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Innovation, Transfer Efficiency, and Stock Returns: Evidence from China

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Abstract

This study examines whether firms' innovation output, measured by patent counts, predicts stock returns in China. We find that patents predict future returns only for non-state-owned enterprises (non-SOEs), where retail investors underreact to innovation signals. This predictability weakens with greater institutional ownership and foreign investor participation, suggesting that sophisticated investors improve the pricing of innovation. In contrast, patents do not predict returns for state-owned enterprises (SOEs), where weak managerial incentives limit patent-to-profit transfer efficiency. Only high-quality invention patents matter for SOEs, while executive stock options improve transfer efficiency. Overall, patents predict returns only when they are converted into firm value yet not fully incorporated into prices. These findings highlight how ownership structure, investor composition, and managerial incentives shape innovation pricing in emerging markets.

Keywords: Innovation; Stock returns; Patent-to-profit transfer efficiency; SOEs

JEL Classifications: G12; G14; O31

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1. Introduction

Innovation-related intangibles, such as patents, constitute an important component of firm value but remain difficult for investors to evaluate and for firms to incorporate into financial disclosures. Patents represent observable outputs of firms' innovation activities and are widely used in the literature as proxies for innovation performance (Griliches, 1990). In developed capital markets, patents are actively traded and often used as collateral in intellectual property markets (Lev, 2001; Mann, 2018). Thus, patent-related information is increasingly incorporated into equity valuations, with evidence showing that patent grants are rapidly reflected in stock prices (Kogan, Papanikolaou, Seru, and Stoffman, 2017). In many emerging markets, however, patenting is a relatively recent phenomenon, and the institutional infrastructure supporting intellectual property rights, such as patent enforcement and technology markets, remains undeveloped (Schneider, 2005; Liu, Tao, and Bi, 2022). Moreover, these markets, including China's, are often dominated by retail investors who have limited capacity to process complex, intangible-related information such as patent grants (Jones, Shi, Zhang, and Zhang, 2023; Chemmanur, Li, Tseng, and Wang, 2026). This raises an important question: are even relatively simple innovation signals, such as patent counts, fully reflected in stock prices in emerging markets? If so, does the mechanism resemble that observed in the U.S. market?

We address this question by examining whether patent counts predict future stock returns in the Chinese stock market, thereby providing new insights into how investors interpret innovation outputs in the presence of institutional and informational frictions. China's stock market provides a distinctive setting for this analysis because it is characterized by the coexistence of two ownership structures: state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). These firms differ substantially in governance, objectives, and innovation incentives. SOE

executives, who are often appointed by government authorities, tend to pursue political or social goals rather than profit-maximizing innovations, resulting in weak incentives to commercialize innovative output (Megginson, 2005; Hu and Jefferson, 2009; Lin, Lin, and Song, 2010; Boeing, Mueller, and Sandner, 2016). In contrast, non-SOEs are more market-oriented, exhibit higher innovation productivity, and place greater emphasis on firm value maximization (Rong, Wu, and Boeing, 2017). These institutional differences motivate a separate examination of the innovation-return relationship across ownership types. For SOEs, the weak link between patenting and profitability, along with limited incentives for innovation commercialization, implies that patent counts may contain little information about future returns. By contrast, non-SOEs are more likely to translate patents into economic gains, thereby improving firm value. Nevertheless, in markets dominated by retail investors with limited attention, even value-relevant information may be underreacted to and gradually incorporated into prices, generating return predictability. We therefore hypothesize that innovation output positively predicts future stock returns for non-SOEs, but not for SOEs.

To test this hypothesis, we analyze Chinese A-share listed firms from 2004 to 2021. We measure innovation output using firms' patent counts normalized by total assets. Different from developed markets (Kogan, Papanikolaou, Seru, and Stoffman, 2017), we find that patent counts significantly predict future stock returns in China. Notably, when we differentiate between SOEs and non-SOEs, this positive relationship holds only for non-SOEs. The results are robust after controlling for R&D expenditures, innovation output from subsidiaries, and other firm characteristics. Portfolio analyses further support our regression findings: among non-SOEs, monthly raw returns increase from 1.41% to 2.00% when moving from the lowest to the highest innovation output portfolios. The alphas of the long-short portfolios remain positive and

statistically significant after adjusting for the Fama-French (1993) three-factor model and the three- and four-factor models of Liu, Stambaugh, and Yuan (2019). In contrast, SOE portfolios show no significant alphas, confirming that the patent-return relationship is unique to non-SOEs.

We next explore the mechanisms behind this predictability among non-SOEs. A plausible explanation is retail investors' limited attention due to their lack of expertise in evaluating patent-related information (Hirshleifer, Hsu, and Li, 2013; Frank and Sanati, 2018). Low participation of institutional investors, who have specialized knowledge and superior information processing capabilities, may further amplify this underreaction. Consistent with this explanation, we find that the predictive power of patent counts weakens among non-SOEs with higher institutional ownership or greater participation by Qualified Foreign Institutional Investor (QFII). Moreover, the introduction of the Shanghai-Shenzhen-Hong Kong Stock Connect Program, which attracts more sophisticated foreign investors, further weakens patent-return predictability.

We then turn to SOEs to examine why patents fail to predict their stock returns. We propose that SOE executives with weaker innovation incentives selectively transfer only high-quality patents into firm value while disregarding low-quality ones. To test this selective transfer hypothesis, we distinguish between invention and utility patents. Invention patents undergo rigorous examination, whereas utility patents are approved under lower scrutiny. Following prior literature (Tong, He, He, and Lu, 2014; Tan, Tian, Zhang, and Zhao, 2020; Rong, Zhang, and Chen, 2023), we classify invention patents as high-quality and utility patents as low-quality. Our analysis shows that for SOEs, only invention patents have predictive power for stock returns. This finding suggests that while SOEs can convert high-quality patents into firm value, they fail to do so for low-quality patents, highlighting how weak incentive structures constrain SOE executives from fully leveraging low-quality innovations.

To further validate the selective transfer efficiency mechanism, we examine whether different types of patents predict firms' future profitability, measured by return on assets (ROA) and return on equity (ROE). The results show that for SOEs, only invention patents are associated with higher future profitability. These findings confirm that SOE executives' limited incentives to utilize low-quality patents contribute to the absence of patent-return predictability among SOEs.

Finally, we investigate heterogeneity in patent transfer efficiency among SOEs from an incentive-based perspective. Executive stock options, which increase personal gains from successful innovation while limiting downside risks, represent a strong mechanism for encouraging innovation (Frydman and Jenter, 2010; Manso, 2011). This incentive logic plausibly extends to the efficiency with which patents are converted into firm value. We therefore examine whether the adoption of executive stock option compensation improves SOEs' patent-to-profit transfer efficiency. Our results show that transfer efficiency exists only for SOEs that grant stock options to executives. Since only a small fraction of SOEs have implemented such compensation schemes, this finding helps explain the lack of patent-based return predictability among SOEs.

This paper contributes to the literature in three aspects. First, it extends the literature on the relationship between innovation and stock returns to emerging markets. While prior studies show that simple information, such as patent grants, is rapidly incorporated into stock prices in the U.S. (Kogan, Papanikolaou, Seru, and Stoffman, 2017), markets tend to underreact to more complex innovation-related information, such as innovation efficiency and originality, that is difficult for investors to process (Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013, 2018). Although this literature is well developed for advanced markets, much less is known about how innovation is priced in less developed markets. Using patent counts as a measure of innovation output, we document a significant and positive relationship between patent counts and future stock

returns among non-SOEs in China. This suggests that in the markets dominated by retail investors, even simple patent-related information may be underreacted to and thus predict future returns.

Second, this paper advances the literature on innovation efficiency by highlighting differences between SOEs and non-SOEs. Previous research shows that R&D investment and innovation efficiency predict future profitability (Gu, 2005; Matolcsy and Wyatt, 2008; Pandit, Wasley, and Zach, 2011), and, more recently, that innovation efficiency affects stock returns through R&D-to-profit or R&D-to-patent transfer channels (Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013). However, these studies assume that managers consistently translate patents into profits. Our results demonstrate that this assumption does not hold in emerging economies, particularly for SOEs. We show that, unlike non-SOEs, patent counts do not predict future stock returns for SOEs, primarily because weaker managerial incentives limit the conversion of patents into profits.¹

Third, this paper deepens our understanding of the innovation incentives in SOEs. While existing research finds that SOE executives have weak innovation incentives (Megginson, 2005; Hu and Jefferson, 2009; Boeing, Mueller, and Sandner, 2016), we show that these incentive distortions influence patent-to-profit transfer efficiency, an underexplored aspect of innovation performance. Our findings indicate that, due to limited personal benefits from innovation, SOE executives selectively convert only high-quality patents into profits, while neglecting low-quality innovations. Moreover, we provide evidence that the adoption of executive stock option compensation significantly improves SOEs' efficiency in transferring patents into profits.

The remainder of this paper is organized as follows. Section 2 reviews China's economic

¹ Yin and Xin (2024) examine innovation-related mispricing in China's A-share market from the perspective of investor cognitive bias. They focus on investors' overweighting of patent quantity relative to patent quality and show that such cognitive bias generates a premium primarily through mispricing. However, their study does not address the role of firm ownership structure.

transition and develops the testable hypotheses. Section 3 describes the data, variable construction, and summary statistics. Section 4 presents empirical analyses, and Section 5 concludes. The Internet Appendix provides additional robustness tests.

2. Background and Hypothesis Development

2.1 SOE reform in China

In the pre-reform planned economy, China's industry was predominantly controlled by state-owned enterprises (SOEs), whose primary objective was to fulfill production quotas rather than to maximize profits. The appointment of senior SOE managers was traditionally overseen by officials within industrial bureaus who exercised decision-making authority (Groves, Hong, McMillan, and Naughton, 1995). Since the initiation of economic reforms in 1978, China has implemented successive rounds of SOE reform to facilitate its transition towards a market-oriented economy. However, the mechanism for selecting SOE managers has remained unchanged. As noted by Shleifer and Vishny (1997), SOEs continue to be controlled by government officials who have significant control rights but limited claims on residual cash flows.

In the contemporary era, industrial bureaus have been replaced by bureaucratic agencies such as the State-Owned Asset Supervision and Administration Commission (SASAC), which represent the state as the ultimate shareholder (Naughton, 2007). While these agencies have no direct cash-flow rights from the enterprises they manage, they retain exclusive authority to appoint managers. Although the Corporate Law grants boards of directors the authority to make personnel decisions, in practice, the appointment of SOE chairman and CEO is decided by the associated bureaucratic agency, with the board merely formalizing the decision *ex post*. This direct governmental intervention in executive appointments often leads SOE managers to prioritize bureaucratic and

political objectives over the interests of minority shareholders.

A key issue arising from this governance structure is the misalignment of incentives between bureaucrats and firm performance. Bureaucrats usually pursue political achievements or personal benefits, which often diverge from, and sometimes conflict with, the objective of improving SOE profitability (Shleifer and Vishny, 1997; Zhou, Gao, and Zhao, 2017). To secure promotion, SOE executives tend to closely follow instructions from bureaucratic agencies rather than engage in independent, profit-oriented decision-making. In particular, they are required to balance profitability with government mandates, such as maintaining social stability and providing public services. Furthermore, SOE managers receive limited personal benefits from R&D activities but must bear significant costs and risks associated with innovation (Megginson, 2010). Therefore, they have weak incentives to improve competitiveness through innovation (Hu and Jefferson, 2009; Boeing, Mueller, and Sandner, 2016).

2.2 Hypothesis development

A firm's patenting activity, widely used as a proxy for innovation output, is generally considered as an important signal of future profitability (Lerner, 1994; Gu, 2005; Matolcsy and Wyatt, 2008; Pandit, Wasley, and Zach, 2011). In well-functioning markets like the U.S., patent-related information is closely monitored by sophisticated investors and rapidly incorporated into stock prices once patents are granted (Kogan, Papanikolaou, Seru, and Stoffman, 2017).

However, in emerging markets like China, the informational efficiency of innovation outputs is limited. Weak intellectual property protection increases uncertainty of the commercial success of granted patents (Schneider, 2005). More importantly, the limited attention theory suggests that investors often fail to fully process or respond to available information, particularly when it is

complex, nuanced, or firm-specific (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006). This limitation is especially salient in China's stock market, where retail investors account for over 80% of trading volume (Barber and Odean, 2008; Liu, Peng, Xiong, and Xiong, 2022). These investors usually lack professional expertise to evaluate the technical and commercial implications of patent disclosures. Compared with institutional investors, retail investors have fewer informational resources and tend to focus on salient, market-wide signals rather than complex, firm-specific fundamentals (Peng and Xiong, 2006; Frank and Sanati, 2018). Consistent with limited attention theory, such cognitive constraints may lead investors to underreact to innovation-related information, causing valuable signals, such as patent granting, to be only partially reflected in stock prices (Chemmanur, Li, Tseng, and Wang, 2026). Thus, patent granting may predict future stock returns, as the market does not immediately or fully incorporate its long-term value.

Nonetheless, the effect of patenting is unlikely to be uniform across firms. In China, the coexistence of SOEs and non-SOEs leads to differences in governance structure and innovation incentives. Non-SOEs operate under stronger market discipline and are subject to more effective governance mechanisms, including performance-linked compensation, scrutiny from institutional investors, and the disciplinary threat of market exit. These mechanisms provide stronger incentives for executives to pursue profitable innovation and to commercialize patents effectively. However, because inattentive retail investors dominate the market, the value created by these innovations is not immediately incorporated into stock prices, leading to predictable returns for non-SOEs.

In contrast, SOEs are subject to more severe agency problems due to weaker incentive structures and less effective monitoring mechanisms (Shleifer, 1998). Managers in SOEs may pursue personal objectives that diverge from shareholders' interests, especially when incentive alignment is weak. These agency conflicts are further amplified by institutional characteristics:

SOE executives usually receive low-powered incentives, such as fixed salaries and limited performance-based compensation, while political objectives, including the maintenance of social stability and employment, often take precedence over profit maximization. These institutional constraints weaken performance monitoring and reduce managerial motivation to engage in long-term, value-enhancing investments, particularly when these projects are costly and their outcomes are uncertain. Therefore, SOEs are less efficient at translating patents into profits, and the value of their innovative output is less likely to be reflected in future stock prices. Based on this analysis, we propose the following hypothesis:

Hypothesis 1. *Patent granting has stronger predictive power for future stock returns in non-SOEs than in SOEs.*

Unlike retail investors who lack professional expertise, institutional investors have superior information-processing capabilities that allow them to interpret patent disclosures more effectively (Fung, Obaid, and Tsai, 2024). When institutional investor participation is low, the market relies more on less-informed retail investors, which may intensify the predictive power of patent granting information for stock returns. Thus, we expect the hypothesis below.

Hypothesis 2. *The predictive power of patent granting on stock returns weakens when non-SOEs have higher institutional investor involvement.*

As discussed earlier, SOE executives usually lack strong incentives to innovate due to weak governance structures (Megginson, 2005; Hu and Jefferson, 2009; Lin, Lin, and Song, 2010; Boeing, Mueller, and Sandner, 2016).² From a cost-benefit perspective, SOE executives may demonstrate selective behavior when converting patents into profits, depending on the relative

² A related strand of the literature, including Cao, Cumming, and Zhou (2020), shows that SOEs may achieve higher innovative efficiency, attributing this advantage to superior access to resources such as finance, talent, and institutional networks.

advantages and challenges associated with high- versus low-quality patents. High-quality patents provide dual advantages. First, they have greater market potential and economic value, increasing the likelihood of substantial financial returns. Second, and more importantly for SOE managers, the successful commercialization of high-quality patents improves enterprise growth, an important performance metric tied to their promotion. Moreover, high-quality patents tend to have greater technical maturity and clearer market applicability, reducing the complexity and managerial effort required for commercialization. These advantages make high-quality patents particularly appealing to SOE managers.

However, low-quality patents typically involve significant costs and uncertain returns. Their successful commercialization requires substantial investment in technical refinement and market development, with no guaranteed success. Given the high resource commitments and the limited expected personal benefits, SOE managers have weak incentives to pursue these projects. Thus, SOEs are more likely to focus on converting high-quality patents, which provide higher returns at lower costs, into profits, while disregarding low-quality ones. This leads to the following hypothesis.

***Hypothesis 3.** SOEs selectively transfer high-quality patents into profits while disregarding low-quality ones.*

3. Data and Variables

3.1 Data

Our sample consists of Chinese main-board A-share firms listed on the Shanghai and Shenzhen Stock Exchanges from 2004 to 2021. Data on stock returns, financial statements, and firm information are obtained from the China Stock Market and Accounting Research (CSMAR)

database, the China Center for Economic Research (CCER) database, and the WIND financial database. Firm ownership data, used to identify SOEs, is collected from the CSMAR database and manually verified for accuracy. We obtain patent data from the Chinese Research Data Services Platform (CNRDS), which provides comprehensive records of patents granted by the State Intellectual Property Office of China (SIPO).

We begin with all A-share firms listed on the Shanghai and Shenzhen Stock Exchanges and exclude (1) financial firms; (2) firm-year observations in the IPO year to mitigate IPO effects; (3) special treatment (ST and *ST) firms due to financial distress; (4) firms with negative equity or missing data for major variables; and (5) micro-cap firms. Following Liu, Stambaugh, and Yuan (2019), we exclude firms in the bottom 30% of market capitalization³. To minimize the influence of outliers, we winsorize all financial variables at the 1% and 99% percentiles. The final monthly sample consists of 219,533 firm-month observations for 872 SOEs and 1,270 non-SOEs.

3.2 Innovation-related measures

Prior studies have used R&D expenditures and patent-related measures as proxies for firm innovation (Chan, Lakonishok, and Sougiannis, 2001; Rong, Wu, and Boeing, 2017; Dou and Xu, 2021). We employ patent-based measures, as R&D expenditures capture only innovation inputs rather than outputs (He and Tian, 2018; Chen, Li, Chu, and Cao, 2024; Au and Tan, 2025). Measuring innovation output through patent data has three advantages. First, patent applications follow a standardized and rigorous process, providing a systematic record of firms' technological progress. Second, China has signed major international intellectual property conventions,

³ This procedure effectively isolates our analysis from the shell-company premium prevalent among Chinese micro-cap stocks. Our results remain robust when using alternative screening rules, such as retaining the top 80% or top 90% of firms by size (not reported).

strengthening the credibility of its patent data.⁴ Third, empirical evidence indicates that China is transitioning from an imitation-based to an innovation-driven economy (Guan, Yam, Tang, and Lau, 2009; Wei, Xie, and Zhang, 2017).

The SIPO grants three types of patents: invention, utility, and design patents. Invention patents, the most innovative, require “novelty, inventiveness, and practical applicability” for approval. Utility patents protect functional improvements to a product’s shape or structure, whereas design patents involve minimal technological innovation. Following Tan, Tian, Zhang, and Zhao (2020), we focus on invention and utility patents and exclude design patents. To ensure comparability and data consistency, we measure patenting activity using the grant date rather than the filing date, since grant dates represent the time when information becomes publicly available. The annual patent count (*Patent*) is defined as the total number of invention and utility patents granted to a firm in a given year. We normalize *Patent* by total assets at the year-end, denoted as *Innov* (Kogan, Papanikolaou, Seru, and Stoffman, 2017; Almeida, Hsu, Li, and Tseng, 2021).

Utility patents are generally less valuable than invention patents for several reasons. First, utility patents require only functional improvements, whereas invention patents must satisfy higher inventiveness standards. Second, invention patents undergo a strict review process lasting three to five years, while utility patents are granted within six months with minimal scrutiny. Third, invention patents are protected for 20 years, compared to only 10 years for utility patents. Accordingly, we classify patent counts into two categories: *Invention* (the number of invention patents granted to a firm each year normalized by total assets) and *Utility* (the number of utility patents granted to a firm each year normalized by total assets).

⁴ These conventions include the World Intellectual Property Organization (WIPO) (1980), the Paris Convention (1985), the Madrid Agreement (1989), and the Integrated Circuits Treaty (1989).

3.3 Defining SOEs and non-SOEs

Following Wei (2021), we classify firms as SOEs or non-SOEs based on their ultimate controller in each year of the sample period. A firm is identified as an SOE if its ultimate controller is the central government, the SASAC of the State Council, a local SASAC, or a local government; otherwise, the firm is classified as a non-SOE. To ensure accurate classification, we manually review each firm's annual reports to verify ownership changes. If a firm is classified as an SOE for less than 30% of the sample period due to a change in ownership, it is unlikely to have functioned as a typical SOE. In such cases, we reclassify the firm as a non-SOE.

3.4 Summary statistics

Table 1 presents the summary statistics of all variables (see Appendix Table A1 for variable definitions). Panel A reports descriptive statistics for the full sample from July 2004 to June 2021. Regarding patenting activity, only 49.9% of firm-year observations include the granting of at least one invention or utility patent. The distribution of *Innov* is highly skewed, with a mean of 0.002 and a maximum of 0.435, reflecting substantial heterogeneity in firms' innovation output. *Utility* displays a similar distributional pattern, with a mean of 0.0013, approximately twice that of *Invention* (0.0006), indicating that utility patents are easier to obtain in China. Firms in our sample have relatively large market capitalizations (*Size*), with a mean of 22.40, reflecting the exclusion of micro-cap firms. On average, the book-to-market ratio is 81.7%, the capital expenditure rate is 5.6%, and the stock turnover rate is 0.4%. Institutional ownership is high at 53.6% and the return on assets (ROA) is 5.5%. Panel B compares summary statistics between non-SOEs and SOEs. Our final sample consists of 103,760 firm-month observations for non-SOEs and 115,773 for SOEs. The average value of *Innov* is 0.003 for non-SOEs and 0.001 for SOEs,

suggesting that non-SOEs generate higher innovation output. Moreover, non-SOEs have higher ROA, while SOEs have higher institutional ownership and book-to-market ratios.

[Insert Table 1 here]

4. Empirical Analysis

In this section, we first examine the return predictability of patent counts for both the full sample and the subsamples of SOEs and non-SOEs. We then focus on non-SOEs and study the impact of institutional involvement on the predictive power of patent counts for stock returns. Next, we analyze patent-to-profit transfer efficiency across different patent types, with a particular focus on SOEs, to explain their weak patent-return relationship. Finally, we investigate the heterogeneity in transfer efficiency among SOEs from an incentive-based perspective.

4.1 Patent-return predictability

We examine the predictability of *Innov* on future stock returns using monthly Fama-MacBeth (1973) cross-sectional regressions. For each month from July of year t to June of year $t + 1$, we regress monthly excess stock returns (ER), calculated as returns over the one-month Treasury bill rate, on *Innov* of year $t - 1$, and a set of control variables, as specified below:

$$\begin{aligned}
 & ER_{i,t} \\
 & = \alpha_1 Innov_{i,t-1} + \alpha_2 X_{i,t-1} + InduFE \\
 & + \mu_{i,t}.
 \end{aligned} \tag{1}$$

Since the SIPO publishes patent-granting information on its website in a timely manner, the lagged innovation measure is expected to be publicly available by July of year t . The control variables X include return on assets (ROA), book-to-market ratio (BM), market capitalization ($Size$), capital

expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). All control variables are measured at the end of year $t - 1$, except for *Size* and *TR*, which are measured at the end of June of year t .⁵ Industry fixed effects are controlled using three-digit industry classification dummies.

Table 2 presents the time-series averages of the estimated slopes and Newey-West (1987) t -statistics. We find that firm innovation output (*Innov*) significantly predicts future stock returns, with a coefficient of 0.2485 and a t -stat of 3.56 (column 1). The coefficient remains positive and significant at the 1% level when controlling for firm characteristics (column 2). These results indicate that patent information predicts future stock returns in China, implying that such information is not fully incorporated into contemporary stock prices.

To evaluate whether this predictive power differs by ownership type, we split the sample into SOEs and non-SOEs and rerun Equation (1). Columns 3 and 4 show that for non-SOEs, the coefficient on *Innov* is positive (0.3719) and statistically significant (t -stat = 3.04), while for SOEs, the coefficient is insignificant (t -stat = 1.41).⁶ These findings indicate that the predictive power of patent granting information on stock returns is mainly driven by non-SOEs, highlighting the role of ownership structure in shaping the patent-return relationship (Hypothesis 1).

[Insert Table 2 here]

A potential concern is that the return predictability of *Innov* reflects risk differentials rather than investor underreaction. Innovation may increase firms' exposure to idiosyncratic volatility and tail risk, which could generate a risk premium (Gharbi, Sahut, and Teulon, 2014; Gu, 2016;

⁵ Using lagged independent variables ensures that all financial and patent-related indicators are fully observable to the public prior to the return estimation period. This approach is a standard convention in existing studies examining the return predictability of innovation (e.g., Hirshleifer et al., 2013; Fitzgerald et al., 2021).

Jia, 2018). We check for this possibility by controlling for these risk-related channels. Table 3 shows that after controlling for idiosyncratic volatility (*IVOL*) and tail risk (*Tail*) separately, the coefficient on *Innov* remains positive and significant among non-SOEs, while it remains insignificant among SOEs. These findings suggest that the patent-return predictability among non-SOEs is unlikely to be driven solely by risk-related channels.

[Insert Table 3 here]

To ensure robustness among non-SOEs, we conduct several additional tests. Prior studies suggest that stock markets may underreact to R&D-related information (Lev and Sougiannis, 1996; Chan, Lakonishok, and Sougiannis, 2001; Eberhart, Maxwell, and Siddique, 2004), raising the possibility that our findings are driven by investors' inattention to R&D expenditures, which are likely correlated with patent grants. To address this concern, we first rerun Equation (1) including R&D expenditures as an additional control variable.⁷ Second, we add subsidiary firms' innovation output (*Innov_sub*) to capture potential spillover effects.⁸ Third, given the importance of liquidity for return predictability in China (Leippold, Wang, and Zhou, 2022), we follow Amihud, Hameed, Kang, and Zhang (2015) and add the Amihud illiquidity ratio (*Illiquidity*) as a control variable. Fourth, we re-consider the sample selection that requires a firm to have at least one patent during the sample period. Finally, we exclude sample periods covering the global financial crisis and the COVID-19 pandemic to mitigate potential biases from extreme market conditions. As shown in Table IA1, our main results remain robust across all specifications, confirming that the

⁷ Since reporting R&D expenditures is not mandatory, we set missing values for R&D expenditures (*RD*) to zero and introduce a dummy variable (*Miss_RD*) that equals one when R&D expenditures are not reported. As shown in Panel A of Table IA1, the coefficients on *RD* are positive and significant at the 10% level, suggesting that firms' R&D expenditures also can predict future stock returns. Moreover, this finding is consistent with the view that investors tend to ignore R&D-related information.

⁸ Panel B of Table IA1 shows that the coefficients on *Innov_sub* are insignificant, justifying our choice to exclude subsidiary patents from our baseline regressions.

predictive power of *Innov* among non-SOEs is not driven by omitted variables such as R&D expenditures, subsidiary innovation, liquidity, or extreme market conditions. Appendix Table A1 provides definition for these variables.

To further investigate whether the predictive power of *Innov* yields an economically significant premium that is robust to well-known risk factors, we conduct portfolio analyses separately for non-SOEs and SOEs. At the end of June of each year, we classify firms with patents into three portfolios based on the 33rd and 66th percentiles of *Innov* within each ownership group. Firms without patents are assigned to a separate portfolio (*Non-patent*). We then calculate value-weighted monthly returns for each portfolio over the next 12 months (July of year t to June of year $t + 1$), and construct a High-Low (H-L) portfolio by taking a long position in the high-*Innov* portfolio and a short position in the low-*Innov* portfolio. We analyze raw returns, excess returns, and risk-adjusted alphas using the Fama-French (1993) three-factor model. We also calculate risk-adjusted alphas using the China-specific three-factor (CH-3) and four-factor (CH-4) models of Liu, Stambaugh, and Yuan (2019).

Panel A of Table 4 presents the portfolio returns for non-SOEs sorted by *Innov*. Raw returns increase from 1.41% in the low-*Innov* portfolio to 2.00% in the high-*Innov* portfolio, generating a return spread of 0.59% (t-stat = 2.35). We observe similar patterns for excess returns and risk-adjusted alphas, indicating that firms with higher patent counts earn significantly higher future returns and that the return spread persists after factor adjustments. We replicate this analysis for SOEs. Panel B of Table 4 shows that the spreads in raw returns, excess returns, and risk-adjusted alphas for SOEs are statistically insignificant. Overall, the portfolio analysis confirms our regression results, showing that the *Innov* effect is pronounced only among non-SOEs, consistent with Hypothesis 1.

[Insert Table 4 here]

4.2. Institutional involvement in non-SOEs

Our previous analysis shows that the predictive power of patents for future stock returns exists only among non-SOEs and is absent in SOEs. We now examine the underlying mechanism. Hypothesis 2 posits that the predictive power of innovation output on stock returns weakens when non-SOEs have higher institutional investor involvement. To test this hypothesis, we use two proxies for institutional involvement: institutional ownership and the introduction of the Shanghai-Shenzhen-Hong Kong Stock Connect Program.

In China, retail investors dominate trading activity and often lack the expertise needed to effectively interpret patent information. Thus, the patent-return predictability among non-SOEs may be attributed to retail investors' limited attention (Hirshleifer, Hsu, and Li, 2013; Frank and Sanati, 2018; Chemmanur, Li, Tseng, and Wang, 2026). In contrast, institutional investors have informational advantages, superior information processing capabilities, and greater professional expertise (Fung, Obaid, and Tsai, 2024), enabling them to process patent-related information more efficiently. Therefore, when institutional participation is low, markets mainly rely on less-informed retail investors, strengthening the predictive power of patent information.

Institutional investors are generally more capable of analyzing firm-specific information and incorporating it into stock prices (Piotroski and Roulstone, 2004; Boehmer and Kelly, 2009). Thus, we expect that higher institutional ownership will improve market efficiency, thereby weakening the patent-return relationship. To measure institutional ownership, we use two indicators: (1) Total institutional ownership, defined as the proportion of a firm's shares held by all institutional investors at the end of the year; and (2) QFII ownership, calculated as the proportion of a firm's

shares held by QFIIs at the end of the year. Previous studies have shown that “independent” institutional investors, such as QFIIs, are particularly effective in information acquisition and corporate monitoring (Chen, Harford, and Li, 2007; Luong, Moshirian, Nguyen, Tian, and Zhang, 2015; Bena, Ferreira, Matos, and Pires, 2017; Rong, Wu, and Boeing, 2017).

To evaluate the impact of institutional ownership on return predictability, we construct two dummy variables (*High* and *Low*) based on the annual median value of institutional ownership. *High* (*Low*) equals one if a firm’s *Innov* is positive and its institutional ownership is above (below) the annual median, and zero otherwise. We then rerun Equation (1) for non-SOEs, replacing *Innov* with *Innov * High* and *Innov * Low*. As shown in column 1 of Table 5 Panel A, the coefficient on *Innov * Low* is positive (0.5911) and statistically significant (t-stat = 2.24), while the coefficient on *Innov * High* is insignificant (t-stat = 1.16). We have similar results when using QFII ownership as the classification criteria (column 2).⁹ These findings support the notion that the patent-return relationship reflects market inefficiency driven by retail investors’ valuation constraints.

The Shanghai-Shenzhen-Hong Kong Stock Connect Program is a major milestone in opening China’s stock market to foreign institutional investors. By facilitating foreign participation, this program improves market efficiency (Jiang, Luo, and Zhu, 2020; Chen, Lin, Lu, and Ma, 2021; Chen, Huang, Li, and Yuan, 2022). We thus expect that the introduction of this program weakens the patent-return relationship for non-SOEs. To test this hypothesis, we construct two dummy variables, *Lib* and *Non_Lib*, based on whether a firm was selected for the program over time. *Lib* equals one for firm-year observations from the year a firm was selected in the program until

⁹ As a robustness check, we rerun the regression on subsamples split by the median value of institutional ownership or QFII ownership and find consistent results (Panel A of Table IA2).

the year prior to its exit, and zero otherwise. *Non_Lib* equals one for firm-year observations before a firm's inclusion in the program, after its exit, or for firms that were never selected, and zero otherwise. We rerun Equation (1) for non-SOEs, replacing *Innov* with *Innov * Lib* and *Innov * Non_Lib*. Column 1 of Panel B shows that the coefficient on *Innov * Lib* is insignificant (t-stat = 0.07), while the coefficient on *Innov * Non_Lib* is positive and weakly significant (t-stat = 1.84). This result implies that the patent-return predictability weakens for non-SOEs included in the Stock Connect Program.¹⁰ Overall, these findings demonstrate that greater institutional participation through either higher institutional ownership or the introduction of the Stock Connect Program improves market efficiency and mitigates the patent-return relationship, supporting Hypothesis 2.¹¹

[Insert Table 5 here]

Beyond cross-sectional differences in institutional participation, we further examine whether the patent-return predictability among non-SOEs also varies over time as the market matures. We rerun Equation (1) for non-SOEs across four rolling sample periods (2004-2015, 2006-2017, 2008-2019, 2010-2021) to assess the evolution of market efficiency. Table 6 shows that the coefficients on *Innov* are positive and significant, supporting the notion that the Chinese stock market displays weak-form efficiency and underdeveloped financial institutions (Groenewold, Tang, and Wu, 2004; Rong, Wu, and Boeing, 2017). Importantly, the coefficient on *Innov* decreases steadily from 0.515 to 0.108 over time. This suggests that investors have become increasingly

¹⁰ To ensure robustness, we rerun the regression for subsamples of selected versus non-selected firms and find similar results (Panel B of Table IA2).

¹¹ We also examine the role of institutional involvement in SOEs. Drawing on agency theory, SOE executives often prioritize bureaucratic or political objectives reducing their responsiveness to investor oversight. Thus, we expect that institutional involvement has little effect on the predictive power of innovation output in SOEs. Re-estimating the regressions using the SOE subsample yields results consistent with this expectation (Table IA3). These results contrast with the finding of Chemmanur, Li, Tseng, and Wang (2026) for SOEs, and instead support the view that SOEs are less responsive to external governance mechanisms (Rong, Wu, and Boeing, 2017).

capable of processing, and then the market has become increasingly efficient in incorporating patent-grant information into stock prices, thereby reducing its predictive power among non-SOEs. Such an evolution is potentially driven by investor learning, improved information availability through the internet, and the growing participation of international investors (Carpenter, Lu, and Whitelaw, 2021). Overall, these results reinforce the view that patent-return predictability reflects retail investors' limits to information processing that diminish as the market matures.

[Insert Table 6 here]

4.3 Patent-to-return transfer efficiency among SOEs

We now turn to SOEs and investigate the mechanisms underlying their weak patent-return relationship by distinguishing between invention and utility patents. We rerun Equation (1) by replacing *Innov* with *Invention* and *Utility* for SOEs. Table 7 shows that the coefficient on *Invention* is positive (0.9020) and significant (t-stat = 2.20), whereas the coefficient on *Utility* remains insignificant (t-stat = -0.76). These results indicate that among SOEs, invention patents (high-quality patents) significantly predict future stock returns, while utility patents (low-quality patents) do not. This finding supports the selective transfer explanation that SOE executives have limited incentives to commercialize low-quality patents but are more likely to transfer high-quality patents into profits, supporting Hypothesis 3.¹²

[Insert Table 7 here]

To provide further empirical evidence, we examine the patent-to-profit transfer efficiency among SOEs by regressing firm profitability on lagged *Invention* and *Utility* as follows:

¹² We also examine the effect of patent-return predictability for non-SOEs and find that both invention and utility patents predict stock returns among non-SOEs, further supporting our Hypothesis 1 (not reported).

$$\begin{aligned}
& Profit_{i,t} \\
& = \beta_1 Invention_{i,t-1} + \beta_2 Utility_{i,t-1} + \beta_3 X_{i,t-1} + InduFE + YearFE \\
& + \varepsilon_{i,t}. \quad (2)
\end{aligned}$$

Following Hirshleifer, Hsu, and Li (2018), we measure firm profitability (*Profit*) using two metrics: return on assets (*ROA*) and return on equity (*ROE*). *ROA* is defined as income before extraordinary items plus interest expenses, divided by one-year lagged total assets. *ROE* is defined as income before extraordinary items plus interest expenses, divided by one-year lagged book equity (common equity plus deferred tax). To account for persistence and mean reversion in profitability, we include lagged profitability and lagged changes in profitability as control variables (David, Fama, and French, 2000; Gu, 2005). We also control for firm characteristics related to profitability, including the book-to-market ratio (*BM*), market capitalization (*SIZE*), capital expenditure (*CapEx*), leverage ratio (*Lev*), turnover (*Turn*), and institutional ownership (*Ins*). All financial variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. Industry and year-fixed effects are also included to control for unobserved heterogeneity.¹³

Table 8 presents the estimated effect of innovation output on firm profitability for SOEs based on Equation (2). When *ROA* is the dependent variable, the coefficient on *Invention* remains positive and significant (t-stat = 1.98) while the coefficient on *Utility* is positive but insignificant (t-stat = 0.75) (column 1). The robust relationship between *Invention* and *ROA* indicates that SOEs can transfer high-quality patents into profits, further supporting Hypothesis 3. The weak relationship between *Utility* and *ROA* confirms that SOEs are reluctant to transfer low-quality patents. Using *ROE* as the dependent variable generates similar results (column 2).¹⁴

¹³ Table IA4 reports the annual summary statistics for SOEs.

¹⁴ We also examine patent-to-profit transfer efficiency for non-SOEs. Using profitability measures (*ROA* or *ROE*) as dependent variables, we find that both invention and utility patents positively predict future firm performance among

[Insert Table 8 here]

4.4 Heterogeneity in transfer efficiency among SOEs

We further examine the heterogeneity in transferring patents into firm value among SOEs from an incentive-based perspective. Equity compensation is a powerful incentive for executives to drive innovation and improve firm performance (Hall and Liebman, 1998; Manso, 2011). In particular, stock option compensation encourages executives to prioritize long-term objectives and invest more in innovations. When innovative projects succeed, rising stock prices generate option gains for executives. Conversely, if R&D is unsuccessful, executives can choose not to exercise their stock options, thereby avoiding personal financial losses. We thus expect that offering executive option compensation enhances patent-to-profit transfer efficiency in SOEs.

In China, listed firms began implementing stock option compensation schemes in 2006. We focus on executive stock option compensation and construct two dummies (*No_option* and *Option*) to indicate whether a firm has adopted such compensation. To evaluate the impact of stock options on innovation efficiency, we rerun Equation (2) including interactions between these two dummies and *Innov* for SOEs.¹⁵ Given that stock option compensation may influence SOE executives' innovation strategies, we focus on *Innov*, which captures both invention and utility patents. Using *ROA* as the dependent variable (column 1 of Table 9), we find that the coefficient on *Innov * Option* is positive (0.5751) and statistically significant (t-stat = 2.66), exceeding that on *Innov * No_option* (0.1693, t-stat = 1.77). When using *ROE* as the dependent variable, the

non-SOEs (not reported). These findings are consistent with our earlier results that both types of patents exhibit predictive power for future stock returns among non-SOEs.

¹⁵ Additionally, we examine non-SOEs and find that the coefficients on both *Innov * No_option* and *Innov * Option* are positive and significant (not reported).

coefficient on *Innov * Option* remains positive (1.6906) and significant (t-stat = 3.18), while the coefficient on *Innov * No_option* is positive (0.2665) but insignificant (t-stat = 0.96) (column 2). These findings indicate that executive stock option compensation significantly improves the patent-to-profit transfer efficiency of SOEs, consistent with the argument that stronger managerial incentives improve the commercialization of innovation output.¹⁶

[Insert Table 9 here]

5. Conclusion

This paper demonstrates that, unlike in developed markets, a simple innovation measure, patent counts, predicts future stock returns in China only among non-SOEs, but not SOEs. For non-SOEs, patent-return predictability weakens with higher institutional ownership and participation in the Stock Connect Program. The weak predictive power among SOEs is attributed to their limited ability to transfer patents into profitability. We find that SOEs selectively transfer high-quality (invention) patents into profits, while neglecting low-quality (utility) ones. Furthermore, the patent-to-profit transfer efficiency of SOEs improves significantly when executive stock option compensation is implemented.

Our findings have important policy implications. First, this study highlights that retail investors in emerging markets like China often have difficulties in assessing innovation output, leading to market inefficiencies that institutional investors can help alleviate. Policymakers could promote investor education on the innovation-performance link and encourage the participation of institutional investors to improve market efficiency. Second, policymakers may create the

¹⁶ To verify the influence of stock options on patent-return predictive power, we rerun the regression using *Innov * Option* and *Innov * No_option* to replace *Innov*. Table IA5 shows that the predictive power of patent-related innovation is pronounced among SOEs that have adopted executive stock options, whereas it remains insignificant among those that have not.

environment that fosters competition, enhances monitoring, and incentivizes executives to innovate, thereby improving innovation effectiveness and overall performance for SOEs. From an investment perspective, ownership structure is important when evaluating innovation as a predictor of firm value. Non-SOEs have greater efficiency in translating innovation into profitability, making them attractive investment opportunities. For corporate managers, particularly in non-SOEs, these results highlight the importance of increasing transparency regarding innovation activities and market potential to attract attention from institutional investors and financial analysts.

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Appendix

Table A1. Variable definitions

Variable	Definition
<i>ER</i>	Excess return, a firm's stock return in a given month minus the risk-free interest rate.
<i>Innov</i>	The number of a firm's invention and utility patents that are granted in a given year, normalized by its total assets at the year end.
<i>Invention</i>	The number of a firm's invention patents that are granted in a given year, normalized by its total assets at the year end.
<i>Utility</i>	The number of a firm's utility patents that are granted in a given year, normalized by its total assets at the year end.
<i>Innov_sub</i>	The number of subsidiary firms' invention and utility patents that are granted in a given year, normalized by its total assets at the year end.
<i>ROA</i>	Income before extraordinary items plus interest expenses divided by one-year lagged total assets at the year end.
<i>ROE</i>	Income before extraordinary items plus interest expenses divided by one-year lagged book equity (common equity plus deferred tax) at the year end.
ΔROA	Annual change in <i>ROA</i> .
ΔROE	Annual change in <i>ROE</i> .
<i>BM</i>	The ratio of book equity to market value at the year end.
<i>Size</i>	The log of market capitalization at the end of June.
<i>SIZE</i>	The log of market capitalization at the year end.
<i>CapEx</i>	Capital expenditure divided by total assets at the year end.
<i>STRev</i>	Short-term reversal, defined as the stock return of the prior month.
<i>Mom</i>	Momentum, defined as the previous 11-month returns (with a one-month gap between the holding period and the current month).
<i>TR</i>	The ratio of shares traded to total shares outstanding at the end of June.
<i>Turn</i>	The ratio of shares traded in a given year to total shares outstanding at the year end.
<i>Ins</i>	Institutional ownership, defined as the proportion of a firm's outstanding shares that are owned by institutional investors at the year end.
<i>Lev</i>	The ratio of total debts to total assets at the year end.
<i>RD</i>	The ratio of R&D expenditures to total assets at the year end.
<i>Miss_RD</i>	A dummy variable indicating whether the R&D value is missing.
<i>Illiquidity</i>	The annual average of the daily ratio between the absolute value of a stock's return and its trading volume (in billion yuan).
<i>IVOL</i>	The standard deviation of residual stock returns from the CAPM estimated using a rolling-window regression.
<i>Tail</i>	The sum of the top five daily returns of a firm.

Table 1. Summary statistics

This table reports the time-series averages of the monthly cross-sectional summary statistics for firms' excess returns (*ER*), innovation output (*Innov*, *Invention*, and *Utility*), and other characteristics, including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The return data are from July 2004 to June 2021.

Panel A. Full sample							
	Mean	S.D.	Min.	P25	P50	P75	Max.
<i>ER</i>	0.011	0.128	-0.038	-0.066	-0.0003	0.077	0.431
<i>Innov</i>	0.0019	0.007	0.000	0.000	0.000	0.001	0.435
<i>Invention</i>	0.0006	0.002	0.000	0.000	0.000	0.0003	0.083
<i>Utility</i>	0.0013	0.006	0.000	0.000	0.000	0.001	0.435
<i>ROA</i>	0.055	0.063	-0.117	0.018	0.043	0.081	0.297
<i>BM</i>	0.817	0.708	0.083	0.346	0.594	1.040	3.972
<i>Size</i>	22.399	1.121	19.749	21.739	22.381	23.073	25.439
<i>CapEx</i>	0.056	0.052	0.000	0.017	0.040	0.077	0.252
<i>Mom</i>	0.166	0.618	-0.661	-0.225	-0.001	0.354	2.833
<i>STRev</i>	0.010	0.130	-0.310	-0.067	-0.001	0.077	0.436
<i>TR</i>	0.004	0.004	0.000	0.001	0.002	0.005	0.020
<i>Ins</i>	0.536	0.212	0.022	0.397	0.559	0.694	0.926
Observations	219,533						
Panel B. Non-SOEs vs. SOEs							
	Non-SOEs		SOEs				
	Mean	S.D.	Mean	S.D.			
<i>ER</i>	0.010	0.129	0.011	0.128			
<i>Innov</i>	0.0026	0.009	0.0013	0.004			
<i>Invention</i>	0.0008	0.003	0.0004	0.001			
<i>Utility</i>	0.0018	0.008	0.0009	0.004			
<i>ROA</i>	0.062	0.067	0.049	0.057			
<i>BM</i>	0.666	0.557	0.952	0.797			
<i>Size</i>	22.406	1.015	22.392	1.208			
<i>CapEx</i>	0.055	0.051	0.056	0.053			
<i>Mom</i>	0.165	0.601	0.167	0.634			
<i>STRev</i>	0.010	0.130	0.011	0.129			
<i>TR</i>	0.004	0.004	0.004	0.004			
<i>Ins</i>	0.457	0.228	0.606	0.167			
Observations	103,760		115,773				

Table 2. Return predictive power of firm innovation

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) and different sets of control variables and industry dummies in year *t*-1. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	All (1)	All (2)	Non-SOEs (3)	SOEs (4)
<i>Innov</i>	0.2485*** (3.56)	0.2360*** (3.34)	0.3719*** (3.04)	0.1530 (1.41)
<i>ROA</i>		0.0062 (0.63)	0.0124 (1.04)	0.0057 (0.49)
<i>BM</i>		0.0005 (0.61)	0.0016 (1.37)	0.0007 (0.68)
<i>Size</i>		-0.0028** (-2.14)	-0.0028* (-1.76)	-0.0028** (-2.23)
<i>CapEx</i>		0.0027 (0.34)	0.0126 (1.15)	-0.0114 (-1.42)
<i>Mom</i>		0.0008 (0.20)	0.0018 (0.44)	-0.0014 (-0.35)
<i>STRev</i>		-0.0536*** (-8.23)	-0.0551*** (-7.60)	-0.0586*** (-8.19)
<i>TR</i>		-1.1414*** (-6.56)	-1.3353*** (-6.66)	-1.0867*** (-4.92)
<i>Ins</i>		-0.0001 (-0.05)	0.0024 (0.91)	-0.0025 (-0.73)
Observations	219,533	219,533	103,760	115,773
Adjusted R^2	0.108	0.176	0.142	0.211
Industry FE	Yes	Yes	Yes	Yes

Table 3. Firm innovation and return predictability: additional risk controls

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) and different sets of control variables and industry dummies in year *t*-1 controlling for idiosyncratic volatility and tail risk separately. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Non-SOEs (1)	SOEs (2)
Panel A. Control for idiosyncratic volatility		
<i>Innov</i>	0.4010*** (3.15)	0.1165 (1.02)
<i>IVOL</i>	-0.1160 (-1.21)	-0.3663*** (-4.35)
Observations	90700	107361
Adjusted R^2	0.144	0.212
Panel B. Control for tail risk		
<i>Innov</i>	0.3585*** (3.01)	0.1630 (1.42)
<i>Tail</i>	0.0021 (0.30)	-0.0198*** (-3.16)
Observations	101724	114307
Adjusted R^2	0.146	0.214
Industry FE	Yes	Yes

Table 4. Value-weighted portfolio analysis: non-SOEs vs. SOEs

This table presents the results of portfolio formation based on *Innov*. At the end of June of each year from 2004 to 2021, non-SOEs and SOEs are ranked by their relative patents and assigned to one of three equally sized portfolios, respectively. Firms with no patents are assigned to a separate non-patent portfolio within each ownership group. We hold these portfolios over the next 12 months (July of year t to June of year $t+1$). We calculate the average monthly value-weighted portfolio returns and alphas over the next 12 months. Raw return is the average monthly value-weighted portfolio return. Excess return is the average monthly value-weighted portfolio return in excess of the one-month Treasury bill rate. To adjust for risk, we consider Fama-French (1993) three-factor model, as well as Liu, Stambaugh, and Yuan (2019) three- and four-factor models.

Value-weighted portfolios sorted by <i>Innov</i>	Non-patent	Low	Middle	High	High-Low
Panel A. Non-SOEs					
Raw return	1.274*	1.405*	1.696**	1.996***	0.592**
	(1.78)	(1.96)	(2.45)	(2.91)	(2.35)
Excess return	1.080	1.210*	1.501**	1.802***	0.592**
	(1.50)	(1.69)	(2.17)	(2.62)	(2.35)
FF3 α	-0.161	0.098	0.376	0.750***	0.652***
	(-0.92)	(0.38)	(1.42)	(2.82)	(2.90)
CH3 α	-0.088	0.109	0.377	0.618**	0.509**
	(-0.64)	(0.46)	(1.23)	(2.42)	(2.06)
CH4 α	-0.079	0.077	0.317	0.521*	0.443*
	(-0.57)	(0.34)	(1.00)	(1.83)	(1.80)
Panel B. SOEs					
Raw return	1.172*	1.496**	0.978	1.301*	-0.195
	(1.73)	(2.25)	(1.49)	(1.95)	(-0.77)
Excess return	0.977	1.301*	0.784	1.106*	-0.195
	(1.44)	(1.95)	(1.19)	(1.66)	(-0.77)
FF3 α	-0.045	0.479**	-0.034	0.051	-0.428**
	(-0.26)	(2.45)	(-0.15)	(0.28)	(-2.26)
CH3 α	-0.334**	0.200	-0.382	0.099	-0.101
	(-2.26)	(1.09)	(-1.35)	(0.46)	(-0.43)
CH4 α	-0.269	0.173	-0.377	0.045	-0.128
	(-1.59)	(0.87)	(-1.35)	(0.20)	(-0.51)

Table 5. Patent-return predictability and institutional involvement among non-SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) in year *t*-1 by including interaction terms with the measure of institutional involvement among non-SOEs. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted *t*-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A. Institutional ownership		
Measured by	Institutional ownership (1)	QFII ownership (2)
<i>Innov * High</i>	0.2132 (1.16)	0.2548 (0.28)
<i>Innov * Low</i>	0.5911** (2.24)	0.4244*** (2.79)
Observations	103,760	103,760
Adjusted R^2	0.143	0.143
Panel B. Shanghai-Shenzhen-Hong Kong Stock Connect Program		
Measured by	Joining the Program or not (1)	
<i>Innov * Lib</i>	0.0040 (0.07)	
<i>Innov * Non_Lib</i>	0.2505* (1.84)	
Observations	94,526	
Adjusted R^2	0.147	
Controls	Yes	
Industry FE	Yes	

Table 6. Return predictive power of firm innovation for different rolling periods among non-SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (ER) from July of year t to June of year $t+1$ on firm innovation ($Innov$) and different sets of control variables and industry dummies in year $t-1$ for four different rolling periods among non-SOEs. Controls is a vector of control variables including return on assets (ROA), book-to-market ratio (BM), market capitalization ($Size$), capital expenditure ($CapEx$), momentum (Mom), short-term reversal ($STRev$), stock turnover (TR), and institutional ownership (Ins). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t -statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Period	2004-2015	2006-2017	2008-2019	2010-2021
	(1)	(2)	(3)	(4)
<i>Innov</i>	0.5151*** (2.86)	0.2428** (2.37)	0.1430** (2.35)	0.1079** (2.35)
<i>ROA</i>	0.0111 (0.62)	-0.0023 (-0.15)	-0.0045 (-0.51)	-0.0017 (-0.18)
<i>BM</i>	0.0018 (1.20)	0.0004 (0.26)	0.0010 (0.67)	0.0008 (0.57)
<i>Size</i>	-0.0040** (-2.28)	-0.0053*** (-2.72)	-0.0050** (-2.50)	-0.0030 (-1.50)
<i>CapEx</i>	0.0001 (0.01)	-0.0039 (-0.29)	-0.0031 (-0.24)	0.0187 (1.39)
<i>Mom</i>	0.0007 (0.12)	-0.0043 (-0.82)	-0.0046 (-0.84)	0.0023 (0.54)
<i>STRev</i>	-0.0666*** (-8.27)	-0.0665*** (-9.50)	-0.0629*** (-7.68)	-0.0462*** (-5.16)
<i>TR</i>	-1.2086*** (-4.40)	-1.3856*** (-5.06)	-1.3422*** (-5.39)	-1.4548*** (-7.49)
<i>Ins</i>	0.0031 (0.82)	0.0014 (0.41)	0.0025 (0.96)	0.0003 (0.15)
Observations	46,113	55,675	68,581	85,394
Adjusted R^2	0.146	0.143	0.142	0.140
Industry FE	Yes	Yes	Yes	Yes

Table 7. Return predictive power of invention and utility patents among SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*, *Invention* and *Utility*) and different sets of control variables and industry dummies in year *t*-1 among SOEs. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted *t*-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	(1)	(2)
<i>Innov</i>	0.1530 (1.41)	
<i>Invention</i>		0.9020** (2.20)
<i>Utility</i>		-0.0995 (-0.76)
<i>ROA</i>	0.0057 (0.49)	0.0058 (0.50)
<i>BM</i>	0.0007 (0.68)	0.0007 (0.72)
<i>Size</i>	-0.0028** (-2.23)	-0.0028** (-2.23)
<i>CapEx</i>	-0.0114 (-1.42)	-0.0118 (-1.48)
<i>Mom</i>	-0.0014 (-0.35)	-0.0014 (-0.34)
<i>STRev</i>	-0.0586*** (-8.19)	-0.0588*** (-8.21)
<i>TR</i>	-1.0867*** (-4.92)	-1.0829*** (-4.94)
<i>Ins</i>	-0.0025 (-0.73)	-0.0027 (-0.78)
Observations	115,773	115,773
Adjusted R^2	0.211	0.212
Industry FE	Yes	Yes

Table 8. Firm innovation and profitability among SOEs

This table presents annual regressions of profitability on firm innovation (*Invention* and *Utility*) among SOEs. We measure profitability by *ROA* and *ROE* in year *t*. Controls is a vector of control variables including the book-to-market ratio (*BM*), market capitalization (*SIZE*), capital expenditure (*CapEx*), leverage ratio (*Lev*), turnover (*Turn*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each annual regression. The t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Dependent variable	<i>ROA</i> (1)	<i>ROE</i> (2)
<i>Invention</i>	0.9154** (1.98)	2.0640** (2.26)
<i>Utility</i>	0.0814 (0.75)	0.1259 (0.38)
<i>lagged ROA</i>	0.6367*** (40.72)	
ΔROA	-0.1155*** (-7.70)	
<i>lagged ROE</i>		0.5921*** (28.52)
ΔROE		-0.1143*** (-5.91)
<i>BM</i>	-0.0090*** (-9.93)	-0.0191*** (-8.24)
<i>SIZE</i>	0.0039*** (5.86)	0.0085*** (5.31)
<i>Lev</i>	-0.0341*** (-9.42)	-0.0297*** (-3.36)
<i>CapEx</i>	-0.0298*** (-2.91)	-0.0097 (-0.39)
<i>Turn</i>	-0.0201 (-0.98)	-0.0856* (-1.66)
<i>Ins</i>	0.0261*** (6.94)	0.0634*** (6.60)
Observations	9,688	9,688
Adjusted R^2	0.473	0.336
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 9. Firm innovation, option-based executive compensation, and profitability among SOEs

This table presents annual regressions of profitability (i.e., *ROA* and *ROE*) on firm innovation (*Innov*) by including interaction terms with executive stock option compensation among SOEs. Controls is a vector of control variables including the book-to-market ratio (*BM*), market capitalization (*SIZE*), capital expenditure (*CapEx*), leverage ratio (*Lev*), turnover (*Turn*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each annual regression. The t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Dependent variable	<i>ROA</i> (1)	<i>ROE</i> (2)
<i>Innov * No_option</i>	0.1693* (1.77)	0.2665 (0.96)
<i>Innov * Option</i>	0.5751*** (2.66)	1.6906*** (3.18)
Observations	9,688	9,688
Adjusted R^2	0.473	0.336
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

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Table IA1. Return predictive power of firm innovation: robustness checks

This table reports robustness checks for the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) and different sets of control variables and industry dummies in year *t*-1. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Sample	All (1)	Non-SOEs (2)	SOEs (3)
Panel A. Control for R&D expenditures			
<i>Innov</i>	0.1988*** (2.83)	0.3026** (2.60)	0.1220 (1.12)
<i>RD</i>	0.1766*** (4.78)	0.1926*** (4.29)	0.1604* (1.79)
<i>Miss_RD</i>	0.0003 (0.34)	0.0003 (0.20)	0.0008 (0.92)
Observations	219,533	103,760	115,773
Adjusted R^2	0.177	0.144	0.212
Panel B. Control for subsidiary innovation			
<i>Innov</i>	0.2378*** (3.33)	0.3723*** (3.08)	0.1507 (1.36)
<i>Innov_sub</i>	0.0178 (0.18)	0.1274 (0.90)	-0.0074 (-0.06)
Observations	219,533	103,760	115,773
Adjusted R^2	0.176	0.143	0.212
Panel C. Control for Amihud illiquidity ratio			
<i>Innov</i>	0.2326*** (3.33)	0.3576*** (3.10)	0.1506 (1.40)
<i>Illiquidity</i>	0.0038 (0.65)	0.0116 (1.53)	-0.0008 (-0.09)
Observations	219533	103760	115773
Adjusted R^2	0.176	0.143	0.212
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel D. Restrict the sample to firms that have at least one patent over the sample period			
<i>Innov</i>	0.2167*** (2.95)	0.3528*** (2.87)	0.1483 (1.40)
Observations	162661	80736	81925
Adjusted R^2	0.179	0.147	0.208
Panel E. Exclude the sample period of financial crisis			
<i>Innov</i>	0.2236*** (2.98)	0.3605*** (2.75)	0.1914* (1.95)
Observations	210,005	100,515	109,490
Adjusted R^2	0.176	0.144	0.212
Panel F. Exclude the sample period of COVID-19 pandemic			
<i>Innov</i>	0.2621*** (3.33)	0.4153*** (3.05)	0.1634 (1.38)
Observations	179,570	79,827	99,743
Adjusted R^2	0.178	0.142	0.211
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table IA2. Patent-return predictability and institutional involvement among non-SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) in year *t*-1 and different sets of control variables and industry dummies within subsamples split by the median value of the measure of institutional involvement among non-SOEs. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted *t*-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A. Institutional ownership				
Measured by	Institution ownership		QFII ownership	
	High (1)	Low (2)	High (3)	Low (4)
<i>Innov</i>	0.1220 (0.52)	0.5432* (1.91)	-0.0916 (-0.11)	0.4088*** (2.75)
Observations	51,837	51,923	11,001	92,759
Adjusted R^2	0.168	0.117	0.206	0.139
Panel B. Shanghai-Shenzhen-Hong Kong Stock Connect Program				
Measured by	Joining the program or not			
	No (1)	Yes (2)		
<i>Innov</i>	0.2824** (2.12)	0.0944 (0.72)		
Observations	67,324	27,202		
Adjusted R^2	0.138	0.174		
Controls	Yes	Yes		
Industry FE	Yes	Yes		

Table IA3. Patent-return predictability and institutional involvement among SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) in year *t*-1 by including interaction terms with the measure of institutional involvement among SOEs. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A. Institutional ownership		
Measured by	Institution ownership (1)	QFII ownership (2)
<i>Innov * High</i>	0.1296 (0.69)	0.7341 (1.38)
<i>Innov * Low</i>	0.1823 (1.01)	0.0955 (0.79)
Observations	115,773	115,773
Adjusted R^2	0.212	0.211
Panel B. Shanghai-Shenzhen-Hong Kong Stock Connect Program		
Measured by	Joining the Program or not (1)	
<i>Innov * Lib</i>	0.0984 (0.86)	
<i>Innov * Non_Lib</i>	0.1095 (1.37)	
Observations	105,758	
Adjusted R^2	0.216	
Controls	Yes	
Industry FE	Yes	

Table IA4. Summary statistics for annual sample among SOEs

This table reports the time-series averages of the annual cross-sectional summary statistics among SOEs for firm's profitability (*ROA* and *ROE*), innovation output (*Innov*, *Invention* and *Utility*) and other characteristics, including the book-to-market ratio (*BM*), market capitalization (*SIZE*), capital expenditure (*CapEx*), leverage ratio (*Lev*), turnover (*Turn*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The sample period is from 2004 to 2020.

	Mean	S.D.	Min.	P25	P50	P75	Max.
<i>ROA</i>	0.042	0.062	-0.219	0.013	0.034	0.066	0.281
<i>ROE</i>	0.081	0.135	-0.590	0.030	0.076	0.134	0.537
<i>Innov</i>	0.0013	0.004	0.000	0.000	0.000	0.001	0.103
<i>Invention</i>	0.0004	0.001	0.000	0.000	0.000	0.000	0.020
<i>Utility</i>	0.0009	0.004	0.000	0.000	0.000	0.000	0.091
ΔROA	-0.001	0.055	-0.259	-0.016	-0.000	0.013	0.241
ΔROE	0.0005	0.137	-0.579	-0.033	-0.000	0.027	0.646
<i>BM</i>	0.920	0.769	0.076	0.385	0.680	1.193	3.794
<i>Lev</i>	0.511	0.188	0.075	0.374	0.523	0.657	0.876
<i>SIZE</i>	22.324	1.248	19.717	21.567	22.323	23.115	25.391
<i>CapEx</i>	0.055	0.053	0.000	0.017	0.038	0.076	0.251
<i>Turn</i>	0.045	0.034	0.004	0.020	0.035	0.060	0.170
<i>Ins</i>	0.601	0.167	0.124	0.485	0.609	0.724	0.922
Observations	9,688						

Table IA5. Patent-return predictability and option-based executive compensation among SOEs

This table reports the average regression coefficients from monthly Fama-MacBeth (1973) cross-sectional regressions of firms' excess returns (*ER*) from July of year *t* to June of year *t*+1 on firm innovation (*Innov*) in year *t*-1 by including interaction terms with executive stock option compensation among SOEs. Controls is a vector of control variables including return on assets (*ROA*), book-to-market ratio (*BM*), market capitalization (*Size*), capital expenditure (*CapEx*), momentum (*Mom*), short-term reversal (*STRev*), stock turnover (*TR*), and institutional ownership (*Ins*). Detailed definitions of these variables are provided in Appendix Table A1. The reported adjusted R^2 is the time-series average of the adjusted R^2 from each monthly cross-sectional regression. Newey-West adjusted t-statistics are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	(1)
<i>Innov * No_option</i>	0.1455 (1.19)
<i>Innov * Option</i>	0.8098** (2.25)
Observations	115,773
Adjusted R^2	0.212
Controls	Yes
Industry FE	Yes