a theoretical analysis and accordingly proposes research hypotheses.

3.1 The Impact of Patent Quantity Signal on Financing Accessibility

Technology-based startups, in their nascent stages, often grapple with issues such as immaturity and underdeveloped corporate governance systems. Additionally, they have not yet established stable internal cash flows or profitability, which complicates their ability to secure financing through traditional means. Hence, the introduction of venture capital becomes particularly vital for these enterprises. However, during this phase, the external environment may be complex, prompting technology-based startups to limit the disclosure of external information to safeguard their core technologies and confidential data. This restriction makes it challenging for venture capital institutions to accurately assess the potential value of startups, thereby exacerbating information asymmetry and increasing the risk of adverse selection.

According to Spence's (1973) signaling theory, in markets characterized by information asymmetry, entities can transmit signals to mitigate decision-making errors caused by this asymmetry. Signaling involves the transmission of valuable information through observable actions, allowing outsiders to ascertain the true value of goods or

services. If financing enterprises experience information asymmetry in their dealings with venture capital institutions, they can use “signaling” to display credible internal information, showcasing the enterprise’s future development prospects and investment value, thus reducing information asymmetry. This strategy not only lowers the adverse selection risk for venture capital institutions but also enhances the financing opportunities for high-quality enterprises. Patents, as indicators of corporate innovation outcomes, constitute an essential element of credible internal information. Particularly after the patent office’s examination and authorization, the authoritative nature of the granted patent information is heightened, making it an effective signal that showcases a company’s innovation capabilities and helps mitigate the effects of information asymmetry.

Given that the quantity of a company's patent applications is publicly accessible, existing research frequently utilizes patent application quantity to gauge the patent signals of enterprises, reflecting the technological innovation capabilities of R&D in technology-based startups. When startups file patent applications, they have already incurred certain R&D and application costs, indicating their strengths in technological innovation. Consequently, the number of patent signals can become a crucial indicator for investors to evaluate the potential of an enterprise. Studies, such as those by Hsu and Ziedonis (2003), Conti (2005), Mann and Sager (2006), Meng Dabin et al. (2017), and Xu Xiangyang et al. (2018), demonstrate that startups with a higher number of patents are more likely to secure venture capital. This is because an increase in patent numbers not

only signals a company's innovative prowess and developmental potential but also builds a competitive edge that attracts investors.

In the case study discussed in this article, EHang Intelligent Holdings Limited in Guangzhou City secured a loan of 60 million yuan between 2020 and 2022 through the pledge of 13 patents, effectively addressing the financial challenges faced by technology SMEs due to the lack of real estate collateral. This case underscores the role of patents as collateral, highlighting particularly how the number of patent applications can facilitate financing.

From a policy support perspective, using Sichuan Province as an example, the Sichuan Provincial Department of Science and Technology and the Department of Finance launched the 'Tianfu Sci-Tech Loan' pilot policy in 2020, aimed at alleviating the financing difficulties and high costs encountered by technology enterprises. By the end of 2023, financial institutions in the province had extended a loan balance of 330.24 billion yuan to high-tech enterprises, reflecting a year-on-year growth of 13.94%. This suggests that the number of patents, as an indicator of corporate innovation capability, might play a positive role in securing government-led fund equity investments. This further evidences that an increase in the number of patents not only boosts a company's market competitiveness but also serves as a crucial foundation for securing financing, especially for technology SMEs, where the number of patents is critical to their development.

In summary, an increase in the number of patents signals that a company has potential in R&D and innovation, and this signal forms the basis for the company to convey various

signals to investors. Based on this observation, we propose the following hypothesis:

H1: The greater the number of patents applied for by technology startups, the stronger the patent signal transmitted, and the greater the scale and likelihood of obtaining venture capital.

3.2 The Impact of Patent Quality Signal on Financing Accessibility

According to the resource-based view, the key to sustaining a competitive advantage lies in a company's unique resources and strategic assets, which are often distinctive and inimitable, making them difficult for other companies to replicate (Wu Shanling and Huang Yizheng, 2023). Patents, as special resources protected by intellectual property rights and characterized by novelty, creativity, and utility, become significant strategic assets of a company, conferring a competitive edge. However, measuring a company's innovation capability solely by the number of patents can be limiting. Some companies may apply for numerous low-quality patents to inflate their numbers, which does not accurately reflect the true level of innovation. Thus, judging a company's innovation capability merely by quantity could be misleading and not fully indicative of its technological research strength and innovation capability. To more accurately assess a company's technological innovation signal from patents, it is also essential to consider the quality of patents.

Compared to mere quantity, the quality of patents more effectively mirrors the depth and breadth of a company's technological innovation capabilities. Liu Deyun et al. (2023) contend that most signal models differentiate features based on quality to fulfill the

demands of signal receivers. Superior patent quality signifies stronger innovation capabilities and more valuable signals, which positively influences financing accessibility. Regarding the evaluation of patent quality, Fan Xiuxiu et al. (2023) assert that it reflects a company's leadership and depth in technological development, embodying the scope and complexity of its innovative knowledge. Consequently, they assess patent quality from two dimensions: the breadth of the distribution of IPC main classification numbers and the number of claims, finding that both dimensions significantly positively influence venture capital amounts, while the quantity and depth of patents markedly boost the post-investment valuation of strategic emerging enterprises.

Furthermore, the frequency with which a patent is cited by others also serves as an indicator of the degree of knowledge flow, technological exchange, innovativeness, and positioning at the technological forefront. These citation metrics not only underscore the significance of the patent but also its quality and status within the trajectory of technological advancement. In summary, the number of citations a patent receives reflects market recognition of a company's patents and underscores their pivotal role in the innovation ecosystem (Ma Zhiguo et al., 2022).

In our case study focusing on the photovoltaic industry, according to the 'Photovoltaic Industry Patent Development Report' jointly issued by the National Industrial Information Security Development Center and other departments, China led the world in the total number of patent applications in the photovoltaic industry in 2023. There were 3,509 patents cited more than 10 times and 194 patents cited more than 50 times, illustrating the expanding influence of these patents. These highly cited patents likely had a positive

impact on related companies' financing efforts, as they demonstrated the companies' innovation leadership and market recognition in the photovoltaic technology field. Additionally, the breadth of knowledge covered by the patents and the number of IPC main classifications also reflect the quality of the patents. Nest Labs, a startup focused on smart home products, is renowned for its innovative smart thermostats and smoke detectors. Nest holds multiple patents across different fields, encompassing both hardware and software innovations. The quality signals from these patents highlight their technological advancement and ultimately attracted Google's attention, leading to its acquisition for $3.2 billion in 2014.

In conclusion, higher-quality patents typically suggest that a company has invested significantly in technological research and development, and that its technology is more innovative and complex. This perception enhances venture capital firms' confidence in the company's innovative capabilities, thus improving the accessibility of financing. The quality of patents can be assessed through the breadth of the IPC main classification number distribution, the annual number of IPC applications, and the number of citations. Based on this understanding, we propose the following hypothesis:

H2: The higher the quality of patents held by a technology-based startup, that is, the greater the annual number of IPC applications, the broader the patent coverage, and the higher the number of citations, the stronger the technical signal transmitted, and the larger the scale and likelihood of obtaining venture capital.

3.3 The Impact of Patent Legal Signal on Financing Accessibility

Due to the legal attributes of patents, they also convey distinct legal signals. Patent law endows patent holders with ownership and exclusive rights to use a technology, but the robustness of these rights hinges on factors such as the patent's duration of protection, stability, scope, and legal status. These factors indicate the stability of a company’s operations concerning technology implementation and product sales, which directly influence investors' risk assessment in venture capital decisions.

When faced with substantial investment risks, investors often reassess the business value, reluctant to assume excessive risk, which in turn impacts the accessibility of financing. Among different patent types, the legal signal of invention patents exerts the most profound influence on venture capital decisions for startups. In China, invention patents have two legal statuses: published and granted. Granted invention patents allow holders to monopolize the technology within legally sanctioned limits and generate revenue from it. Conversely, published invention patents undergo a six-month examination period during which all details are public, allowing anyone to challenge or question their validity.

Current research shows that the legal status of patents sways venture capital investment decisions in startups. For example, studies of foreign patents have demonstrated that published invention patents more accurately reflect a startup's technological level than granted patents (Schilling et al., 2015), as the grant status is significantly influenced by human factors. However, this conclusion has yet to be widely confirmed in technology startups. Additionally, as a fundamental aspect denoting the legal

status of a patent, the number of valid claims mirrors the level of legal protection provided by the patent. The more complex the technical content a company aims to protect, the more comprehensive the protection it seeks through its claims. From the perspective of patent drafting, more claims should correspond to these demands, thus showing a correlation between the number of claims and a company's legal rights (Ernst, 2001). Therefore, the number of claims is closely linked to a company's legal protection and can, to a degree, signify the legal signal of a patent. Lastly, the number of patents within the same family is also deemed an effective measure of a patent's legal signal. Due to the territorial nature of patents, their legal effectiveness is confined to their sovereign jurisdictions, and most countries adopt a "publish early, examine late" patent approval system. Consequently, many patents are registered in various countries as part of a patent family under the Patent Cooperation Treaty (PCT), forming a collection of patents with similar characteristics. Patent families not only allow for an understanding of a patent's application status across different countries or international patent organizations but also provide insights into potential market expansions, thereby conveying a series of legal signals to investors.

In our case study, numerous companies on the Sci-Tech Innovation Board (STAR Market) have been unable to list due to intellectual property litigation. From 2019 to 2021, there were 7,839 related judicial lawsuits among companies listed on the Sci-Tech Innovation Board, with disputes over infringement of invention patent rights ranking third. Suzhou Minxin Microelectronics Technology Co., Ltd. (Minxin Shares) and Nanjing Milan Medical Technology Co., Ltd. (Milan Medical) faced patent ownership litigation

during their IPO processes on the Sci-Tech Innovation Board, while Yifang Biological Technology (Shanghai) Co., Ltd. (Yifang Biological) encountered delays in listing due to intellectual property disputes. These incidents underscore the critical role of intellectual property and the legal signals of patents in the financing trajectory of companies, where certain strategic non-market actions can enable companies to capture market opportunities and sustain organizational legitimacy.

Therefore, to further explore the influence of the legal status of invention patents on financing accessibility, we utilize the number of published invention patents, the number of valid claims, and the number of family patents as indicators for measuring the legal signal of patents. Based on this analysis, we propose the following hypothesis:

H3: The greater the number of published invention patents, valid claims, and family patents held by a technology-based startup, the stronger the legal signal transmitted, and the greater the scale and likelihood of obtaining venture capital.

3.4 The Impact of Patent Business Signal on Financing Accessibility

Since companies do not operate in isolation and often have various interconnections, their patents also reflect relationships between different companies. From this perspective, patents not only possess standalone signals such as quantity, quality, and legality but also transmit business signals among companies. The business signals of a patent primarily encompass its potential for commercialization, industrialization, and marketability. These capabilities illustrate how a company can translate theoretical innovations into practical applications and generate value in a competitive market environment. Consequently, a

patent’s business signals are crucial for evaluating a company’s potential for business growth and its future prospects. Upon perceiving these signals, investors perform a comprehensive assessment of the company's technological value, which influences their valuation of the enterprise.

In terms of measuring the business signals of patents, technological similarity plays a pivotal role. According to Reinganum (1981), due to knowledge spillover, technologically similar companies may exchange knowledge and technology even without formal cooperation. This spillover can lower R&D costs, boost productivity, and ultimately increase market value. Existing research has demonstrated that effects of technological similarity are observable in the stock market, where the technological congruence between companies influences their market performance and returns (Lee et al., 2019). Similarly, in the financing market for technology startups, technologically related startups can impact each other's financing accessibility. The primary reasons are twofold: First, companies operating in similar technological sectors, thus sharing similar factor and product markets, encounter comparable market risks, leading their investment values to fluctuate in parallel; second, from the perspective of collaboration among startups, some technologically similar companies may opt for joint R&D endeavors, which reduces innovation costs and shares the risks of innovation, with mutual benefits influencing each other’s investment values.

In our case study, using Illumina Inc. and Regeneron Pharmaceutical Inc. as examples, although their core businesses in gene sequencing technology and biopharmaceuticals do not directly overlap, their shared classifications in the International Patent Classification

(IPC) may disclose technological similarities in specific areas. For instance, they might share foundational technologies in fields like bioinformatics (G06F) or drug delivery systems (A61M). For venture capitalists, this technological similarity is perceived as a positive business signal because it suggests that both companies have strong R&D capabilities and substantial innovative potential. Furthermore, technological similarity may prompt the two companies to explore strategic collaborations or cross-investment opportunities to leverage each other's technologies and expand their market reach. For example, Regeneron might be interested in Illumina's genomic technologies for developing personalized medical solutions, while Illumina could find potential in collaborating with Regeneron on drug development.

Thus, technological similarity can serve as a metric to gauge a patent's business signals. This can be deduced by analyzing the patent portfolios and technological fields of startups. When two or more companies demonstrate high technological similarity in their patents, it suggests they may share knowledge in their R&D processes or possess technological synergies, which, in turn, enhances their investment opportunities and scale. Building on this, from the perspective of inter-company associations, we propose the following hypothesis regarding the business signals conveyed by patents:

H4: Technological similarity between companies can characterize the business signals of patents, and the investment scale of technologically similar companies positively influences the scale and accessibility of venture capital obtained by technology-based startups.

IV. Data and Research Design

4.1 Data sample and sources

The data for this study is sourced from two primary platforms: IT Juzi (itjuzi.com) and the Incopat global patent database (incopat.com). IT Juzi is a seasoned provider of venture capital data services for the new economy, offering extensive information on equity investment activities, exit events, venture capital firms, and invested companies. This robust data foundation is crucial for the analysis of investment and financing activities discussed in this paper. Within IT Juzi, the criteria used to filter companies include the abbreviated and complete industrial and commercial names, addresses, financing dates, investment rounds, amounts financed, investing institutions, and estimated valuations. Incopat, on the other hand, is an exhaustive search system that contains a vast array of patent information from across 157 countries, organizations, and regions, encompassing over 150 million patent documents. Utilizing company names derived from IT Juzi that are associated with investment and financing events, a comprehensive set of patent application data is retrieved from Incopat.

This research focuses on startups in the advanced manufacturing and healthcare sectors that have engaged in investment and financing activities. Given the emphasis on technology-driven startups, financing events post-IPO are omitted. After the removal of duplicates, a total of 16,497 startups were pinpointed, associated with 28,610 financing events. Subsequent data extraction from the Incopat patent database yielded 1,897,517 patent records for these companies, spanning the entire sample period. Pertinent patent attributes such as patent application numbers, IPC classifications, the number of valid

claims, family counts, and citation counts were extracted to develop corresponding indicators from the angles of quantity, quality, legal status, and business signals.

4.2 Variable Design

Building on the analysis of patent signal theory previously addressed, numerous factors influence the accessibility of financing for startups. This paper examines these factors from the perspectives of patent quality, quantity, legal, and business signals. The designs for the main independent variables, dependent variables, control variables, and moderating variables are delineated below.

(1)Independent variable

Drawing on the work of Zhang (2019) and Fan Xiuxiu (2023, 2024), this paper identifies five major types of independent variables related to different patent signals. To measure technological patent similarity, we employ the method proposed by Xi Xiaowen et al. (2023), which integrates Word2Vec with the LDA topic model. This approach enables precise semantic modeling at the enterprise level through word granularity, constructing a bi-modal network that effectively captures both the technological framework and similarity relationships among technology-based startups.

Signal type	Variable name	Variable Abbreviation	Description
Quantity signal	**Number of Patent**	**$\mathbf{Application\_num_{i,t}}$**	**Cumulative number of patent applications up to the year of the**

	Applications		financing event
Quality signal	Patent width	$\mathbf{Patentwidth_{i,t}}$	Utilizing the method for measuring industry concentration, the company's invention and utility model patents are weighted according to the Herfindahl-Hirschman Index at the main group level of the IPC classification.[1]
	Number of IPCs	$\mathbf{IPC\_num_{i,t}}$	Cumulative number of IPC classification codes up to the year of the financing event $\frac{\sum_{k=starting\ year}^{financing\ year} number\ of\ IPCs}{cumulative\ applicaiton\ year}$
	Number of citations	$\mathbf{Citation\_num_{i,t}}$	Cumulative number of citations up to the year of the financing event $\sum_{k=starting\ year}^{financing\ year} number\ of\ citations$
Legal signal	Number of public inventions	$\mathbf{Public\_invention\_num_{i,t}}$	Cumulative number of public inventions up to the year of the financing event $\sum_{k=starting\ year}^{financing\ year} number\ of\ public\ inventions$
	Number of required rights	$\mathbf{Required\_rights\_num_{i,t}}$	Cumulative number of required rights up to the year of the financing event $\sum_{k=starting\ year}^{financing\ year} number\ of\ required\ rights$

[1] The calculation is $1-\sum\alpha^2$, where α is the proportion of each main group category in the patent classification numbers.

	Number of families	**$\text{Family\_num}_{i,t}$**	**Cumulative number of required rights up to the year of the financing event $\sum_{k=\text{starting year}}^{\text{financing year}}$ number of families**
Business signal	**Technogical closeness-based investment amount**	**$\text{Tech\_closeness}_{i,t}$**	**For the calculation method concerning the technological relevance of the financing amount for related technology companies, constructed based on the technology similarity index, refer to the appendix for further details.**

Table 4-1 Definition of Independent Variables

(2)Dependent variables

Based on Xu Xiangyang's (2015) study, this paper utilizes the venture capital amount from each company's financing event to evaluate the influence of different patent signals on the financing accessibility of technology-based startups. To standardize the related variable data, we use the logarithm of the venture capital amount. Additionally, since the cumulative investment count reflects the frequency and continuity of investment a company receives over time, indicating investors' growing confidence, it also partially indicates the company's financing accessibility. We further use the cumulative investment count at each financing event ($Cum\_invest_{i,t}$) for the dependent variable design concerning the venture capital situation of technology-based startups. The primary rationale for selecting this variable is that the more frequently a tech startup receives

venture capital, the greater the likelihood it will secure subsequent rounds of financing, and consequently, the higher the amount of venture capital in these rounds tends to be.

(3)Moderating variables

The reputation of venture capital institutions is built upon multiple successful exits in the investment market. Highly reputable venture capital firms typically boast extensive investment experience and robust capabilities in information gathering and analysis. As a result, venture capital firms with higher reputations are more adept at identifying patent signals. We use the number of successful exits by venture capital firms（$VC\_rep_{i,t}$）to measure the reputation of these firms as a moderating variable indicator for assessing the impact of patent signals on financing accessibility (Ma Ning, 2019).

In examining the mechanism of business signals at the company association level, this paper employs the attention level of the investment firm as a moderating variable. Specifically, we measure the investor's attention level by the number of participating venture capital firms（$VC\_num_{i,t}$）.

(4)Control variables

To account for other factors that might affect patent signals, this paper selects the number of years between financing events of the financed company ($Age_{i,t}$), whether the financed company is located in Beijing, Shanghai, or Guangzhou ($VC\_num_{i,t}$), the number of venture capital firms involved（$VC\_mktexp_{i,t}$）, and the industry experience of the venture capital firms（$VC\_indexp_{i,t}$）as control variables.

Variable type	Variable name	Description
Dependent variable	$\mathbf{VC\_Amount_{i,t}}$	$\mathbf{Ln(1 + amount\ of\ venture\ capital\ financing)}$
	$\mathbf{Cum\_invest_{i,t}}$	**Cumulative amount of venture capital financing up to the current year**
Moderating variable	$\mathbf{VC\_Rep_{i,t}}$	$\mathbf{Ln(1 + number\ of\ venture\ capital\ cases\ occurred)}$
	$\mathbf{VC\_num_{i,t}}$	**Number of venture capital activities participated in at the time of the financing event**
Control variable	$\mathbf{Age_{i,t}}$	**Time elapsed since the establishment of the firm, calculated by the years since establishment**
	$\mathbf{Bsg_{i,t}}$	**Whether the firm is listed; 1 if yes, 0, otherwise**
	$\mathbf{VC\_mktexp_{i,t}}$	$\mathbf{Ln(1 +\ years\ of\ VC\ investment\ experience\ in\ the\ Chinese\ market)}$
	$\mathbf{VC\_indexp_{i,t}}$	$\mathbf{Ln(1 + growth\ rate\ of\ VC\ investment\ in\ the\ same\ industry\ over\ the\ past\ five\ years)}$

Table 4-2 Definition of Dependent Variables, moderating variables and control variables

4.3 Empirical model design

Based on the research hypotheses and theory, this paper employs multivariate panel regression analysis to construct regression models that evaluate the impact of various patent signals from technology startups on venture capital amounts and cumulative

investment occurrences, as outlined in Hypotheses 1-4:

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Application\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (1)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 IPC\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (2)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Patentwidth_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (3)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Citation\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (4)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Family\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (5)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Public\_invention\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (6)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Required\_rights\_num_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (7)$$

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 Tech\_closeness_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (8)$$

Equations (1) - (8) examine Hypotheses 1-4, specifically addressing the influence of patent quality, quantity, legal, and business signals on the scale of financing amount. In these models, $VC\_Amount_{i,t}$ represents the venture capital amount received by company$i$ at the time of financing, t, $\varepsilon_{i,t}$is the random error term, α_1 is the coefficient of the explanatory variable, and $control_{i,t}$ represents the set of control variables. Given the scaling effect inherent in the patent quantity signal, this study also incorporates patent quantity as a control effect in Equations (2) - (8), and controls for fixed effects related to the sub-industry and investment rounds of startups. Moreover, based on the independent variables in Equations (1) - (8), this study further examines the impact of patent quality, quantity, legal, and business signals on the number of cumulative venture investments, replacing the venture capital amount（$VC\_Amount_{i,t}$）with cumulative investment occurrences ($Cum\_invest_{i,t}$) in the same empirical regression model design. Due to length constraints, the latter models are not reiterated.

To further examine the moderating effect of venture capital firms, namely, the reputation and attention of venture capital firms as moderators between patent signals and financing accessibility, and to substantiate the hypothesis, this paper, referencing Liu and Yang (2018), utilizes Principal Component Analysis (PCA) to reduce dimensions and assign different weights to three major categories of firm-level patent signals, resulting in a patent integration dimension signal representation[2], $patent\_pca_{i,t}$, and designs the following multivariate regression model for mechanism testing:

$$VC\_Amount_{i,t} = \alpha_0 + \alpha_1 patent\_pca_{i,t} + \alpha_2 VC\_rep_{i,t} + \alpha_3 patent\_pca_{i,t} \times VC\_rep_{i,t} + \beta_k \sum control_{i,t} + v_i + \varepsilon_{i,t} \quad (9)$$

where $VC\_rep_{i,t}$ is the moderating variable, $patent\_pca_{i,t} \times VC\_rep_{i,t}$ is the interaction term between patent signals and the reputation of investment institutions, the definitions of other variables remain consistent with those previously described.We focus on the sign of α_3, if it is significantly positive, it indicates that the reputation of venture capital institutions positively moderates the relationship between patent signals and financing accessibility. Conversely, a negative sign indicates a negative moderating effect.

This paper employs survival analysis models to further explore the impact of patent quality, quantity, legal, and business signals on whether startups can secure financing, aiming to control for reverse causality and endogeneity issues from financing on patents. The survival analysis models used include parametric models such as the Accelerated Failure Time (AFT) model, semi-parametric models such as the Cox Proportional Hazards model, and discrete-time survival analysis models such as the

[2] The specific steps of principal component analysis are detailed in the appendix.

cloglog model. The AFT model, being a parametric approach, requires the establishment of a baseline hazard, which constrains its application scenarios. The Cox Proportional Hazards model, due to its semi-parametric nature, does not necessitate a baseline hazard and enjoys a broader application, making it the most commonly employed survival analysis model today. However, the Cox model may overlook individual heterogeneity effects and has specific requirements regarding the proportional hazards assumption, which can lead to inaccuracies in regression outcomes. In contrast, the cloglog model addresses these issues and accounts for the impact of individual heterogeneity. Given the context and application concerning financing accessibility, this paper constructs a cloglog model following Xu Jiayun and Mao Qilin (2015), and Zhang Wenfei and Jin Xiangyi (2019), as presented in the following equation:

$$F(h_{it}) = cloglog(1 - h_{it}) = \alpha_0 + \alpha_1 FD_{it} + b_k \sum control_{i,t} + \varphi_t + \varepsilon_{it} \quad (10)$$

Here, $F(h_{it}) = \log(-log(1 - h_{it}))$ represents the likelihood that startup i will secure funding at time t, with a higher h_{it} indicating a greater probability that the company i will receive funding. φ_t denotes the baseline hazard, which is a function of survival time. FD_{it} encompasses various patent-level indicators. This model delineates the influence of different types of patent signals on a firm's ability to obtain financing and the duration until subsequent funding is secured, while controlling for the reverse causality effects of financing activities on patent acquisition.

4.4 Summary statistics

Table 4-3 presents the descriptive statistical outcomes for the primary variables.

From these results, it is evident that the average amount of venture capital for technology startups ($VC\_Amount_{i,t}$) is approximately 1.3967 billion yuan. The standard deviation is around 21 billion yuan, with a minimum venture capital amount of 80 thousand yuan and a maximum of 30.5 billion yuan. This wide range illustrates the significant disparity in the sizes of venture capital allocations for technology startups. Additionally, the variable representing the number of years since the establishment of financed companies ($Age_{i,t}$) at the time of their first financing round shows that, on average, companies require about 5.29 years to secure initial venture financing. In terms of patent signals, the annual averages for patent applications ($Application\_num_{i,t}$), IPC classifications ($IPC\_num_{i,t}$), patent breadth ($Patentwidth_{i,t}$), number of family patents ($Family\_num_{i,t}$), number of claims ($Required\_rights\_num_{i,t}$), and number of citations ($Citation\_num_{i,t}$) for technology startups are 23.00, 27.59, 0.71, 32.47, 241.84, and 56.89 respectively. The corresponding standard deviations are 86.96, 46.01, 0.25, 146.35, 1302.03, and 315.51, highlighting the variability among startups regarding different patent signals. Concerning the type of venture capital firms, the average logarithmic value of the number of successful exits by venture capital firms in the sample is 3.83, peaking at 4.52 and bottoming out at 0, which suggests disparities among different venture capital firms. The average number of venture capital firms participating in each financing event is 2.19, with a minimum of 1 and a maximum of 37, underscoring the considerable variability in how attractive technology startups are to venture capital firms. Geographically, approximately 46% of technology startups are situated in economically developed regions such as Beijing, Shanghai, Guangzhou, and Shenzhen.

VarName	Obs	Mean	SD	Median	P25	P75	Min	Max
vc_amount	26757	13967.43	216416.39	2999.999	2000.000	10000.003	8.000	3.05e+07
cum_invest	26760	2.03	1.41	2.000	1.000	3.000	1.000	13.000
application_num	11873	23.00	86.96	9.000	3.000	21.000	1.000	5702.000
IPC_num	11873	27.59	46.01	14.000	6.000	32.000	0.000	1222.000
Patentwidth	11873	0.71	0.25	0.797	0.626	0.885	0.000	1.000
Required_rights_num	11873	241.84	1302.03	79.000	28.000	198.000	0.000	69984.000
Family_num	11873	32.47	146.35	12.000	5.000	29.000	1.000	7831.000
Citation_num	11873	56.89	315.51	18.000	5.000	50.000	0.000	26136.000
Public_invention_num	11873	5.40	27.84	2.000	0.000	5.000	0.000	1539.000
tech_closeness	11873	15.30	37.41	25.008	14.000	16.000	0.000	123.325
VC_num	23575	2.27	1.99	2.000	1.000	3.000	1.000	30.000
age	27480	6.01	5.29	4.000	2.000	8.000	0.000	51.000

Note: This table provides descriptive statistics for the patent and financing variables,where 'Obs' denotes the number of observations, 'Mean' denotes the average value, 'Sd' denotes standard deviation, 'Min' denotes the minimum value, and 'Max' denotes the maximum value.

Table 4-3 Descriptive Statistics of Main Variables

	vc_amount	cum_invest	application_num	IPC_num	Patentwidth	Required_rights_num	Family_num	Citation_num	Public_invention_num	tech_closeness	VC_num	age	vc_indexp	vc_mktexp	vc_rep
vc_amount	1	0.354***	0.129***	0.185***	0.120***	0.148***	0.138***	0.080***	0.086***	0.243***	0.318***	0.444***	0.224***	0.214***	0.169***
cum_invest	0.357***	1	0.074***	0.108***	0.060***	0.142***	0.075***	0.060***	0.005	0.197***	0.291***	0.263***	0.237***	0.138***	0.066***
application_num	0.118***	0.041***	1	0.863***	0.540***	0.626***	0.754***	0.715***	0.580***	0.688***	0.060***	0.200***	0.023**	0.114***	0.059***
IPC_num	0.190***	0.093***	0.769***	1	0.687***	0.859***	0.850***	0.676***	0.566***	0.691***	0.113***	0.218***	0.082***	0.172***	0.069***
Patentwidth	0.117***	0.072***	0.124***	0.324***	1	0.498***	0.518***	0.387***	0.316***	0.433***	0.058***	0.165***	0.017	0.120***	0.044***
Required_rights_num	0.108***	0.046***	0.740***	0.681***	0.086***	1	0.737***	0.776***	0.659***	0.697***	0.113***	0.149***	0.093***	0.124***	0.066***
Family_num	0.111***	0.028***	0.754***	0.710***	0.101***	0.773***	1	0.780***	0.701***	0.693***	0.084***	0.188***	0.054***	0.102***	0.082***
Citation_num	0.092***	0.025***	0.703***	0.612***	0.086***	0.861***	0.877***	1	0.810***	0.589***	0.059***	0.139***	0.027**	0.063***	0.053***
Public_invention_num	0.096***	0.008	0.856***	0.625***	0.086***	0.774***	0.704***	0.716***	1	0.525***	0.066***	0.155***	0.030***	0.037***	0.078***
tech_closeness	0.184***	0.087***	0.551***	0.782***	0.171***	0.749***	0.769***	0.634***	0.705***	1	0.139***	0.266***	0.073***	0.144***	0.069***
VC_num	0.349***	0.279***	0.071***	0.122***	0.077***	0.084***	0.080***	0.047***	0.055***	0.119***	1	0.041***	0.475***	0.146***	0.133***
age	0.353***	0.156***	0.063***	0.146***	0.104***	0.029***	0.045***	0.034***	0.044***	0.122***	0.021***	1	-0.021***	0.146***	0.100***
vc_indexp	0.207***	0.212***	0.004	0.020*	0.032***	0.028**	0.018*	0.005	0.010	0.018	0.406***	-0.055***	1	0.285***	0.359***
vc_mktexp	0.215***	0.144***	0.059***	0.120***	0.117***	0.038***	0.044***	0.054***	0.040***	0.075***	0.149***	0.118***	0.288***	1	0.488***
vc_rep	0.171***	0.063***	0.039***	0.051***	0.051***	0.031**	0.039***	0.035***	0.033**	0.043***	0.114***	0.092***	0.365***	0.464***	1

Note: *, **, *** indicate significance levels at 10%, 5%, and 1% respectively; the upper triangle represents the Spearman correlation coefficients, and the lower triangle represents the Pearson correlation coefficients.

Table 4-4 Correlation Matrix

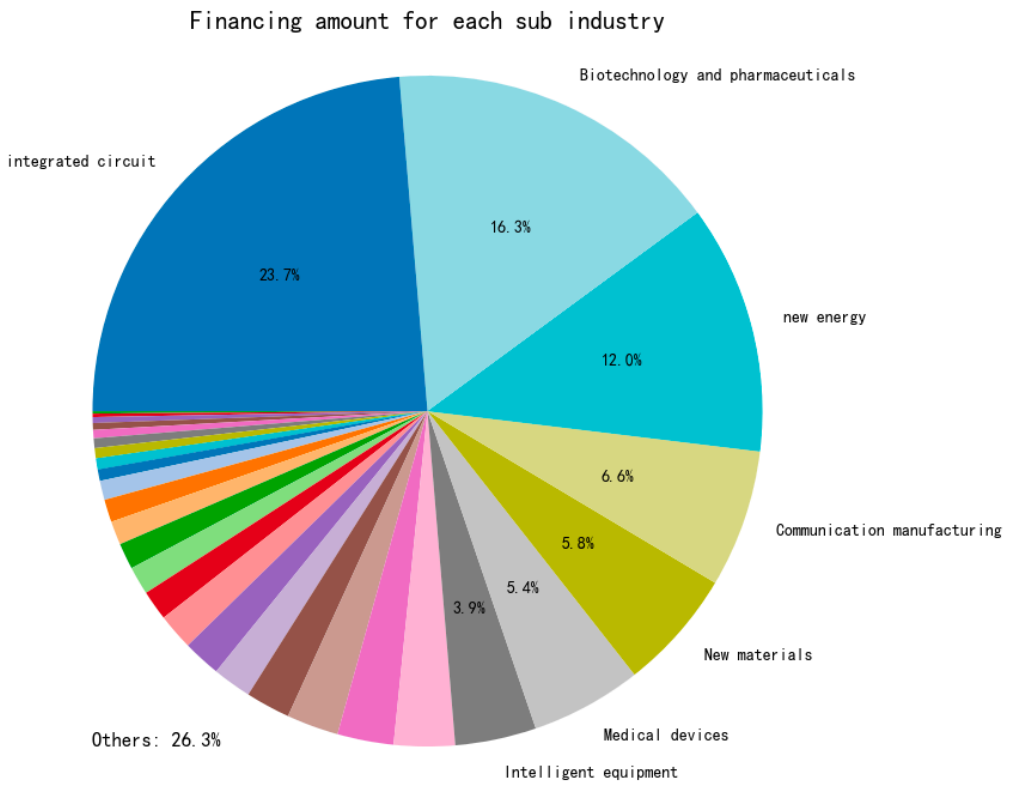


Figure 4-1: Proportion of Total Financing Amount by Sub-Industry

Additionally, this study conducts further descriptive exploratory analysis on the financing and patent characteristics across various sub-industries. From a financing perspective, among the 16,504 companies in the sample, each company averages 1.97 financing occurrences, with an average financing amount of 72.21 million yuan per occasion. As illustrated in Figure 4-1, the sub-industries receiving the largest financing amounts are integrated circuits, biotechnology and pharmaceuticals, and new energy, with integrated circuits alone accounting for 23.7% of the total sample's financing amount.

From the viewpoint of average financing occurrences, as depicted in the left chart of Figure 4-2, sub-industries such as integrated circuits, robotics, biopharmaceuticals, and medical devices report a higher average number of financings, typically around two times.

After categorizing all startups into initial financing stage and commercialization financing stage based on financing rounds, as shown in the right chart of Figure 4-2, companies in the biotechnology and pharmaceuticals sector predominantly remain in the initial financing stage, whereas companies in the new materials and new energy sectors are largely in the commercialization financing stage.

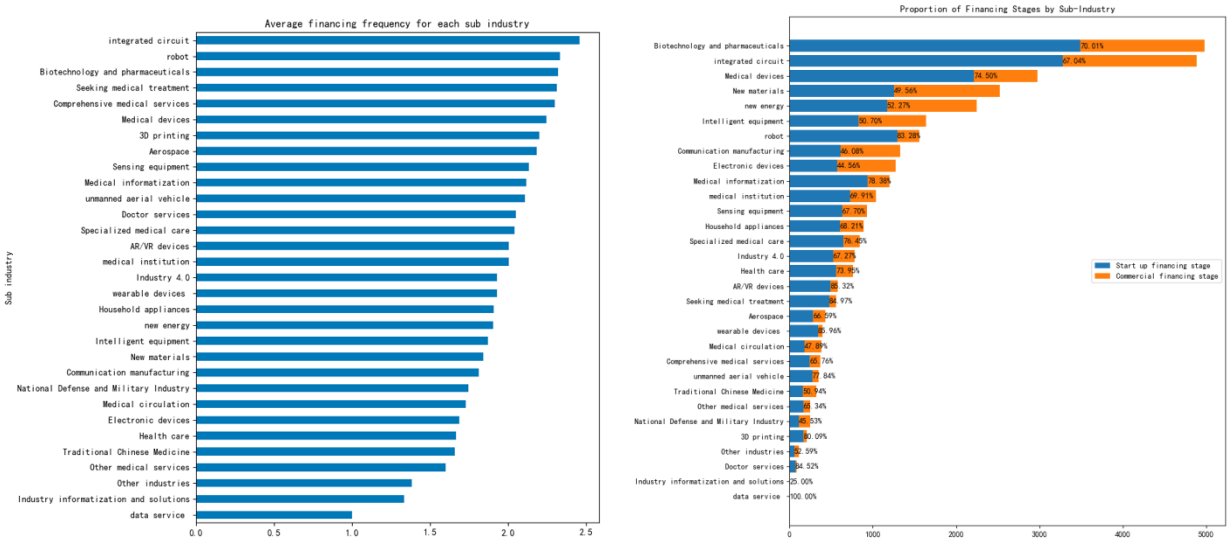


Figure 4-2: Average Number of Financings and Proportion of Financing Stages by Sub-Industry

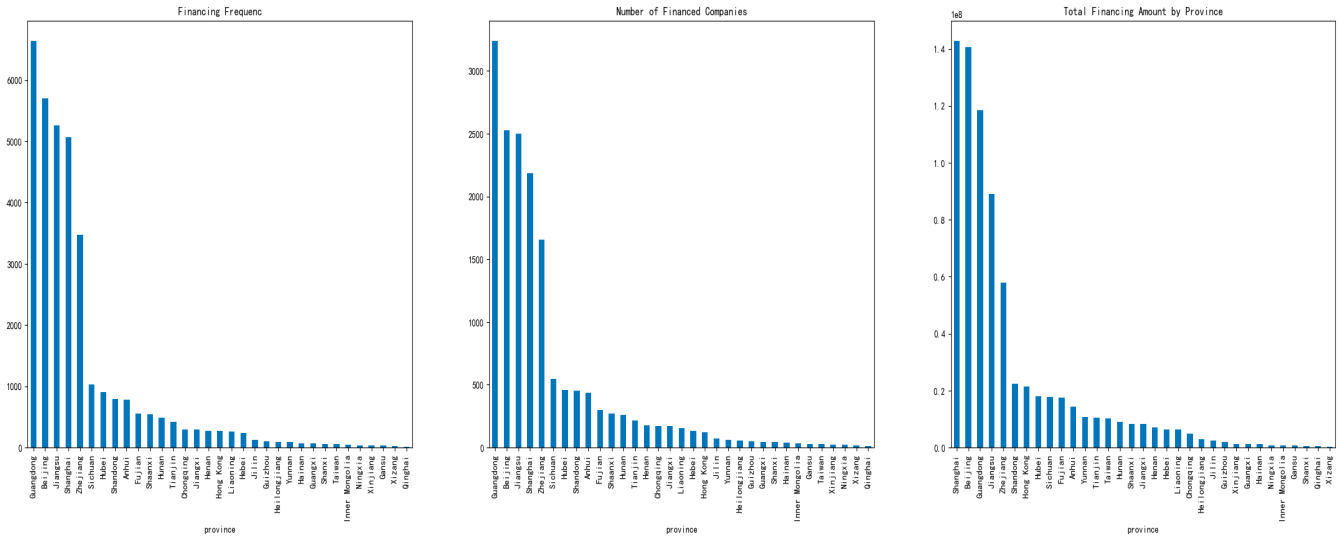


Figure 4-3: Financing Frequency, Number of Financed Companies,

and Total Financing Amount by Province

From the regional perspective, as depicted in Figure 4-3, companies that experienced financing events are primarily concentrated in Guangdong, Beijing, Jiangsu, Shanghai, and Zhejiang. From a time-series perspective, as illustrated in Figure 4-4, the number of financings in healthcare and advanced manufacturing peaked in 2020, followed by a decline in the overall scale of financing.

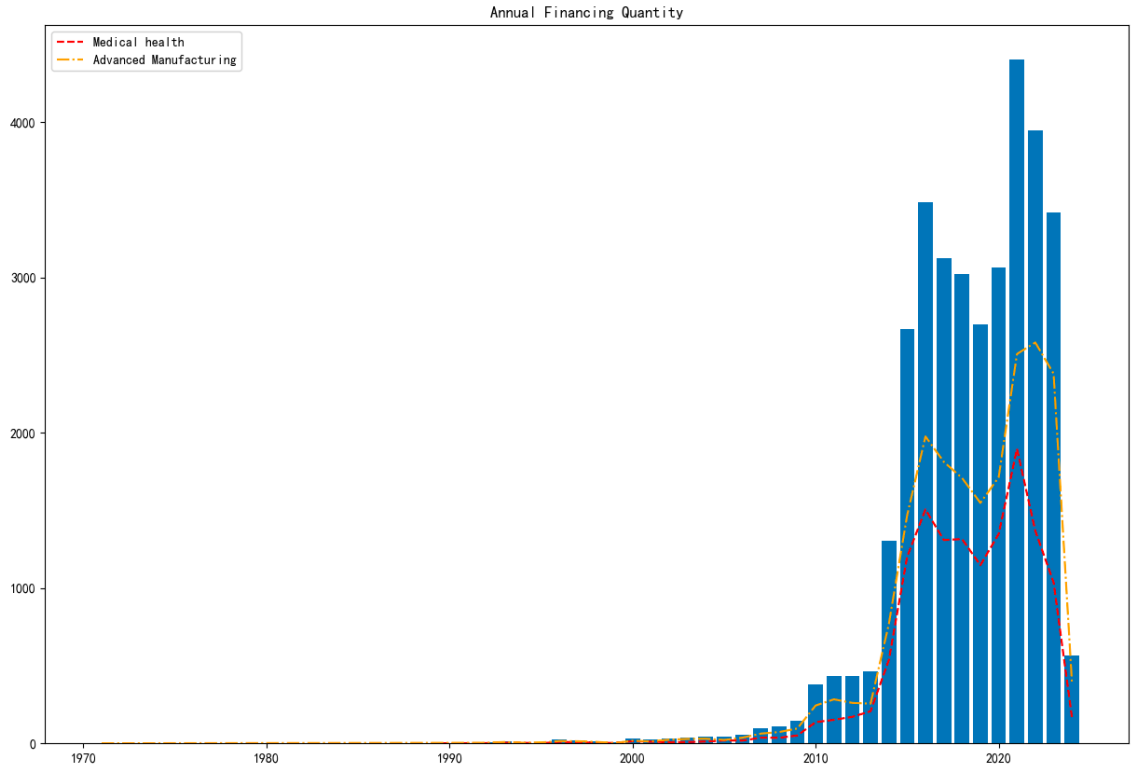


Figure 4-4 Annual Financing Quantity

From the perspective of investor participation, Figure 4-5 details the total number of investment institutions involved in each sub-industry. Mirroring the trends observed in financing scale and frequency, the integrated circuits and biotechnology and pharmaceutical industries have attracted the highest level of investor involvement, with around 4,000 institutions participating.

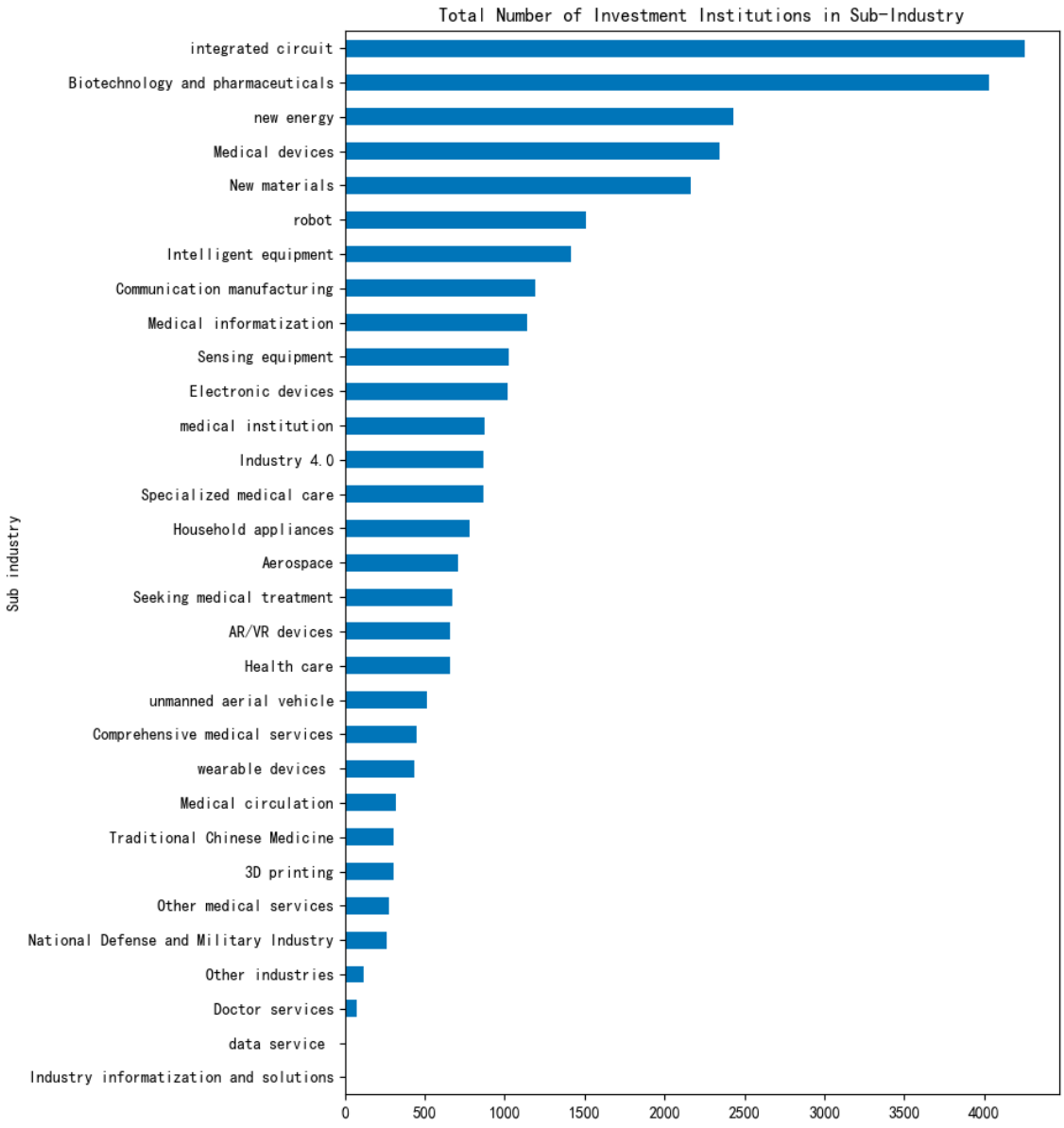


Figure 4-5 Total Number of Investment Institutions in Sub-Industry

Regarding patent applications, Figure 4-6 charts the annual trends in patent applications by sub-industry. It shows that the household appliances and integrated circuits industries command a substantial share of patent applications. Notably, in 2020, there was a surge in patent applications within the communications manufacturing industry, which subsequently decreased, while patent applications in the new energy industry reached their peak in 2022.

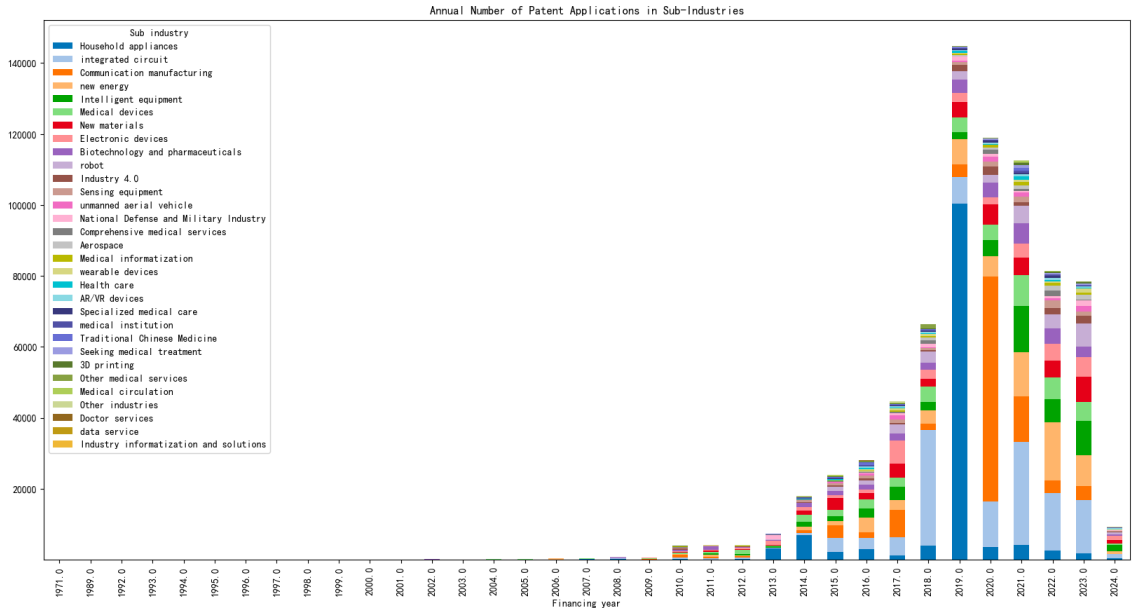


Figure 4-6 Annual Number of Patent Applications in Sub-Industries

Table 4-4 presents the correlation coefficients for the main variables. It reveals that the correlation coefficients between the number of patent applications ($Application\_num_{i,t}$) and the scale of venture capital ($VC\_Amount_{i,t}$) and cumulative investment occurrences ($Cum\_invest_{i,t}$) are significantly positive. This suggests that more patent applications indicate stronger technological innovation capabilities, a higher future investment value, and greater potential to enhance the scale of venture capital for the financing enterprise. Additionally, this study conducted multicollinearity tests on various signal variables in the model. By normalizing all variables to the company's number of patent applications, we observed a significant reduction in multicollinearity among other patent signals, particularly for the number of publicly disclosed invention patents and the number of claims, with the VIF values decreasing from 9.25 and 9.35 to 1.44 and 1.31, respectively. This reduction is attributed to the scale effect of the number of patent applications. Therefore, in the empirical tests that follow, after assessing the impact of the number of patent signals on the accessibility of financing, the number of

patents was incorporated as a control variable in other regression equations. Table 4-5 reports the results after this adjustment, showing that the average VIF value for the variables is less than 5, indicating no significant multicollinearity issues among the variables, making them suitable for panel regression analysis. In the empirical regressions, the top and bottom 1% of data samples for all variables were winsorized to trim the tails.

Variable	VIF	1/VIF
Public_invention_num	1.44	0.696725
IPC_num	1.43	0.697091
Patentwidth	1.39	0.71909
Citation_num	1.39	0.719318
Family_num	1.36	0.735706
Required_rights_num	1.31	0.76111
tech_closeness	1.25	0.796907
Application_num	1.04	0.961484
Mean VIF	1.27	

Note: This table presents the VIF test results for multicollinearity of patent-level variables.

Table 4-5 Multicollinearity VIF Test

V. Empirical analysis

This chapter explores the influence of various patent signals on the financing of technology-based startups within China's advanced manufacturing and healthcare sectors. It utilizes panel regression and survival analysis models to assess these effects from both individual company and inter-company perspectives.

5.1 The Impact of Patent Signals on Financing Accessibility

To test Hypotheses 1-4, the study initially applies models (1)-(8) to evaluate the influence of patent signals at the company level on financing accessibility. The regression analysis accounts for temporal effects and investment rounds, with findings detailed in Tables 5-1 and 5-2. Table 5-1 illustrates the impact of different company-level patent signals on the financing scale, where the dependent variable is the scale of each financing round for startups ($VC\_Amount_{i,t}$). Table 5-2 examines the influence of various company-level patent signals on the number of venture capital investments received, where the dependent variable is the cumulative number of venture capital investments accrued by startups since their inception ($Cum\_invest_{i,t}$).

(1)Analysis of the Impact of Patent Quantity Signal on Financing Accessibility

To substantiate Hypothesis 1, the quantity of patents ($Application\_num$) serves as an explanatory variable in column (1) of Tables 5-1 and 5-2. The findings reveal that for the venture capital scale, the coefficient estimate for the quantity of patent applications is positive (0.013) and statistically significant at the 1% level, supporting Hypothesis 1: a

higher number of patent applications by a technology-based startup correlates with an increased scale of venture capital received. This result is consistent with prior studies, such as those by Liu Linqing et al. (2020), which suggest that a greater patent count enhances the scale of venture capital for companies. Nevertheless, regarding the cumulative number of venture capital rounds, both the magnitude and significance of the estimated coefficient are reduced, indicating a lesser impact of patent quantity signals on the cumulative investment count compared to their effect on financing scale.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount	vc_amount
application_num	0.013***	0.010***	0.014**	0.014***	0.014*	0.012***	0.012***	0.014**	0.015**	0.011**
	(3.99)	(2.99)	(2.00)	(3.99)	(1.69)	(4.99)	(3.01)	(4.93)	(4.79)	(2.02)
IPC_num		0.002***			0.003***					0.002***
		(4.82)			(4.93)					(4.06)
Patentwidth			0.160***		0.036					-0.038
			(3.95)		(0.64)					(-0.68)
Citation_num				0.000**	0.000***					0.001***
				(2.49)	(2.81)					(2.93)
Family_num						0.000			0.001*	0.001**
						(0.27)			(1.90)	(2.34)
Public_invention_num							0.001		0.001	-0.004**
							(0.71)		(0.50)	(-2.16)
Required_rights_num								0.002**	0.001***	0.001**
								(2.32)	(3.53)	(2.28)
vcnum	0.187***	0.185***	0.186***	0.187***	0.185***	0.187***	0.187***	0.187***	0.187***	0.185***
	(30.56)	(30.23)	(30.49)	(30.54)	(30.19)	(30.56)	(30.56)	(30.55)	(30.56)	(30.20)
age	-0.004	-0.007*	-0.005	-0.004	-0.006*	-0.004	-0.004	-0.005	-0.005	-0.006*
	(-1.29)	(-1.91)	(-1.35)	(-1.18)	(-1.79)	(-1.27)	(-1.26)	(-1.52)	(-1.55)	(-1.84)
Bsg	0.043	0.046*	0.044*	0.042	0.045*	0.043	0.043	0.045*	0.045*	0.047*
	(1.62)	(1.73)	(1.65)	(1.59)	(1.69)	(1.61)	(1.60)	(1.69)	(1.70)	(1.76)
vc_indexp	0.300***	0.299***	0.300***	0.303***	0.303***	0.300***	0.301***	0.303***	0.307***	0.305***
	(8.62)	(8.60)	(8.60)	(8.71)	(8.71)	(8.62)	(8.64)	(8.70)	(8.80)	(8.75)
vc_mktexp	0.032	0.017	0.029	0.031	0.016	0.032	0.032	0.027	0.026	0.014
	(0.71)	(0.37)	(0.64)	(0.69)	(0.37)	(0.72)	(0.72)	(0.60)	(0.59)	(0.32)
Constant	7.200***	7.190***	7.170***	7.201***	7.212***	7.200***	7.200***	7.199***	7.198***	7.213***
	(147.89)	(147.81)	(123.12)	(147.96)	(122.78)	(147.87)	(147.88)	(147.91)	(147.94)	(122.86)

Observations	6,028	6,028	6,028	6,028	6,028	6,028	6,028	6,028	6,028	6,028
R-squared	0.660	0.661	0.660	0.660	0.662	0.660	0.660	0.660	0.661	0.662
Invest_round FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

(1) This table displays the empirical regression results detailing the effects of company-level patent signals on financing amounts, adjusting for investment rounds and fixed effects within sub-industries. Column (1) presents the parameter estimates for the influence of patent quantity signals on the scale of venture capital. Columns (2) to (5) present the parameter estimates for the effects of patent quality signals on venture capital scale. Columns (6) to (9) outline the parameter estimates for the effects of patent legal signals on venture capital scale. Column (10) presents the parameter estimates for the impact of all company-level patent signals on venture capital scale. (2) The symbols *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-1 Regression Results of the Impact of Company-level Patent Signals on Financing Amount.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest	cum_invest
application_num	0.001***	0.000***	0.001***	-0.000	-0.001***	0.001	0.001**	0.002***	0.001**	0.001*
	(5.57)	(2.85)	(5.44)	(-0.02)	(-2.61)	(1.47)	(2.21)	(4.12)	(2.25)	(1.94)
IPC_num		0.001**			0.002**					0.000
		(2.04)			(2.14)					(0.15)
Patentwidth			0.046*		0.033					0.038
			(1.64)		(0.61)					(0.70)
Citation_num				0.000*	0.000*					0.000*
				(1.87)	(1.88)					(1.93)
Family_num						-0.001***			-0.002***	-0.002***
						(-2.77)			(-4.16)	(-4.10)
Public_invention_num							-0.003***		-0.002	-0.004**
							(-3.26)		(-1.47)	(-2.44)
Required_rights_num								0.000**	0.000***	0.000***
								(2.26)	(5.93)	(5.94)
vcnum	0.039***	0.039***	0.039***	0.039***	0.040***	0.039***	0.039***	0.039***	0.040***	0.039***
	(6.63)	(6.63)	(6.60)	(6.66)	(6.64)	(6.62)	(6.64)	(6.65)	(6.68)	(6.57)
age	-0.005	-0.005	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.005	-0.004	-0.004
	(-1.62)	(-1.59)	(-1.66)	(-1.70)	(-1.68)	(-1.80)	(-1.74)	(-1.38)	(-1.30)	(-1.29)
Bsg	0.170***	0.170***	0.171***	0.171***	0.171***	0.172***	0.172***	0.168***	0.168***	0.169***
	(6.60)	(6.60)	(6.61)	(6.63)	(6.63)	(6.65)	(6.67)	(6.53)	(6.52)	(6.55)
vc_indexp	0.155***	0.155***	0.155***	0.153***	0.152***	0.155***	0.151***	0.152***	0.143***	0.143***
	(4.58)	(4.59)	(4.57)	(4.51)	(4.50)	(4.59)	(4.47)	(4.51)	(4.24)	(4.23)
vc_mktexp	0.031	0.031	0.029	0.031	0.031	0.027	0.029	0.035	0.037	0.032
	(0.71)	(0.71)	(0.67)	(0.72)	(0.71)	(0.62)	(0.68)	(0.81)	(0.85)	(0.73)
Constant	1.812***	1.812***	1.796***	1.812***	1.792***	1.812***	1.812***	1.813***	1.816***	1.794***

	(38.35)	(38.31)	(31.77)	(38.34)	(31.37)	(38.37)	(38.37)	(38.38)	(38.56)	(31.50)
Observations	6,029	6,029	6,029	6,029	6,029	6,029	6,029	6,029	6,029	6,029
R-squared	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.589	0.589
Invest_round FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

(1) This table outlines the empirical regression results regarding the impact of company-level patent signals on cumulative investment rounds, taking into account investment rounds and fixed effects of sub-industries. Column (1) displays the parameter estimates for the influence of patent quantity signals on cumulative investment rounds. Columns (2) to (5) provide the parameter estimates for the effects of patent quality signals on cumulative investment rounds. Columns (6) to (9) detail the parameter estimates for the effects of patent legal signals on cumulative investment rounds. Column (10) presents the parameter estimates for the impact of all company-level patent signals on cumulative investment rounds. (2) The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Table 5-2 Regression Results of the Impact of Company-level Patent Signals on Cumulative Investment Rounds.

(2)Analysis of the Impact of Patent Quality Signal on Financing Accessibility

To evaluate Hypothesis 2, columns (2) to (5) of Tables 5-1 and 5-2 incorporate patent quality variables, namely IPC_num, $Patentwidth$, and $Citation\_num$, as explanatory factors. Regarding the scale of venture capital, the estimated coefficients for the number of IPC classification numbers and knowledge width are positive (0.002 and 0.160) and significant at the 1% level. This supports Hypothesis 2, suggesting that the greater the number of IPC classification numbers a technology-based startup's patents encompass and the broader the knowledge width, the more effectively it reflects the breadth of the enterprise's patent knowledge. A positive coefficient indicates that a broader cross-knowledge application of a company's patents, which correlates with more patent applications, signifies more advanced technological innovation, stronger technical signals, higher future investment potential, and increased appeal to venture capital institutions. As a result, such enterprises can secure higher levels and frequencies of financing. This conclusion is in line with previous studies (Xu Xiangyang et al., 2018; Meng Dabin and Li Yang, 2019), which contend that patent quality enhances the scale of enterprise financing. However, in terms of citation frequency, the influence of patent citations on the scale of venture capital is modest, with the coefficient being positive but relatively slight (0.000). This observation is consistent with robustness checks in subsequent sections, where citation counts of Chinese patents exhibit minimal impact on the scale of enterprise financing.

Similar to the patent quantity signal, for cumulative investment rounds, the overall

economic impact and significance of the estimated coefficients are reduced. The estimated coefficient for IPC classification numbers decreases to 0.001 and is only significant at the 5% level, indicating that the influence of patent quality signals on cumulative investment rounds is less pronounced than on the scale of financing.

(3)Analysis of the Impact of Patent Legal Signal on Financing Accessibility

To examine Hypothesis 3, columns (6) to (9) of Tables 5-1 and 5-2 incorporate the number of public invention patents (Public_invention_num), the number of claims (Required_rights_num), and the number of family patents (Family_num) as explanatory variables. For the scale of financing, the estimated coefficient for effective claims is positive and significant at the 1% level (0.002), affirming Hypothesis 3. This result suggests that the greater the number of effective claims a technology-based startup possesses, the stronger the legal signal it projects, enhancing its ability to protect intellectual property, fend off competitors, and penetrate competitive markets. Consequently, it can draw more venture capital investors, boosting both the scale and frequency of its financing. However, the influence of the number of public invention patents and family patents is not statistically significant, with the significance of family patents only emerging when all three variables are considered together. Therefore, Hypothesis 3 is only partially supported, and the findings regarding the number of family patents and public invention patents are inconclusive.

For cumulative investment rounds, the legal signal does not exhibit a significant impact, with the coefficient for effective claims even turning negative (-0.002). This may be attributed to a time delay effect, suggesting that the legal signal from patents does not immediately reflect in the number of investment rounds. It is possible that investors have

already reacted to the legal signals in prior investment rounds, hence cumulative investment rounds fail to capture this effect. Furthermore, the advanced manufacturing and healthcare sectors might prioritize the quantity and quality of patents over legal signals, rendering cumulative investment rounds less responsive to legal influences.

(4)Analysis of the Impact of Patent Business Signal on Financing Accessibility

To evaluate Hypothesis 4, we incorporated the financing scale of associated technology companies, utilizing the technology relevance index, to ascertain the impact of patent business signals on financing accessibility. The regression findings are displayed in Tables 5-3 and 5-4.

From the regression outcomes in Table 5-3, it is evident that the estimated coefficients for the business signal (tech_closeness) are positive (0.843) and statistically significant at the 1% level. This reveals that companies with similar technological profiles achieve higher financing amounts, thereby enhancing the financing scale for the core enterprise. This outcome is consistent with existing research on technological similarity in the stock market (Lee et al., 2019). Moreover, the business signal of patents continues to exert a significant positive impact even when controlling for other company-level patent signals such as quantity, quality, and legal signals. This reinforces the credibility of the technology similarity index developed in this study, demonstrating that the index accurately reflects the technological similarities between companies and the business implications of patents. It also confirms that technology-based startups with comparable technologies benefit from a linkage effect in terms of their financing scale.

	(1)	(2)
VARIABLES	vc_amount	vc_amount
tech_closeness	0.843***	0.804***
	(7.22)	(2.75)
application_num		0.062***
		(6.67)
IPC_num		0.002***
		(10.17)
Patentwidth		0.160***
		(3.94)
Citation_num		0.722***
		(3.75)
Family_num		0.002*
		(1.85)
Public_invention_num		0.001
		(0.98)
Required_rights_num		-0.285*
		(-1.70)
vcnum	0.156***	0.145***
	(40.43)	(34.77)
age	-0.001	-0.001
	(-0.34)	(-0.57)
Bsg	0.076***	0.075***
	(3.72)	(3.67)
Constant	7.389***	7.484***
	(240.17)	(312.47)
Observations	10,303	10,303
R-squared	0.638	0.640
Invest_round FE	YES	YES
Industry FE	YES	YES

Note: (1) This table presents the empirical regression results on the impact of company patent association business signals on the scale of venture capital. The regression controls for the effects of investment rounds and industry fixed effects. Column (1) outlines the parameter estimates of the impact of patent business signals on the scale of venture capital. Column (2) outlines the parameter estimates of the impact of all patent signals on the scale of venture capital. (2) The symbols *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.

Table 5-3 Regression Results of the Impact of Business Signals on the Scale of Venture Capital

	(1)	(2)
VARIABLES	cum_invest	cum_invest
tech_closeness	0.510***	0.481***
	(3.43)	(3.41)
application_num		0.399***
		(5.47)
IPC_num		0.009
		(1.01)
Patentwidth		0.510***
		(3.43)
Family_num		0.037
		(1.22)
Citation_num		0.386***
		(5.52)
Public_invention_num		0.723***
		(3.69)
Required_rights_num		0.001
		(1.08)
vcnum	0.198***	0.195***
	(40.40)	(39.77)
age	-0.001	-0.001
	(-0.34)	(-0.57)
Bsg	0.076***	0.075***
	(3.72)	(3.67)
Constant	7.389***	7.484***
	(240.17)	(312.47)
Observations	10,303	10,303
R-squared	0.638	0.640
Invest_round FE	YES	YES
Industry FE	YES	YES

Note: (1) This table displays the empirical regression results concerning the impact of company patent association business signals on the cumulative rounds of venture capital. The regression analysis accounts for the effects of investment rounds and industry fixed effects. Column (1) provides the parameter estimates of the influence of patent business signals on cumulative rounds of venture capital. Column (2) provides the parameter estimates of the influence of all patent signals on cumulative rounds of venture capital. (2) The symbols *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 5-4 Regression Results of the Impact of Business Signals on Cumulative Rounds of Venture Capital

From column (1) of Table 5-4, akin to findings concerning investment scale, we observe a noticeable correlation between the number of investments received by companies with higher technological similarity. Specifically, companies that exhibit a high degree of technological resemblance also tend to receive similar numbers of investment rounds. This observation further substantiates the presence of business signals among companies, thereby supporting the validity of hypothesis 4. However, this conclusion has not yet been corroborated in the stock market.

5.2 Moderating Effects of Venture Capital Reputation and Attention

(1)Analysis of the Moderating Effect of Venture Capital Reputation

Signal theory suggests that the decoding capabilities of the signal receiver significantly influence the effectiveness and efficiency of signal transmission (Liu Du et al., 2017). In the realm of investment and financing, venture capital institutions, as receivers of corporate patent signals, filter and interpret various patent signals. Their proficiency in deciphering this information directly impacts their investment decisions, consequently affecting the relationship between multiple patent signals and financing accessibility. Prevailing studies typically indicate that the more reputable the venture capital institution, the more extensive its investment experience and the more robust its capacity to assimilate and utilize knowledge. This proficiency enables them to gather, interpret, and differentiate diverse patent information with greater precision (Ma Renmin et al., 2023; Xiang Xianguo et al., 2021; Tang Manping et al., 2019; Xu Yan et

al., 2016). As a result, these institutions can access a broader array of information, diminish information asymmetry with the companies they invest in, and reduce their dependence on patent signals when evaluating a company's investment value, thus mitigating the positive influence of patent signals on financing accessibility. In contrast, venture capital institutions with lesser reputations may have inadequate information interpretation skills, making patent signals more crucial in their financing decisions.

Thus, this study proposes that the reputation of a venture capital institution moderates the relationship between multiple patent signals and financing accessibility. The higher the reputation of the venture capital institution, the lesser the positive impact of patent signals on financing accessibility; conversely, the lower the institution's reputation, the greater the positive impact of patent signals on financing accessibility.

In light of this, the study hypothesizes that the reputation of venture capital institutions serves as a mechanism through which patents influence financing accessibility. We employ a multiple regression model (10) to assess the moderating role of venture capital institution reputation. During the operational phase, we initially apply principal component analysis to amalgamate different types of patent signals, resulting in a comprehensive patent signal ($patent\_pca$) that encapsulates the overall effect of various patent signals. Subsequently, we incorporate an interaction term between this consolidated patent signal and the reputation of venture capital institutions (vc_rep) into the regression analysis, with the results displayed in Table 5-5.

The regression analysis presented in column (1) of Table 5-5 reveals that the interaction term between patent signals and venture capital institution reputation has a

negative regression coefficient (-0.003), which is statistically significant at the 1% level. This suggests that the reputation of venture capital institutions negatively moderates the relationship between comprehensive patent signals and venture capital scale. This could be attributed to the fact that high-reputation venture capital institutions possess strong capabilities in information collection, assimilation, and interpretation, enabling them to gather more diversified information about companies and thus diminish the degree of information asymmetry with prospective investment companies. Consequently, these institutions are less dependent on patent signals when assessing the investment value of enterprises, thereby diminishing the positive influence of patent signals on financing accessibility.

The regression findings in column (2) of Table 5-5, which consider cumulative investment rounds as the dependent variable, mirror those of column (1). The interaction term between patent signals and venture capital institution reputation also exhibits a negative regression coefficient and achieves statistical significance at the 1% level. This implies that high-reputation venture capital institutions are adept at evaluating the risks associated with patent information, thus reducing the impact of patent signals on financing accessibility for such institutions.

In summary, echoing the conclusions of Fu Haojie (2019) and Zheng Ying et al. (2018), this research demonstrates that the reputation of venture capital institutions mitigates the positive effect of patent signals on financing accessibility. This is likely due to high-reputation venture capital institutions having enhanced abilities to discern patent information, thereby lessening the degree of information asymmetry and consequently weakening the signal efficacy of patents.

	(1)	(2)
VARIABLES	vc_amount	cum_invest
patent_pca	0.056***	0.076***
	(6.12)	(7.93)
vc_rep	0.037***	0.097***
	(6.85)	(17.23)
patent_pca*vc_rep	-0.003***	-0.004***
	(-3.26)	(-4.50)
vcnum	0.195***	0.044***
	(39.56)	(8.55)
age	0.000	0.002
	(0.18)	(0.81)
Bsg	0.077***	0.174***
	(3.73)	(8.13)
Constant	7.459***	1.831***
	(273.60)	(64.79)
Observations	10,162	10,164
R-squared	0.639	0.542
Invest_round FE	YES	YES
Industry FE	YES	YES

Note: (1) This table evaluates the moderating impact of venture capital institutions' reputations. Column (1) denotes the parameters of the moderating effect of reputation on the scale of venture capital, and Column (2) denotes the parameters of the moderating effect of reputation on cumulative investment rounds. (2) The symbols *, **, *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-5 Regression Results of the Moderating Effect of Venture Capital Institution Reputation

(2)Analysis of the Moderating Effect of Venture Capital Attention

The limited attention theory of investors highlights that due to the complexity of information processing, venture capital institutions often depend on simplified models and imperfect decision-making procedures. Consequently, they are inclined to invest in companies that have high visibility or are widely followed, resulting in stronger predictability in financing information for less noticed enterprises. Prior research has demonstrated that technologically similar companies exhibit a certain correlation in

returns, a relationship that is particularly pronounced among companies overlooked by investors, thus underscoring the impact of investors' limited attention mechanisms on investment decisions. Specifically, the more intricate the technical correlation between companies, the less attention investors pay to these companies, and the more pronounced the effect of technical similarity becomes. Therefore, it is posited that the focus of venture capital institutions and the complexity of company relationships moderate the impact of patent commercial signals. The less attention paid by venture capital institutions and the more complex the company relationships, the stronger the influence of technical similarity, and vice versa.

This study delves further into the moderating effects of venture capital attention and the complexity of company relationships on the influence of patent commercial signals. We begin by using the number of participating venture capital institutions during each financing event to construct the variable of investor attention (no_investor), assuming that higher participation indicates greater visibility to investors. The regression results displayed in Table 5-6 illustrate these dynamics. Observing the results in column (1), we find that the coefficient for the interaction term between tech_closeness and no_investor is negative (-0.002) and statistically significant at the 1% level, suggesting that companies with lower visibility experience a stronger effect of technical similarity. This empirical finding validates that the limited attention mechanism of investors is a key factor in how the commercial signal of patents influences the financing accessibility of enterprises.

Furthermore, we explored the limited attention mechanism of investors through

the lens of the complexity of company technical similarity. If the technical similarity effect among associated companies stems from investors' constrained information processing capabilities, then for a single investment institution, the greater the complexity of technical similarity between companies, the more challenging it becomes to acquire and process information, leading to more dispersed investor attention. This suggests that investors' delayed responses to patent information might be more pronounced, and the leading and lagging relationships in terms of financing scale or financing information among technologically similar companies may intensify. To test this hypothesis, we incorporated a measure of relationship complexity—the number of companies with technical similarity exceeding 0.7 (#Connected Firms)—into our existing commercial signal regression analysis. The results in columns (3) and (4) of Table 5-6 reveal that the coefficients of the interaction terms are positive and statistically significant at the 1% level. This finding indicates that the greater the number of companies that are technologically similar or related to the core company, the higher the technical similarity among these companies, and the more pronounced the impact on financing accessibility, thereby further substantiating the limited attention mechanism of investors.

	(1)	(2)	(3)	(4)
VARIABLES	vc_amount	cum_invest	vc_amount	cum_invest
tech_closeness	0.237***	0.229***	0.056***	-0.076***
	(3.96)	(4.02)	(6.12)	(-7.93)
no_investor	0.014**	0.097***		
	(2.28)	(17.23)		
tech_closeness *no_investor	-0.002***	-0.004***		
	(-6.81)	(-4.50)		
#Connected Firms			0.006***	0.371*
			(11.24)	(1.82)

tech_closeness *#Connected Firms			0.390***	0.047*
			(3.35)	(1.92)
vcnum	0.078***	0.081***	0.195***	0.044***
	(4.50)	(4.73)	(39.56)	(8.55)
age	0.081***	0.047*	0.000	0.002
	(4.73)	(1.92)	(0.18)	(0.81)
Bsg	-0.003***	-0.009***	0.077***	0.174***
	(-4.53)	(5.47)	(3.73)	(8.13)
Constant	7.459***	1.831***	7.459***	1.831***
	(273.60)	(64.79)	(273.60)	(64.79)
Observations	10,162	10,164	10,162	10,164
R-squared	0.639	0.542	0.639	0.542
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results concerning the moderating effect of venture capital institutions' attention. Columns (1) and (3) present the parameters related to the moderating influence of attention and company complexity on the scale of venture capital, whereas Columns (2) and (4) present the parameters concerning the moderating effect of attention and company complexity on cumulative investment rounds. (2) The symbols *, **, *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-6 Regression Results of the Moderating Effect of Venture Capital Institutions' Attention

5.3 Robustness test

To achieve more robust and reliable conclusions, this study continues by segmenting the sample based on whether it consists of high-tech enterprises and examines the dynamic impact of patents across various financing stages for robustness testing. The rationale for this approach is as follows:

(i) Non-high-tech enterprises typically hold fewer patents, and some may not possess any patents at all. High-tech enterprises, on the other hand, face higher information asymmetry and greater uncertainty in their development, necessitating a distinct analysis.

(ii) Enterprises at different financing stages exhibit varying product characteristics

and levels of commercialization, which can lead to different degrees of information asymmetry and patent-related risks. Consequently, the influence of patent signals on financing accessibility may vary across different stages.

(iii) The significance of patent signals can also differ among various sub-industries. For example, biopharmaceutical companies, characterized by high revenue, high risk, and long development cycles, are more reliant on innovation and patents. In contrast, sub-industries such as medical services and telecommunications manufacturing may be less dependent on patents, potentially diminishing their influence in the investment and financing processes. Thus, the different financing stages and technological attributes in various sub-industries can also impact the effect of patents on financing accessibility.

(ix) The study further refines the sample to include only those patents that are invention-authorized, constructs company-level patent variables for sub-samples, and conducts robustness tests on the primary regression results.

(x) Additionally, the study employs an endogeneity test using survival analysis to address potential issues of reverse causality and omitted variables, thereby validating the robustness of the main regression findings.

(1)High-Tech v.s. non High-Tech enterprises

The findings presented in Table 5-7 illustrate the influence of integrated patent signals (patent_pca) on the investment scale and cumulative investment times for both high-tech and non-high-tech startups. Specifically, for the investment scale, columns (1) and (2) of Table 5-7 indicate that patent signals positively and significantly affect the

financing scale for both high-tech and non-high-tech enterprises, with a notably stronger impact on high-tech enterprises. However, the coefficient difference test (bdiff) reveals no significant difference in the impact of patents between high-tech and non-high-tech enterprises. Similarly, regarding cumulative investment times, columns (3) and (4) of Table 5-7 demonstrate that the comprehensive patent signal has a more pronounced effect on the cumulative investment times for high-tech enterprises than for non-high-tech enterprises, although the significance of the coefficients diminishes.

	(1)	(2)	(3)	(4)
VARIABLES	vc_amount	vc_amount	cum_invest	cum_invest
	High-tech enterprises	Non High-tech enterprises	High-tech enterprises	Non High-tech enterprises
patent_pca	0.038***	0.027**	0.004***	0.003***
	(6.71)	(2.51)	(3.82)	(4.13)
vcnum	0.200***	0.200***	0.026***	0.040***
	(29.82)	(24.67)	(3.12)	(4.46)
age	0.003	-0.002	0.014**	-0.002
	(0.97)	(-0.37)	(1.99)	(-0.45)
Bsg	0.093***	0.026	0.034	0.220***
	(3.16)	(0.59)	(0.78)	(5.63)
Constant	8.057***	7.987***	2.642***	3.022***
	(208.62)	(154.94)	(48.06)	(57.52)
Observations	3,949	2,088	2,052	3,907
R-squared	0.484	0.485	0.393	0.437
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results derived from subsamples of various high-tech enterprises. Columns (1) and (3) present the parameters concerning the impact of integrated patent signals on the scale of venture capital within the subsample of high-tech enterprises, whereas Columns (2) and (4) present the parameters concerning the impact of integrated patent signals on cumulative investment rounds within the subsample of non-high-tech enterprises. (2) The symbols *, **, *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-7 Grouped Regression Results Based on Different Types of High-Tech Enterprises

(2)Different financing stages

According to the theory of the enterprise life cycle, the developmental stages of startups prior to listing can be categorized into the startup stage and the commercialization stage. The startup stage primarily encompasses early financing (angel rounds) to the first round of financing (round A), while the commercialization stage includes all periods from post-Series A financing to pre-IPO. The function of patents as financing signals exhibits significant differences between these two stages.

In the startup stage, companies may already hold patents or possess initial concepts for technological products. However, despite patents reflecting a company's technological and innovation level at this stage, they often do not play a pivotal role in attracting venture capital. This is largely due to the high degree of uncertainty surrounding the startups' innovation concepts, ideas, and business models, as well as the complex environment faced by venture capitalists (Qi Su and Liu Lichun, 2020; Wang Lanfang and Hu Yue, 2017; Wu Xinwang and Zhu Quantao, 2016). Patents during this period may convey risk information, potentially impacting the startups' ability to secure venture capital. Furthermore, venture capital institutions at this stage tend to focus more on the quality of the entrepreneur and the management team rather than solely on patents. The same patent can yield vastly different economic outcomes depending on the capabilities of the entrepreneurial teams handling it.

Upon entering the commercialization stage, the circumstances change markedly. At this stage, products are progressively maturing, business models are becoming more defined, and organizational management systems are being refined, which considerably

lowers uncertainty and risk. Additionally, with the involvement and oversight of early investors, the level of information asymmetry between startups and venture capital institutions diminishes. At this juncture, the significance of patents begins to manifest. Patents, having been transformed into marketable products, not only demonstrate their innovativeness and feasibility, thus reducing information asymmetry and investment risk, but also, through their property protection function, aid startups in managing intellectual property disputes in the market, preserving market share, and consequently, becoming more attractive to venture capitalists. Thus, in the commercialization stage, patents become a crucial factor for startups in drawing venture capital (Hoenig and Henkel, 2015; Vo, 2019; Zhang et al., 2019).

Based on the preceding analysis, this study further segments the sample based on the financing stages of the enterprise from a time-series perspective and conducts sub-sample testing. Specifically, the study uses the financing events that occurred before and after Series A as the division standard, categorizing them into the startup stage and commercialization stage. Group regression and inter-group coefficient difference tests are performed to analyze the differential impact of patent signals on financing accessibility at various stages of enterprise financing. The regression results are displayed in Table 5-8. From the sub-sample results, it is observed that in the startup stage, the regression coefficient of patents on investment scale is smaller and less significant compared to the commercialization stage. Moreover, the inter-group coefficient difference test (bdiff) indicates that the coefficient difference of patent signals is significant, demonstrating that the financing stage of the enterprise influences

the scale of investment received. However, for cumulative investment times, the difference in significance between the two stages is not marked, indicating that the impact of patent signals on cumulative investment times is not significantly affected by the financing stage of the enterprise. Overall, the sub-sample test results align with the main conclusions of this study, affirming the robustness of the fundamental conclusions.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	vc_amount	vc_amount	cum_invest	cum_invest
	Startup stage	Commercialization stage	Startup stage	Commercialization stage
patent_pca	0.034***	0.064***	0.016*	0.016*
	(6.24)	(6.51)	(1.86)	(1.86)
vcnum	0.136***	0.213***	0.055***	0.035**
	(12.75)	(38.67)	(11.35)	(2.19)
age	0.024***	-0.015***	-0.015***	0.017***
	(5.68)	(-4.87)	(-5.83)	(2.71)
Bsg	0.027	0.083***	0.086***	0.535***
	(0.52)	(3.76)	(4.48)	(6.74)
Constant	8.687***	7.280***	2.050***	2.265***
	(152.09)	(273.62)	(88.47)	(26.30)
Observations	1,959	8,344	8,345	1,960
R-squared	0.242	0.643	0.618	0.345
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table presents the empirical regression results based on subsamples at different financing stages. Columns (1) and (3) estimate the parameters of the impact of integrated patent signals on the scale of venture capital for enterprises in the startup stage, while Columns (2) and (4) estimate the parameters of the impact of integrated patent signals on cumulative investment rounds for enterprises in the commercialization stage. (2) The symbols *, **, *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-8 Grouped Regression Results Based on Different Financing Stages of Enterprises.

(3) Different sub-industries

Due to the varying influence of different types of patent signals on corporate financing across industries, this study further divides the samples into two sub-industries: advanced manufacturing and healthcare. This division is based on initial financing scales and patent signal data from these major industries. The aim is to analyze the differentiated impacts of single and integrated patent signals on financing accessibility in different sub-industries. The regression results are presented in Tables 5-9 and 5-10.

From the subgroup sample results, differences emerge in the effects of integrated patent signals between different sub-industries. Firstly, considering single-layer patent signals, the impact of patents in the advanced manufacturing field appears stronger regarding patent application quantity, IPC classification number, family patent number, and the number of required rights. The regression coefficients for these factors are 0.009, 0.003, 0.004, and 0.000, respectively, all statistically significant at the 1% level. Conversely, in the healthcare field, the effects of various patent signals are relatively weaker. For example, while the regression coefficient for the commercial signal of patents is 0.649, it is not statistically significant. This suggests that in the healthcare industry, the influence of various patent signals on financing accessibility is smaller compared to advanced manufacturing.

Regarding cumulative investment times, the differences in the signal effects of patents between the advanced manufacturing and healthcare fields are not substantial. For instance, the regression coefficient for citation times is 0.001 in both fields, with significance observed only at the 1% level in the advanced manufacturing field.

Upon further integration of quantity, quality, and legal signals of patents, it becomes apparent that for the financing scale, the effect of integrated patent signals is more significant in the advanced manufacturing field. This finding aligns with the regression results of single signal effects. However, for cumulative investment times, the effect of integrated patent signals is more significant in the healthcare field, with a regression coefficient of 0.040, significant at the 1% level.

	(1)	(2)	(3)	(4)
VARIABLES	vc_amount	vc_amount	cum_invest	cum_invest
	advanced manufacturing	healthcare	advanced manufacturing	healthcare
application_num	0.009***	0.004	0.005**	0.005**
	(3.97)	(1.43)	(2.25)	(2.00)
IPC_num	0.003***	0.002	-0.000	0.002*
	(3.16)	(1.51)	(-0.15)	(1.69)
Patentwidth	-0.041	-0.010	0.102	0.043
	(-0.55)	(-0.12)	(1.46)	(0.53)
Citation_num	0.000*	0.001**	0.001***	0.001
	(1.77)	(2.21)	(2.66)	(1.54)
Family_num	0.004**	0.000	-0.007***	-0.003**
	(2.51)	(0.27)	(-3.90)	(-1.97)
Public_invention_num	-0.003	-0.005	-0.023***	-0.018***
	(-0.52)	(-0.72)	(-4.67)	(-2.76)
Required_rights_num	0.000***	0.000*	0.001***	0.000**
	(2.67)	(1.68)	(8.78)	(2.19)
tech_closeness	0.838***	0.649	0.323***	0.681***
	(7.15)	(1.25)	(2.13)	(3.78)
vcnum	0.168***	0.195***	0.030***	0.049***
	(23.36)	(16.91)	(4.43)	(4.63)
age	-0.006	-0.001	-0.007*	0.014***
	(-1.32)	(-0.16)	(-1.68)	(2.65)
Bsg	0.034	0.011	0.199***	0.050
	(1.02)	(0.26)	(6.31)	(1.30)
vc_indexp	0.222***	0.430***	0.093**	0.228***
	(4.88)	(7.81)	(2.19)	(4.53)
vc_mktexp	0.056	-0.098	0.002	-0.010
	(1.00)	(-1.34)	(0.03)	(-0.16)
Constant	7.206***	7.277***	1.824***	1.782***
	(95.34)	(78.55)	(25.77)	(21.06)

Observations	3,827	2,199	3,828	2,199
R-squared	0.665	0.667	0.592	0.632
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results derived from different industry subsamples. Columns (1) and (3) provide estimates for the parameters concerning the impact of various patent signals on venture capital scale within the subsample of advanced manufacturing enterprises. In contrast, Columns (2) and (4) provide estimates for the parameters related to the impact of various patent signals on cumulative investment rounds within the subsample of medical health enterprises. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-9 Grouped Regression Results of Various Signals in Sub-Industries

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	vc_amount	vc_amount	cum_invest	cum_invest
	advanced manufacturing	healthcare	advanced manufacturing	healthcare
patent_pca	0.039***	0.024*	0.022***	0.040***
	(5.80)	(1.86)	(3.44)	(3.46)
vcnum	0.171***	0.197***	0.033***	0.051***
	(23.88)	(17.10)	(4.82)	(4.82)
age	-0.008*	-0.002	-0.012***	0.012**
	(-1.74)	(-0.33)	(-2.90)	(2.35)
Bsg	0.050	0.015	0.226***	0.051
	(1.48)	(0.35)	(7.12)	(1.32)
vc_indexp	0.234***	0.441***	0.121***	0.245***
	(5.15)	(8.05)	(2.81)	(4.88)
vc_mktexp	0.060	-0.095	0.022	0.004
	(1.08)	(-1.30)	(0.41)	(0.07)
Constant	7.229***	7.306***	1.810***	1.735***
	(117.28)	(91.87)	(31.02)	(23.81)
Observations	3,827	2,199	3,828	2,199
R-squared	0.663	0.667	0.580	0.628
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results based on subsamples from various industries. Columns (1) and (3) estimate the parameters of the impact of integrated patent signals on the scale of venture capital within the subsample of advanced manufacturing enterprises, while Columns (2) and (4) estimate the parameters of the impact of integrated patent signals on cumulative investment rounds within the subsample of medical health enterprises. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-10 Regression Results of Integrated Patent Signals Based on Different Sub-Industries

This study further investigates the variations in the impact of patent signals on financing scale across different industry sectors, within samples of varying technological attributes, and at different financing stages. The regression results are presented in Tables 5-11 and 5-12. The results indicate that the signaling effect of individual patents differs across various sub-sectors, financing stages, and technological attributes.

As illustrated in Table 5-11, within the advanced manufacturing sector, high-tech enterprises generally exhibit stronger patent signal effects compared to their non-high-tech counterparts. For instance, the regression coefficients for the number of family patents and the number of claims are 0.006 and 0.000, respectively, both significant at the 1% level. In contrast, in the healthcare sector, it is predominantly the non-high-tech enterprises that demonstrate stronger signal effects. For example, the regression coefficients for the number of IPC classifications and the number of claims are 0.005 and 0.001, respectively.

As detailed in Table 5-12, within the advanced manufacturing sector, the signal effect of patents is more pronounced during the commercialization stage than in the startup stage. Conversely, in the healthcare sector, the patent signal effect is stronger during the startup stage compared to the commercialization stage. For instance, the coefficient for the quality signal of patents is 0.003, significant at the 1% level.

	(1)	(2)	(3)	(4)
VARIABLES	vc_amount	vc_amount	vc_amount	vc_amount
	advanced manufacturing	advanced manufacturing	healthcare	healthcare
	Non High-tech	High-tech	Non High-tech	High-tech

	enterprises	enterprises	enterprises	enterprises
application_num	0.009	0.012***	-0.005	-0.002
	(1.26)	(5.16)	(-1.06)	(-0.64)
IPC_num	0.002	0.003***	0.005*	0.001
	(0.85)	(2.75)	(1.85)	(0.34)
Patentwidth	-0.102	0.027	0.117	-0.145
	(-0.81)	(0.30)	(0.81)	(-1.34)
Citation_num	-0.002	0.000	-0.002	0.001
	(-1.39)	(0.15)	(-1.43)	(1.31)
Family_num	-0.006	0.006***	-0.002	0.003
	(-1.13)	(3.34)	(-0.65)	(1.00)
Public_invention_num	0.013	-0.006	-0.002	-0.004
	(1.03)	(-1.12)	(-0.14)	(-0.50)
Required_rights_num	0.000	0.000**	0.001**	-0.000
	(0.65)	(2.52)	(2.56)	(-0.70)
vcnum	0.162***	0.176***	0.184***	0.209***
	(13.97)	(18.77)	(10.00)	(13.80)
age	-0.009	-0.003	0.004	0.002
	(-1.04)	(-0.56)	(0.34)	(0.35)
Bsg	0.080	0.014	-0.019	0.088*
	(1.34)	(0.36)	(-0.28)	(1.67)
vc_indexp	0.224***	0.183***	0.428***	0.354***
	(2.91)	(3.29)	(4.76)	(5.17)
vc_mktexp	0.194*	-0.055	-0.122	-0.079
	(1.85)	(-0.87)	(-0.96)	(-0.91)
Constant	6.884***	7.419***	7.056***	7.419***
	(51.48)	(82.43)	(45.28)	(66.32)
Observations	1,574	2,252	968	1,229
R-squared	0.635	0.700	0.634	0.718
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results derived from subsamples across different industries and types of high-tech enterprises. Columns (1) and (3) estimate the impact parameters of various patent signals on the scale of venture capital in non-high-tech enterprises within the advanced manufacturing and medical health industries. Conversely, Columns (2) and (4) estimate the impact parameters of various patent signals on the scale of venture capital in high-tech enterprises within these same subsamples. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-11 Grouped Regression Results of Financing Scale Based on Different Types of High-Tech Enterprises Within Different Industries

	(1)	(2)	(3)	(4)
VARIABLES	vc_amount	vc_amount	vc_amount	vc_amount
	advanced manufacturing	advanced manufacturing	healthcare	healthcare
	Startup stage	Commercialization stage	Startup stage	Commercialization stage
application_num	-0.008***	-0.014***	-0.003	0.002
	(-2.99)	(-2.67)	(-1.31)	(0.15)
IPC_num	-0.001	0.005***	0.003*	-0.005
	(-0.30)	(3.62)	(1.77)	(-1.34)
Patentwidth	-0.067	0.203	-0.005	-0.061
	(-0.83)	(1.01)	(-0.06)	(-0.18)
Citation_num	-0.001*	0.002	-0.000	0.001
	(-1.79)	(1.29)	(-0.49)	(0.34)
Family_num	0.003*	0.005	0.000	0.004
	(1.73)	(1.37)	(0.05)	(0.49)
Public_invention_num	-0.002	-0.009	-0.008	0.014
	(-0.25)	(-0.83)	(-1.02)	(0.74)
Required_rights_num	0.000**	0.001**	0.001**	-0.001
	(2.26)	(2.10)	(2.07)	(-1.14)
vcnum	0.187***	0.097***	0.207***	0.116***
	(22.83)	(6.37)	(16.45)	(4.14)
age	-0.012**	0.012	-0.008	0.033***
	(-2.23)	(1.44)	(-1.27)	(2.78)
Bsg	0.053	-0.044	0.038	-0.267**
	(1.47)	(-0.48)	(0.86)	(-2.05)
vc_indexp	0.234***	0.106	0.454***	0.184
	(4.65)	(0.98)	(7.75)	(1.21)
vc_mktexp	0.017	0.323**	-0.120	0.133
	(0.28)	(2.32)	(-1.54)	(0.62)
Constant	6.977***	8.354***	7.122***	8.651***
	(85.63)	(41.03)	(73.49)	(26.92)
Observations	3,257	570	1,982	217
R-squared	0.650	0.292	0.660	0.381
Invest_round FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Note: (1) This table showcases the empirical regression results based on subsamples from different industries and financing stages. Columns (1) and (3) provide estimates for the impact of various patent signals on the scale of venture capital during the startup financing stage for enterprises within the subsamples of advanced manufacturing and medical health industries. Conversely, Columns (2) and (4) provide estimates for the impact of various patent signals on the scale of venture capital during the commercialization financing stage for enterprises within these same subsamples. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-12 Grouped Regression Results of Financing Scale Based on Different Types of High-Tech Enterprises Within Different Industries

(4)Subsample for Invention Patents

Since the main regression results of this paper are derived from the statistics of all patents held by enterprises, the significant role of invention patents in the Chinese patent market has led us to further refine our sample data. For a more focused analysis, we selected only invention patents for statistical computation and variable construction. We assessed the impact of patents on financing availability from the independent, associated, and integrated levels of patent signals, with results presented in Table 5-14.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	vc_amount	cum_invest	vc_amount	cum_invest	vc_amount	cum_invest
application_num	-0.005*	-0.004	-0.008***	-0.005*		
	(-1.83)	(-1.55)	(-2.66)	(-1.69)		
IPC_num	0.003**	0.002**	0.001	0.002*		
	(2.27)	(2.34)	(0.50)	(1.95)		
Patentwidth	0.011	0.029	0.000	0.027		
	(0.20)	(0.54)	(0.00)	(0.50)		
Citation_num	-0.000	0.000	-0.000	0.000		
	(-0.95)	(0.28)	(-0.59)	(0.35)		
Family_num	0.002	-0.008***	0.002	-0.008***		
	(1.07)	(-5.82)	(1.11)	(-5.82)		
Public_invention_num	-0.003	-0.018***	-0.007*	-0.018***		
	(-0.77)	(-4.45)	(-1.66)	(-4.57)		
Required_rights_num	0.001***	0.001***	0.001***	0.001***		
	(2.89)	(8.47)	(2.98)	(8.48)		
tech_closeness			0.010***	0.002		
			(6.47)	(1.16)		
patent_pca					0.044**	0.076***
					(1.96)	(3.54)
vcnum	0.173***	0.035***	0.168***	0.035***	0.174***	0.037***
	(27.91)	(6.09)	(27.14)	(5.93)	(28.12)	(6.40)
age	-0.005	-0.002	-0.006*	-0.002	-0.006*	-0.005
	(-1.35)	(-0.66)	(-1.71)	(-0.72)	(-1.69)	(-1.45)
Bsg	0.027	0.146***	0.033	0.147***	0.036	0.161***
	(0.99)	(5.67)	(1.20)	(5.70)	(1.31)	(6.23)
vc_indexp	0.312***	0.118***	0.320***	0.120***	0.324***	0.145***

	(8.66)	(3.50)	(8.90)	(3.54)	(9.00)	(4.26)
vc_mktexp	0.010	0.007	0.009	0.007	0.015	0.030
	(0.21)	(0.16)	(0.18)	(0.15)	(0.33)	(0.68)
Constant	7.238***	1.857***	7.221***	1.854***	7.305***	1.730***
	(121.69)	(33.26)	(121.73)	(33.18)	(122.10)	(30.54)
Observations	5,604	5,605	5,604	5,605	5,604	5,605
R-squared	0.658	0.600	0.661	0.600	0.657	0.591
Invest_round FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Note: (1) This table displays the empirical regression results based on subsamples of granted invention patents. Columns (1) and (2) estimate the parameters of the impact of company-level patent signals on the scale of venture capital, Columns (3) and (4) assess the impact of various patent signals on the scale of venture capital, and Columns (5) and (6) analyze the impact of integrated patent signals on the scale of venture capital. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-13 Regression Results Based on Subsamples of Granted Invention Patents

Compared to the patent signal effects of the full sample, focusing solely on invention patents reveals that the impact of the quantity signal of patents on financing availability turns negative (-0.005) and its significance also diminishes. Regarding patent quality signals, the impact of citation counts is reduced, yet the results for the number of IPC classifications remain significant, indicating that quality signals still play a crucial role in influencing financing availability. From the legal signals perspective, the number of claims continues to have a positive effect (0.001), aligning with the main regression results. In terms of commercial signals, while patent commercial signals still positively influence financing scale, their impact on cumulative investment rounds is minimal. From an integrated perspective, various comprehensive patent signals positively affect both financing scale and cumulative investment rounds, with regression coefficients of 0.044 and 0.076, respectively.

(5)Endogeneity test

This study utilizes a survival analysis model to test for potential endogeneity among variables. Patent signals, such as the number of patent applications, IPC classifications, and citation counts, might be correlated with unobservable factors like a firm's R&D capabilities, market prospects, and management quality, which can also influence financing availability. For example, a startup with strong R&D capabilities and an effective management team may find it easier to secure patents, and these attributes might also attract more investment. Therefore, without accounting for these latent variables, it is challenging to ascertain whether the observed effects are attributable to patent signals or these underlying factors. Additionally, there may be reverse causality between patent signals and financing availability, implying that the funding a company secures could influence its capacity to apply for and maintain patents, as financing provides essential resources for innovation and R&D activities in tech startups.

To address these concerns, the study compiles yearly financing and patent information for each company from its founding until the occurrence of investment events, including a financing label variable for all supplementary samples in the survival analysis regression. This approach helps mitigate the influence of existing financing information on patent signals, thus overcoming the model's endogeneity issues.

As demonstrated in Table 5-14, the regression results reveal that the coefficients for patent quantity and quality signals (number of IPC classifications and patent width)

are 0.042, 0.563, and 1.125, respectively, significant at the 1% level. This indicates a positive correlation between patent quantity and quality signals and a company's ability to secure subsequent financing. Likewise, patent legal signals positively affect the likelihood of a company securing the next round of financing. However, the number of claims has a negative impact on the likelihood of obtaining subsequent financing (-0.527), suggesting that the more claims a company has, the less likely it is to secure the next round of financing. Thus, consistent with the main conclusions, even after accounting for endogeneity, patent signals still have a positive impact on a company’s ability to obtain subsequent financing.

Furthermore, the results in columns (6)-(7) of Table 5-14 further validate the influence of patent commercial signals on the likelihood and duration of obtaining financing. Consistent with the original findings, the study observes that commercial signals significantly enhance the probability of a company securing financing and mitigate the effects of other company-level patent signals. After including commercial signals, the impact of some quantity, quality, and legal signals on the duration of securing the next round of financing diminishes or becomes insignificant. For example, the significance level of the quantity signal decreases from 1% to 10%. Therefore, in alignment with the main conclusions, after considering the reverse causality of financing on patents, commercial signals exert a more substantial influence than other patent signal effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Receive the investment or not	Receive the investment or not	Receive the investment or not	Receive the investment or not	Receive the investment or not	Receive the investment or not	Receive the investment or not
application_num	0.042***	0.038***	0.040***	0.052***	0.041**	0.042***	0.054*
	(3.48)	(4.18)	(3.56)	(3.24)	(2.05)	(2.99)	(1.95)
IPC_num		0.563***			0.517***		0.521***
		(16.73)			(13.15)		(13.12)
Patentwidth		1.125***			0.164		0.143
		(11.37)			(1.41)		(1.20)
Family_num			0.582***		0.377***		0.378***
			(12.44)		(5.93)		(5.94)
Citation_num			-0.032		-0.047*		-0.047*
			(-1.58)		(-1.79)		(-1.79)
Public_invention_num				1.201***	1.183***		1.170***
				(21.69)	(13.45)		(13.08)
Required_rights_num				-0.527***	-0.392***		0.027
				(-22.11)	(-13.45)		(0.77)
tech_closeness						0.086***	0.393***
						(2.87)	(13.47)
Observations	5,962	5,962	5,962	5,962	5,962	5,962	5,962

Note: (1) This table displays the empirical regression results from the survival analysis on the impact of patent signals on the likelihood of securing investment. Column (1) estimates the parameters of the impact of patent quantity signals on the likelihood of securing investment. Columns (3)-(5) estimate the parameters of the impact of patent quality and legal signals on the likelihood of securing investment. Column (6) estimates the parameters of the impact of patent business signals on the likelihood of securing investment. Column (7) estimates the parameters of the impact of various patent signals on the likelihood of securing investment. (2) The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 5-14 Survival Analysis Results of the Impact of Patent Signals on the Likelihood of Securing Investment Events

VI. Conclusions and Implications

This chapter synthesizes the research findings of this paper based on the results of the empirical analysis presented earlier and draws conclusions from the study. It also offers relevant recommendations for technology-based startups, venture capital institutions, and government departments based on these conclusions. Lastly, it discusses the limitations of this study and outlines prospects for future research.

6.1 Research conclusions

In recent years, the momentum of technological finance in China has been robust, with significant advancements in the technological financial system and market structure. A comprehensive and multi-level technological financial service network encompassing bank credit, bonds, stocks, venture capital, insurance, and financing guarantees has begun to take shape. Despite these developments, challenges remain in the deep integration of technological innovation and patent financing. As critical outputs of technological innovation, patents hold considerable economic value in the corporate financing process. However, many technology-based SMEs continue to encounter substantial hurdles in patent layout, application, legal protection, and utilization, which in turn limits the efficacy of patents in the financing process. Thus, enhancing the integration of patents with corporate financing is an urgent priority.

This paper investigates the impact of different types of patent signals on the financing accessibility of technology-based startups, considering the multifaceted signaling effects of patents. It explores whether corporate patents can serve as effective

signals in corporate financing and whether different types of signals yield varied impacts. Drawing on signaling theory and information asymmetry theory, the paper analyzes the effects of quantity, quality, legal, and commercial patent signals on financing accessibility. Utilizing financing and patent data from all technology-based startups in the advanced manufacturing and healthcare sectors from 1992 to 2023, it constructs various patent signal variables at both independent and associated company levels. The influence and sources of these multiple patent signals on financing accessibility were empirically examined, leading to the conclusions presented herein.

(i) The study reveals that patent quantity, quality, and legal signals positively influence corporate financing scale. However, legal signals negatively impact the frequency of cumulative investment rounds. Notably, the number and quality of patents applied by a company have the most substantial effect on corporate financing scale. Some legal patent signals adversely affect the timing of subsequent financing rounds, highlighting that investment institutions recognize various types of patent signals, with higher quantities and better quality of patents increasing the likelihood of enhanced financing scale.

(ii) Associated Company-Level Analysis: Commercial signals from technology-based startups positively influence their financing scale and the frequency of cumulative investment rounds. This suggests that venture capital institutions also consider the technological relationships between companies, observing that companies with similar technologies often exhibit comparable trends in financing scale and investment rounds.

(iii) Mechanism Examination: The research identifies that the reputation of venture

capital institutions significantly moderates the relationship between various patent signals and financing accessibility. High-reputation venture capital institutions diminish the influence of comprehensive patent signals on financing accessibility. This moderation could be due to these institutions possessing greater investment experience, more robust information collection and utilization capabilities, and enhanced integration and discernment of different patent data. These competencies help alleviate the information asymmetry in financing interactions and reduce the potency of patent signals. Furthermore, from the associated company level, empirical findings suggest that investors' limited attention and focus are crucial mechanisms that influence the impact of commercial signals on financing accessibility.

(ix) Robustness Test: Robustness testing of the sample indicates that the impact of patent signals on financing accessibility varies between high-tech and non-high-tech companies and between companies at different stages of development (startup versus commercialization). However, these differences do not negate the positive role of patent signals in enhancing financing accessibility.

6.2 Implications

(1)Technology-Based Startups Should Ensure Patent Quality and Optimize Patent Strategy and Business Models

Our study underscores that both the quantity and quality of patents significantly influence financing accessibility. Therefore, technology-based startups should concentrate on enhancing both the number and quality of their patent applications to emit positive patent signals to venture capital institutions. This strategic approach can diminish the probability of information asymmetry and boost the chances of securing financing. Moreover, startups, particularly those in advanced manufacturing, should prioritize patent applications that possess actual commercial value. While some patents might be innovative and practical, they may lack potential commercial viability. Our findings indicate that venture capital institutions also consider the development potential and commercial value of patents in their investment decisions. Consequently, it is crucial for companies to showcase their innovation potential and market readiness through patent information to gain more financing opportunities and support. Lastly, while patent disclosure poses a risk of technical spillover, our research reveals that technological similarity among enterprises in the startup phase can provide investors with more related technical information, thereby enhancing investment prospects. Thus, startups should focus on the commercialization model of their products and develop a viable strategic layout to attract venture capital.

(2)Venture Capital Institutions Should Improve the Patent Value Assessment System

Assessing patents from various dimensions enables venture capital institutions to gauge the commercial model and product value of enterprises, thereby refining their enterprise value evaluation and effectively mitigating potential investment risks. Therefore, venture capital institutions should establish targeted evaluation systems and patent risk alert mechanisms tailored for companies across different industries. This strategy will enhance the assessment of enterprise value and further optimize investment decisions.

(3)Government Departments Should Strengthen the Public Disclosure and Management of Patent Information

Given the significant impact that the quality and quantity of patents have on financing, government patent management departments must refine patent application procedures and enhance the supervision of the patent approval process to elevate the overall quality of patents. Specifically, relevant government departments could leverage big data methods to establish a patent information platform that reflects multidimensional patent information in real-time. This would enhance the openness and transparency of patents and facilitate the development of a more scientific and objective system for classifying and evaluating corporate patent information. Concurrently, the government should proactively guide venture capital towards technology-based startups, augment the scale of investment, and bolster support for these enterprises, addressing their R&D funding shortages and enhancing the policy framework for technological finance.

6.3 Limitations and Research outlook

Although this paper analyzes the impact of various types of patent signals on financing accessibility and enriches the understanding of the relationship between patent signaling effects and venture capital, it acknowledges the following limitations:

(1)Sample Limitations

Due to data availability constraints, this study only includes advanced manufacturing and healthcare companies as research samples. Nonetheless, differences in the number and quality of patent applications and the level of technological innovation across industries may introduce biases in the sample, precluding comprehensive empirical testing across all sectors. Future studies could incorporate additional sub-sectors and industries, such as the service and financial industries, to broaden the understanding of how patent signals influence financing accessibility across diverse industries.

(2)Measurement, Construction, and Classification of Various Patent Signal Indicators

The construction and measurement of patent indicators in this study primarily draw on traditional paradigms from existing research. However, some indicators may not be suitable for specific industries or stages of financing. Certain measurements and constructions of variables may be redundant, and more appropriate proxy variables for patent signals may exist.

(3)Mechanism Effect Testing

In examining the mechanism of patent signals on financing accessibility, this study focuses solely on the influence of venture capital institutions' reputation and attention, neglecting factors such as policy systems and industry dynamics. Future research could incorporate these elements to yield more comprehensive findings.

From the perspective of practice and commercialization models, the ability to identify the technological connections of startups using deep learning can be expanded to include the identification of multidimensional relationships of startups and the development of corresponding commercial applications. Currently, the author has successfully experimented with and achieved preliminary results in exploring business practice models by analyzing the multidimensional relationships of enterprises and financial services. Zhejiang IDEATECH Software Co., Ltd.'s Rongyintong platform seeks to accurately profile enterprises through digital capabilities and offline personnel. It connects commercial banks, third-party institutions, and enterprises using matching models, marketing models, and risk control models, thereby facilitating efficient financial service delivery and connectivity to enterprises.

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Appendix

Deep Learning-Based Model for Identifying Technological Associations in Startups

This section details the development of a deep learning-based model for identifying technological associations in startups using the TechNet model. The construction process involves learning feature word vector representations from document collections, integrating the LDA topic model to create a three-layer probability distribution of enterprise-patent-technical topics, generating topic vectors and enterprise vectors from word vectors, and calculating the degree of technological association between enterprises using vector similarity indicators. The comprehensive research steps are as follows:

(1)Data preprocessing

This study aims to analyze startups by extracting technical feature words from the patent text content (abstracts and titles) to represent the technical topics of startups. It is essential to preprocess the patent text content of startups to facilitate the selection of research subjects and the extraction of technical topics. Specific steps include text segmentation, removal of stop words, fuzzy semantic matching, and elimination of low-frequency words to decrease text noise and improve the information quality of patent texts.

(2)Feature engineering with TechNet model

The TechNet method (S. Sarica, J. Luo, and K.L. Wood, 2020) employs Word2Vec and GloVe algorithms to train feature words' contextual semantic information within

domain-specific patent documents, representing feature vectors as low-dimensional, dense vectors. Similar to the CBOW and skip-gram methods, this approach allows for a more refined representation of research topic features of companies based on contextual semantic information.

(3)Constructing Enterprise-Patent-Technical Topic Probability Distribution with LDA Model

The fundamental concept of the LDA topic model is to view documents as mixtures of various latent topics and to simulate the document generation process repeatedly to identify potential topic information within the corpus or documents. By modeling large-scale corpora or documents, latent topic information within the documents can be uncovered. Following the work of Xi Xiaowen et al. (2021), this study trains the LDA topic model using patent document collections to establish the probability distribution relationships between patents and topics, and topics and topic terms. Subsequently, using the correlation between patent texts and enterprises, a three-layer probability distribution of enterprise-patent-technical topics is constructed.

(4)Enterprises' representation learning with word vectors

Assuming a collection of n patent documents, $D = \{d_1, d_2, \cdots, d_n\}$, containing v words $\{w_1, w_2, \cdots, w_v\}$. Initially, the TechNet model is utilized to train word vectors $\{\boldsymbol{v}(w_1), \boldsymbol{v}(w_2), \cdots, \boldsymbol{v}(w_v)\}$ within the document collection. Utilizing the LDA topic model, the topic-term probability distribution is subsequently derived. Assuming the

patent texts encompass N topics $\{t_1, t_2, \cdots, t_n\}$, the likelihood of generating $j-th$ word by the $i-th$ topic t_i is represented as θ_{i_j}. A higher likelihood of a topic term's association with a topic signifies a more robust representation of the topic information by the term. Consequently, such a term should be accorded a greater weight. The normalization formula used to calculate this weight w_{i_j} is depicted in equation (1)

$$w_{i_j} = \frac{\theta_{i_j}}{\sum_{n=1}^{h} \theta_{i_n}} \ , \qquad (1)$$

The topic vector $\boldsymbol{v}(t_i)$ represents the aggregate of the weighted word vectors for the top h words of the topic, as outlined in equation (2):

$$\boldsymbol{v}(t_i) = \sum_{n=1}^{h} w_{i_n} \boldsymbol{v}\left(t_{i_n}\right), \quad (2)$$

Based on the three-layer probability distribution encompassing enterprise, patent, and technical topic, the higher the probability that a technical topic represents a patent document, the stronger its representation of the topic information. The probability of generating the j-th technical topic by the i-th patent document d_i is denoted as X_{i_j}. The weights of the top m technical topics for each patent document are subsequently normalized, as outlined in equation (3):

$$w_{i_j} = \frac{X_{i_j}}{\sum_{n=1}^{m} X_{i_n}} \ , \quad (3)$$

The vector for each patent document, $\boldsymbol{v}(d_i)$, is the sum of the weighted vectors of the top m technical topics, as detailed in equation (4):

$$\boldsymbol{v}(d_i) = \sum_{n=1}^{h} w_{i_n} \boldsymbol{v}\left(d_{i_n}\right), \quad (4)$$

At the enterprise level, the vector for enterprise c_i, $\boldsymbol{v}(c_i)$, is calculated as the average of the vectors of the documents it contains, as demonstrated in equation (5):

$$\boldsymbol{v}(c_i) = \frac{1}{n} \sum_{i=1}^{n} d_i, (5)$$

(5)The calculation of technological closeness with word vectors

Each tech startup is represented within a fixed-dimension space as vector $\boldsymbol{v}(c_i)$. The technological association measurement between enterprises is thus transformed into a spatial similarity issue involving enterprise vectors. A higher similarity score implies a greater likelihood of the entities becoming competitors or collaborators in the future. Cosine similarity is selected to assess the technological proximity, termed Tech_closeness. Let $\boldsymbol{C}_i = (c_1, c_2, c_3, \cdots, c_n)$ and $\boldsymbol{C}_j = (c_1, c_2, c_3, \cdots, c_n)$ denote the technical vectors of two enterprises. The formula for calculating Tech_closeness is shown in equation (6):

$$\text{Tech\_closeness}(\boldsymbol{v}(c_i), \boldsymbol{v}(c_j)) = \frac{\boldsymbol{v}(c_i) \times \boldsymbol{v}(c_j)}{\|\boldsymbol{v}(c_i)\| \times \|\boldsymbol{v}(c_j)\|}, \quad (6)$$

Employing this approach, the study constructs an enterprise-patent-technical topic graph database focusing on healthcare and advanced manufacturing[3]. Figure 1 illustrates the company associations within the graph database, highlighting three companies with technologies most similar to Shanghai Xinhua Pharmaceutical Technology Co., Ltd., and their technologically akin counterparts.

[3] The visualization website for some graph databases is https://research.ideatech.info.

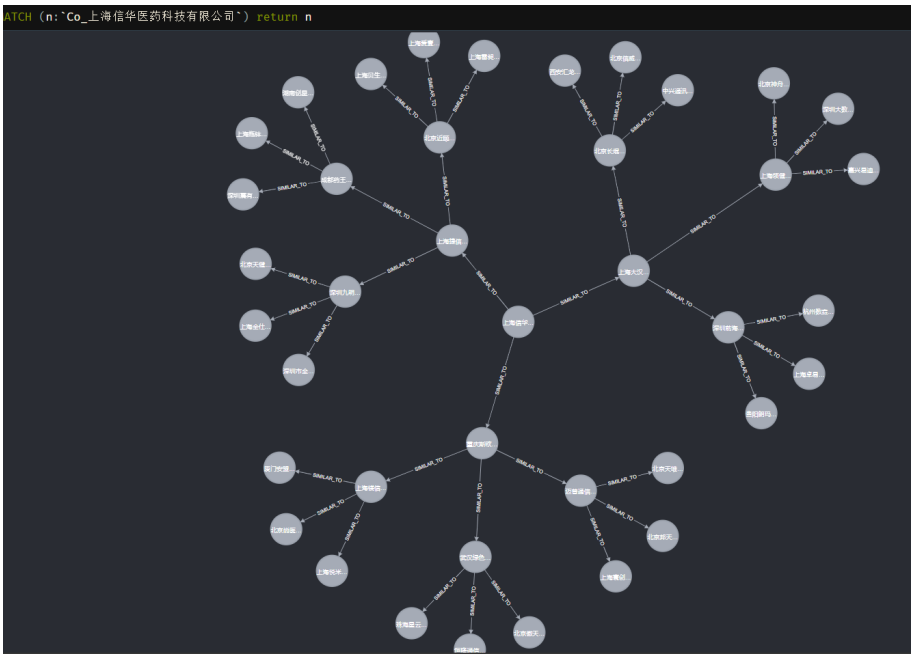

Figure 1 Visualization of graph-based data

Specific Steps for Principal Component Analysis

(1)Feasibility test

Before applying principal component analysis and factor analysis, this paper first employs the KMO (Kaiser-Meyer-Olkin) test and Bartlett's test of sphericity to assess whether the data fulfill the conditions necessary for principal component analysis. The results are displayed in Figure 1. The outcomes of Bartlett's test of sphericity reveal that the approximate chi-square value from Bartlett's test is 10900, with a p-value of less than 0.001, confirming that the original patent signal variables are not correlated and suitable for principal component and factor analysis. The KMO value is 0.887, exceeding the 0.5 threshold, thus meeting the criteria for factor analysis.

```
Determinant of the correlation matrix
Det               =     0.000


Bartlett test of sphericity

Chi-square        =          1.09e+05
Degrees of freedom =                21
p-value           =             0.000
H0: variables are not intercorrelated


Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KMO               =     0.887
```

Figure 1 KMO/Bartlett Test

(2)Factor identification

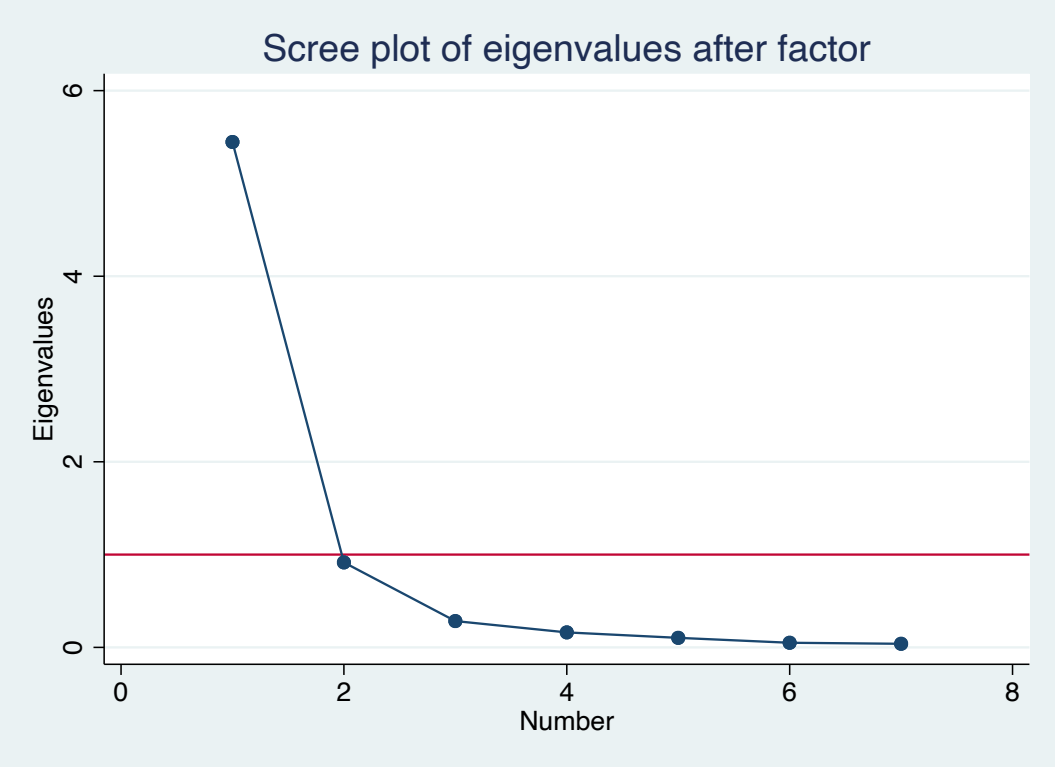

Figure 2 Principal Component Analysis Scree Plot

Principal components/correlation — Number of obs = 10,918; Number of comp. = 7; Trace = 7; Rotation: (unrotated = principal); Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.44654	4.53072	0.7781	0.7781
Comp2	.915819	.631964	0.1308	0.9089
Comp3	.283856	.122216	0.0406	0.9495
Comp4	.161639	.058472	0.0231	0.9726
Comp5	.103167	.0531887	0.0147	0.9873
Comp6	.0499785	.0109776	0.0071	0.9944
Comp7	.039001	.	0.0056	1.0000

Figure 3 Weights Assigned to Each Common Factor

The scree plot in Figure 2 clearly shows that the eigenvalues of the first two common factors exceed 1, substantiating the appropriateness of selecting one principal component.

(3)Factor Extraction and Generation of Integrated Level Factors

After transforming the initial patent signal variables, we identified one principal component, denoted as f1, which effectively represents the integrated level signal of the patents. The component matrix for this principal component is illustrated in Figure 4.

Variable	Factor1	Uniqueness
applicatio~m	0.9670	0.0648
IPC_num	0.8958	0.1975
Patentwidth	0.3907	0.8474
Family_num	0.9628	0.0730
Citation_num	0.9409	0.1148
Public_inv~m	0.9099	0.1721
Required_r~m	0.9571	0.0839

Figure 4 component matrix