Patents, Profitability, and Stock Returns: Evidence from China

Abstract

Firms' innovation output, measured by their patent counts, provides valuable information to investors. However, investors in developing countries like China may be uninformed about how efficient firms are in transferring innovation output into increased profitability, and they may therefore undervalue innovation output. Through examining the return predictability of innovation output among state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) in China, we find that in contrast to SOEs, non-SOEs' innovation output strongly predicts higher future stock returns. Consistent with the idea of transfer efficiency, we find that non-SOEs transfer innovation output to profitability while SOEs do not. Furthermore, the predictive power of patent counts is more pronounced among non-SOEs with higher value uncertainty.

Keywords: Innovation; Stock returns; Patent-to-earnings transfer; SOEs & non-SOEs

JEL Classifications: G12; G14; O31

1. Introduction

Patents are the most important proxy for firms' innovation output (Griliches, 1990). They are actively traded in intellectual property markets (Lev, 2001) and used as collateral (Mann, 2018) in the US. Information about firms' patent granting attracts investors' attention and should be reflected in stock price (Kogan et al., 2017). Though the above argument is true for developed economies, where both the stock market and the patent-related market are well developed, it may not be true in developing economies. In China, for example, patenting is a relatively new phenomenon and the patent-related market is under-developed (Lei et al., 2012; Li, 2012; Dang and Motohashi, 2015). We thus expect that patent granting information, though easy to observe, may not be fully exploited by stock market in China, leading patent counts to predict stock returns.

Making things more complicated, the strong presence of state ownership in China results in the coexistence of two types of listed firms, state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Unlike non-SOEs, the top managers of SOEs are essentially officials assigned by governments, and they have little incentive to innovate (Megginson, 2005; Hu and Jefferson, 2009; Lin et al., 2010; Boeing et al., 2016). However, Chinese governments have implemented various policies to promote innovation in recent years. Since SOEs are closely connected with local governments, their patenting is likely driven by public policies. Consequently, though SOEs generate a large number of patents, it is doubtful that these patents would positively affect the SOEs' future earnings. Furthermore, some patent information that seems easy to process, such as patent granting, may be neglected by investors in developing countries due to patent value being seen as uncertain. We thus expect that patent counts cannot predict stock returns among SOEs due to their transfer inefficiency; by contrast, patent counts have predictive power for stock returns of non-SOEs.

To test these conjectures, we examine the predictive power of innovation output on stock returns by investigating Chinese-listed firms from 2004 to 2021. Using the ratio of a firm's patent counts over its total assets as the proxy for its innovation output, we run Fama-Macbeth regressions of future stock returns on firm innovation output. To avoid using any future information, we follow Hirshleifer et al. (2013, 2018) and count a firm's patents according to the grant time, including both invention and utility patents. For the full sample, including both SOEs and non-SOEs, we find that patent counts have strong predictive power on future stock returns. We then investigate non-SOEs and SOEs, respectively. The results reveal that the predictive power remains significantly positive for non-SOEs, but turns insignificant for SOEs. Additionally, our major results remain unchanged after controlling for the effects of other innovation measures, such as R&D expenditures and innovation output within subsidiaries.

We also examine the relationship between innovation output and future stock returns by using portfolio analysis. On average, raw return increases from 1.46% to 2.02% per month among non-SOEs when moving from the portfolio with the lowest innovation output to the portfolio with the highest innovation output. Furthermore, the alphas of the long-short portfolios among non-SOEs remain positive and statistically significant after adjusting for Fama-French three factors, Carhart four factors, and Fama-French five factors. In contrast, the alphas of the long-short portfolios among SOEs are insignificant. These results further confirm that the positive relationship between innovation output and future stock returns only exists among non-SOEs.

There are two potential explanations for the insignificant return predictability of innovation output among SOEs. One explanation is that the stock market is efficient enough to incorporate patent information, leaving little room for predictable returns. The other explanation is that SOEs fail to transfer their patents into future earnings. Since concerns about management skills and the innovation output of SOEs are documented by extensive empirical evidence (Hu and Jefferson, 2009; Lin et al., 2010; Boeing et al., 2016; Zhang and Zhong, 2016), we conjecture that such a difference in the patent-return relationship between SOEs and non-SOEs is due to in their different patent-to-earnings transfer capabilities. To confirm this, we regress a firm's innovation output on its subsequent operating performance. The results indicate that innovation output positively predicts operating performance (i.e., ROA and $NCF\ ratio$) among non-SOEs but not among SOEs, suggesting that the transfer capability is poor among SOEs. Undoubtedly, top management's incentives should play an essential role in a firm's transfer capability. CEOs who are approaching retirement age could no longer benefit from the transfer capability. We therefore expect that their efforts to enhance transfer capability would be weakened. Consistent with this expectation, we find that even among non-SOEs, a firm's transfer capability is weakened when the CEO is approaching retirement age.

We explore the mechanisms behind the predictive power of innovation output on stock returns among non-SOEs. One possible explanation is that the positive patent-return relationship among non-SOEs is driven by investors' limited attention, particularly among non-SOEs with higher value uncertainty. To explore this, we split non-SOEs based on analyst forecast inaccuracy and institutional ownership, respectively. By rerunning the Fama-Macbeth regressions, we find that the predictive power of innovation output on stock returns is more pronounced among non-SOEs with either higher analyst forecast inaccuracy or lower institutional ownership.

This paper contributes to the literature in three aspects. First, it adds to the literature measuring innovation output, and it documents that patents contain valuation-related information from a long-term perspective. The literature uses complex measures (e.g., patent citations; journal citations; innovation efficiency) as proxies for innovation output and finds that firms' innovation output is positively related to firms' future earnings and stock returns (Gu, 2005; Matolcsy and Wyatt, 2008). Moreover, Kogan et al. (2017) use a sample of US-listed firms and find that the stock price reaction within a few days after a patent is granted contains important information about the value of the patent. In contrast to the literature which uses more sophisticated measures of innovation, we adopt the most straightforward one (i.e., patent counts divided by total assets) and focus on the long-term effect. We notice a significant relationship between this innovation measure and future stock returns among non-SOEs in China.

Second, this paper contributes to the literature regarding the predictive power of firm innovation on stock returns. While the relationship between firm innovation and future stock returns has been found to be positive in developed economies (Cohen et al., 2013; Hershleifer et al., 2013, 2018; Hou et al., 2020), the impact in developing economies is largely ignored. Numerous studies address unique characteristics of China's capital market, political, economic transition, and economic environment (Allen et al., 2005; Li and Zhou, 2005; Chen et al., 2011; Brunnermeier et al., 2017; Rong et al., 2017; Zhang et al., 2021; Liu et al., 2022). Accordingly, we attempt to investigate whether there exists any predictive power on stock returns regarding firms' patent granting information in China, which is one of the largest emerging economies. We find that innovation output does not exhibit significant predictive power on stock price among SOEs in China, which differs from the facts observed in developed economies. By highlighting the unique context of China's capital market and ownership structure, our study contributes to a better understanding of the relationship between innovation output and stock returns in different economic environments.

Third, this paper enriches the literature on the relationship between innovation output and firm future profitability. The literature mainly finds that firms with higher R&D investment or innovation output tend to maintain sustainable profitability (Eberhart et al., 2004, 2008; Pandit et al., 2011; Hirshleifer et al., 2013; Fitzgerald et al., 2020). However, given the unique ownership structure in China, the patent-to-earnings transfer capabilities of SOEs and non-SOEs may differ. Moreover, we propose that the difference in the patent-return relationship is due to different patent-to-earnings transfer capabilities. Our paper provides evidence by finding that non-SOEs can transfer innovation output into future profitability, while SOEs cannot. Our results support the argument by Megginson (2005) and Zhang and Zhong (2016) that top managers of SOEs have little incentive to innovate and produce high-quality innovation. We further find that the transfer capability of non-SOEs is weakened when the CEO is close to retirement, which is consistent with our incentive story.

The remainder of this paper is organized as follows. Section 2 discusses the background of China's economic transition and presents the logic underlying our hypotheses. Section 3 describes our dataset, defines key variables, and reports summary statistics. Section 4 investigates the predictive power of innovation output on stock returns. Section 5 explores the possible explanations for the distinct return predictability of SOEs and non-SOEs from the perspective of the patent-to-earnings transfer capabilities. Section 6 analyzes the underlying channels of the patent-return relationship among non-SOEs. Section 7 concludes.

2. Background and Hypothesis Development

2.1 SOE reform in China

In the pre-reform planned economy, China's industry was dominated by SOEs, whose primary function was to fulfill production quotas rather than pursue profits. In terms of choosing SOE top managers, officials in the industrial bureaus usually had decision-making power (Groves et al., 1995).[1] Since 1978, SOEs have gone through two major reforms to comply with China's transition towards a market economy. However, the system of choosing SOE managers has barely changed. Consistent with Shleifer and Vishny (1997), SOEs are controlled by government officers with strong rights of control but barely any rights over cash flow.

Instead of industrial bureaus, SOEs are now managed by other bureaucratic agencies, such as the State-Owned Asset Supervision and Administration Commission (SASAC). Representing the interest of the state as a shareholder (Naughton, 2007), these bureaus have no cash-flow rights from the shares they manage, but they do have an exclusive right to appoint SOE managers. According to the Corporate Law, the board of directors makes personnel decisions. In practice, however, the board chairman and CEO of an SOE are selected by the associated bureaucratic agency, and the board merely rubber-stamps the decision. With direct governmental control of CEO appointments, it is not surprising that SOE managers tend to give priority to the interests of bureaucrats while minority stakeholders' interests are largely ignored. The major problem is that the interests of these two groups clash: bureaucrats are generally interested in achieving their political goals and pursuing their own private benefits, but these goals are often different from, and sometimes contradictory to, the goal of improving the profitability of SOEs (Shleifer and Vishny, 1997; Zhou et al., 2017).

To meet the performance targets set by the government and to secure promotion, executives in SOEs generally choose to closely follow instructions from the bureaucratic agencies rather than engaging in independent inquiry. With the introduction of the National Medium- and Long-Term

[1] Groves et al. (1995) provide the following discussion: "Enterprise managers were hired and fired by officials in the industrial bureaus, which were in turn organized into sectoral and geographical divisions. The entire industrial system was accountable to a national or regional planning commission, which steered the entire system through a complex system of highly specific commands that extended all the way down the hierarchy to managers at the plant level. Authority relations were complicated by the intrusive role of the Communist Party, which functioned more or less as the personnel department of this enormous corporation, maintaining dossiers and tracking managerial careers."

Program for Science and Technology Development (MLP) in 2006, innovation performance indicators have become strongly emphasized in governmental evaluations of SOEs in a top-down approach (Chen and Naughton, 2016). These indicators are specified in terms of the quantity of patent applications rather than their quality, the latter being hard to evaluate ex ante. Consequently, a typical SOE has an incentive to "produce" the required amount of patent applications while caring little about its innovation quality. Combined with complementary patent subsidies offered by local governments, the MLP has further encouraged SOEs to file more low-quality patent applications (Zhang and Zhong, 2016; Long and Wang, 2018; Boeing and Mueller, 2019).

2.2 Hypothesis development

As a key proxy for firm innovation output, patent information is viewed as containing favorable information about future profitability and firm value (Lerner, 1994; Gu, 2005; Matolcsy and Wyatt, 2008; Pandit et al., 2011; Hirshleifer et al., 2018). Intuitively, such value-relevant firm fundamental information should be fully incorporated in the current stock price. However, the presence of limited investor attention retards firms' information processing, resulting in market under-reaction and return predictability (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hirshleifer et al., 2012; Ben-Rephael et al., 2013; Frank and Sanati, 2018). As revealed by this literature, investors prefer to process market-wide information. They pay less attention to difficult-to-process specific information such as firm innovation, which is complex and requires professional knowledge to evaluate. Also, compared with explicitly forward-looking information about the prospects for a particular ongoing R&D project, past innovation information is less salient to investors (Hirshleifer et al., 2013). We thus expect that investors may neglect patent information, which leads to an under-reaction and then predicts stock return.

H1: *Innovation output has predictive power on stock returns.*

The predictive power of innovation output makes an implicit assumption that the firm must have the ability to transform patents. However, the process, features, and outcomes of innovation are influenced by firms' internal and external characteristics, such as ownership structure (Rong et al., 2017), CEOs (Hirshleifer et al., 2012; Balsmeier et al., 2017), institutional investors (Aghion et al., 2013), and market characteristics (Bradley et al., 2017). Especially in China, ownership structure plays a crucial role in corporate governance and has a complex influence on innovation. The strong presence of state ownership in China results in the coexistence of two types of listed firms, SOEs and non-SOEs. As discussed in subsection 2.1, top managers in SOEs are usually treated as government officers, who have little incentive to innovate or produce high-quality patents (Hu and Jefferson, 2009; Lin et al., 2010; Zhang and Zhong, 2016; Boeing et al., 2016). Hence, we expect that SOEs often fail to transfer patents into their future earnings and thus cannot exhibit strong predictive power on stock returns. But that may not be the case for non-SOEs.

H2: *Among firms which fail to transfer innovation output into profitability (e.g., SOEs), innovation output has little predictive power on stock returns; however, among firms which can transfer innovation output into profitability (e.g., non-SOEs), innovation output may have predictive power on stock returns.*

For firms that can transfer innovation output into profitability, the characteristic of hard-to-value tends to impose a cognitive burden on investor attention (Hirshleifer et al., 2013). Individuals are sensitive to their feelings about the ease (or difficulty) of processing information (Song and Schwarz, 2010). When making judgments or decisions, individuals are inclined to avoid, or pay less attention to, information that is hard to process. A high level of hard-to-value also means that the stock price may not reflect fundamental information (Zhang, 2006). We thus expect that the predictive power of innovation output on stock returns is more prominent for firms with higher valuation uncertainty.

H3: *Among firms which can transfer innovation output into profitability (e.g., non-SOEs), when stocks have higher value uncertainty, the predictive power of innovation output on stock returns is stronger.*

3. Data and Variables

3.1 Data

Our sample consists of Chinese main-board A-share firms listed on both the Shanghai and Shenzhen Stock Exchanges between 2004 and 2021. The data on capital market information, financial statements, and firm industry information are obtained from the China Stock Market & Accounting Research (CSMAR) database, the China Center for Economic Research (CCER) database, and the WIND financial database. The firm ownership data used for identifying SOEs and non-SOEs are obtained from the CSMAR database and are checked manually for correctness. Listed firms' patent information comes from the Chinese Research Data Services Platform (CNRDS), including all patents granted by the State Intellectual Property Office of China (SIPO).

Using the data of all A-share firms listed on the Shanghai and Shenzhen Stock Exchanges, we exclude (1) financial firms; (2) the IPO year data to mitigate the IPO effect; (3) ST and *ST listed firms; (4) firms with negative equity and missing values for major variables (e.g., stock returns, return on assets, market value, book-to-market ratio, turnover, and capital expenditure); and (5) micro-cap stocks (Fama and French, 2008). In China, the smallest listed firms are potential shells due to tight IPO restrictions, making their value deviate substantially from their fundamentals. Following Liu et al. (2019), we exclude those firms at the bottom 30% of firm size (i.e., micro-cap stocks). To eliminate the influence from outliers, we winsorize all financial variables at the 1% and 99% levels (Beaver and Ryan, 2000). The finalized monthly sample consists of 219,533 observations for 2,142 firms, including 872 SOEs and 1,270 non-SOEs.

3.2 Innovation-related measures

Previous studies usually focused on R&D expenditures and patent-based measures as proxies for firm innovation (Chan et al., 2001; Penman and Zhang, 2002; Lev et al., 2005; Shefer and Frenkel, 2005). Our paper uses the patent-based measure since R&D expenditures may only capture one particular observable quantitative input (He and Tian, 2018). Using patent data to measure firms' innovation output has the following advantages. First, the examination of patent applications follows a consistent and rigorous process. As a result, patent data systematically capture the progress of innovation. Second, China has signed all major international conventions regarding intellectual property rights (Yang and Clarke, 2005)[2]. Third, it has been documented that China is transitioning to an economy of innovation from one of imitation (Cai and Tylecote, 2008; Guan et al., 2009; Wei et al., 2017).

The Chinese patent system grants three types of patents: invention, utility, and design patents. To be granted, an *invention patent* must meet the requirements of "novelty, inventiveness, and practical applicability." *Utility patents* are granted for new and practical technical solutions related to the shape and/or structure of a product to protect new and functional aspects of a product. *Design patents* involve limited technological advancements. We construct our innovation measures using only invention and utility patents (Tan et al., 2015).[3] Following Hirshleifer et al. (2013, 2018), to

[2] 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] These three types of patents also differ in application processing time and strength of protection. It generally takes more than one year to grant an invention patent. The processing time is about six months for utility patents, and even

avoid look-ahead bias and truncation error, we choose patent *granting* instead of patent *application filing* to time a firm's patenting. Specifically, we generate a firm-year's patent counts ($Patent$) by computing the number of the firm's invention and utility patents granted in a given year. After counting firms' patents, we measure a firm's innovation output ($Innov$), $Patent/TA$, as $Patent$ over its total assets at the year end. $Patent/TA$ is an innovation indicator widely used in the literature (Kim et al., 2009; Kogan et al., 2017; Almeida et al., 2021).

3.3 Defining SOEs and non-SOEs

We define a firm's SOE or non-SOE status based on its ultimate controller information in a given year. We first match our sample firms with the CSMAR firm-year level ownership database. When the ultimate controller of a listed firm is the central government, the SASAC of the State Council, the local SASAC, or the local government, the firm is defined as an SOE. Otherwise, the firm is a non-SOE. We then check whether the controller of a firm changed in our examination period and manually search their background information through annual reports. When a firm changed its controller during 2004-2021 and the years in which the firm was defined as an SOE accounted for less than 30%, it is unlikely the firm functioned like a typical SOE. In this case, we re-classify this firm as a non-SOE.

3.4 Summary statistics

Table 1 presents summary statistics of major variables (See Appendix Table 1 for definitions of these variables). Panel A reports the descriptive statistics for the full sample from July 2004 to June 2021. The distribution of innovation, $Innov$, was highly skewed, with a mean of 0.002 and

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shorter for external-design patents. The term of protection is 20 years for invention patents, but only 10 years for the other two types.

a maximum of 0.435. The median value of innovation was 0, which is in line with the actual situation of Chinese listed firms. Only 49.9% of listed firms have been granted for at least one invention or utility patent. Our observations had relatively large market capitalizations ($Size$) with a mean of 22.40, since we excluded the 30% of listed firms with the lowest market capitalization. The book-to-market ratio was 81.7%, the capital expenditure divided by total assets was appropriate (5.9%), the stock turnover rate was 0.4%, the institutional ownership was high (53.6%), and the return on assets reached 5.5%. Panel B presents the summary statistics for non-SOEs and SOEs. Our final sample has 103,760 observations of non-SOEs and 115,773 observations of SOEs. The average value of the innovation for non-SOEs was 0.03 and 0.01 for SOEs. This suggests that among large firms, non-SOEs are superior regarding patent output in China, and it also illustrates the necessity of investigating non-SOEs and SOEs separately. In addition, non-SOEs have higher leverage ratios and turnover rates, while SOEs have higher institutional ownership and book-to-market ratios.

[Insert Table 1 Here]

4. Return Predictability of Firm Innovation

In this section, we examine the return predictability of firm innovation for full sample and subsamples of SOEs and non-SOEs, respectively. We also conduct robustness checks.

4.1 Full-sample Fama-MacBeth regressions

We examine the predictive power 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 returns net of the one-month treasury bill rate on $Innov$ of year $t-1$

and other control variables. We include industry dummies at the three-digit industry level to control for industry-fixed effects. Since the SIPO fully releases patent granting information on their website on time, our lagged innovation measure should already be publicly available by July in year t. To control for the widely used predictors of stock returns, we consider the variables linked to fundamental information: return on assets (ROA), book-to-market ratio (BM), market value ($Size$), 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 $Size$ and TR, which are measured at the end of June of year t.

Table 2 presents the time-series average slopes and Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust t-stat from monthly Fama-MacBeth (FM hereafter) cross-sectional regressions. Firm innovation output ($Innov$) is significant in predicting future stock returns with a coefficient of 0.2485 and a t-stat of 3.56 (column 1). The coefficients on $Innov$ remain positive and significant at the 1% level when control variables are included in columns 2 and 3. This result reveals that firms' innovation output can predict future stock returns, supporting Hypothesis 1. Note that this result contradicts the view of Kogan et al. (2017) that the informativeness of innovation output has been fully reflected in the contemporary stock price, thereby having limited predictive power on future stock returns. The coefficients on control variables are consistent with the literature. Firm size has a negative effect on stock returns, and the book-to-market ratio is positively related to future stock returns. The coefficient on short-term reversal ($STRev$) is significantly negative at the 1% level, confirming the strong cross-sectional returns predictability of the short-term reversal (Hirshleifer et al., 2018). In line with Chen et al. (2010), the coefficient on stock turnover (TR) is negative and significant at the 1% level.

[Insert Table 2 Here]

4.2 Firm ownership and return predictability

As we have argued, management in SOEs and non-SOEs may perform differently regarding the transformation of innovation output into profits. If the market does not recognize this difference, the predictive power of firms' innovation output can be homogeneous across different types of ownership. To determine whether the return predictive power of firm innovation for SOEs and non-SOEs follows distinct empirical patterns, we split the sample by firm ownership types and perform monthly FM cross-sectional regressions. As shown in Table 3, firm innovation ($Innov$) is strongly and positively related to future stock returns for non-SOEs (columns 1 and 2). In contrast, for SOEs (columns 3 and 4), the coefficients on $Innov$, though still positive (0.1657 and 0.1530), turn insignificant (t-stat = 1.51 and 1.41). This suggests that the return predictive power of firm innovation only exists among non-SOEs. It is consistent with the view that SOEs have incentive to generate low-quality patents (Li, 2012; Dang et al., 2015) and have little incentive to introduce new products. Table 3 thus supports our hypothesis that the market couldn't differentiate SOEs and non-SOEs and under-react to patent information. To further confirm that SOEs fail to transfer patent output into profitability but non-SOEs do not, we conduct corresponding tests in section 5.

[Insert Table 3 Here]

4.3 Portfolio analysis

In this subsection, we conduct portfolio analysis to investigate the ability of $Innov$ to predict portfolio returns for non-SOEs (SOEs) and whether such an $Innov$ effect is explained by risk or mispricing. At the end of June of each year, we split non-SOEs (SOEs) with patents into three deciles based on the 33rd and 66th percentiles of $Innov$, respectively. Non-SOEs (SOEs) with no patents are assigned to a separate portfolio (Non-patent). After forming these four portfolios, we calculate the equal-weighted monthly returns on these portfolios over the next 12 months (July of year t to June of year $t+1$). We also form an H-L portfolio that takes a long position in the high-$Innov$ portfolio and a short position in the low-$Innov$ portfolio.

We first consider the raw returns and excess returns of portfolios. The raw returns of portfolios are defined as the average monthly equal-weighted monthly returns, and the excess returns of portfolios are the raw returns of portfolios in excess of the one-month Treasury bill rate. We also calculate risk-adjusted alphas using the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model. Table 4 presents the portfolio returns. Panel A provides results for portfolios among non-SOEs sorted by $Innov$. The first row shows that among non-SOEs, the raw return increases from 1.46% to 2.02% per month when moving from the low-$Innov$ portfolio to the high-$Innov$ portfolio. Thus, the H-L portfolio has a raw return of 0.56%, with a t-stat of 2.17. The similar results can be found for excess returns and risk-adjusted alphas, indicating that innovation output of non-SOEs is positively related to their future stock returns.

We then present the results of SOEs' portfolio tests in Panel B of Table 4. The raw returns for the low-, middle-, and high-$Innov$ portfolios are 1.46%, 1.55%, and 1.67%, respectively. Unlike non-SOEs, the raw return of the H-L portfolio among SOEs is insignificant. The excess return of the H-L portfolio shows a similar pattern. Furthermore, the risk-adjusted alphas of the H-L portfolios are ignorable in magnitude and insignificant. These contrasting results in Panel B reveal that SOEs' innovation output have little predictive power on future stock returns. As our results are robust to various risk factors, the $Innov$ effect likely comes from mispricing. Overall, these robustness tests are supportive of our main results.

[Insert Table 4 Here]

4.4 Controlling for other innovation-related factors

We run several robustness checks to rule out the influence of other innovation-related factors. It is possible that our results could be driven by investors ignoring firms' R&D expenditures; R&D expenditures may be positively correlated to patents granted and have predictive power on stock returns (Cohen et al., 2013). To address this concern, we rerun the monthly FM cross-sectional regressions by controlling for R&D expenditures. Since reporting R&D expenditures is not mandatory, we set missing values for R&D expenditures ($R\&D$) to zero and include a dummy variable ($Miss\_RD$) that equals one for firms that choose not to report R&D expenditures. As shown in Panel A of Table 5, for non-SOEs, when $R\&D$ and $Miss\_RD$ are included, the coefficients on $Innov$ remain positive and significant. The magnitude only drops mildly. The coefficients on R&D expenditures are positive and significant at least at the 5% level, suggesting that R&D information is also somewhat ignored by investors.

We also consider the effect of subsidiary firms' innovation output. We denote $Patent\_sub$ as the number of subsidiary firms' invention and utility patents that are granted in a given year. We then generate $Innov\_sub$, which is defined as $Patent\_sub$ over total assets. As shown in Panel B of Table 5, our major results remain unchanged. Additionally, the return predictive power of $Innov\_sub$ is generally insignificant, rationalizing our choice of excluding this variable in our baseline regressions. Overall, we conclude that the predictive power of $Innov$ on future stock returns among non-SOEs is not driven by the omission of R&D expenditures or subsidiary innovation as a control variable.

[Insert Tables 5 Here]

5. Firm Innovation and Profitability

In this section, we investigate the patent-to-earnings transfer efficiency among SOEs and non-SOEs, respectively. Then, we examine the effect of CEO duration on this transfer efficiency.

5.1 Patenting-to-earnings transfer efficiency

As we have discussed, SOEs may fail to transfer innovation output into profitability but non-SOEs do not, and thus the return predictability of $Innov$ only exists among non-SOEs. In this subsection, we examine whether $Innov$ contains favorable information about a firm's future profitability to verify the transfer efficiency story.

To evaluate the patent-to-earnings transfer efficiency, we investigate the relationship between firm innovation output and future profitability. Specifically, following Han et al. (2019), we conduct panel regressions of firm profitability on its one-year lagged $Innov$ as well as a vector of control variables as follows:

$$OP_{i,t} = \alpha + \beta Innov_{i,t-1} + \gamma X_{i,t-1} + YearFE + FirmFE + \varepsilon_{i,t}\,. \tag{1}$$

Following Gu (2005) and Hirshleifer et al. (2013), we use the return on assets (ROA) and net cash flow ratio ($NCF\ ratio$) to measure firm profitability (OP). ROA is defined as the income before extraordinary items plus interest expenses divided by one-year lagged total assets. $NCF\ ratio$ is defined as net profits plus depreciation expenses divided by one-year lagged total assets. We control for capital expenditure because of its predictive power on firms' operating performance (Lev and Sougiannis, 1996; Pandit et al., 2011; Fitzgerald et al., 2020). Following Gu (2005), we include lagged profitability (lagged ROA or lagged $NCF\ ratio$) to control for persistence in profitability. We include lagged changes in profitability ($\triangle\, ROA$ or $\triangle\, NCF\ ratio$) to control for the mean reversion in profitability (David et al., 2000). We also consider firm fundamentals linked to firm profitability, including the book-to-market ratio (BM), market value ($SIZE$), capital expenditure ($CapEx$), the leverage ratio (LR), turnover ($Turn$), and institutional ownership (Ins). Appendix Table 1 provides the definitions for the above variables. All financial variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers (Beaver and Ryan, 2000). In all regressions, firm-fixed and year-fixed effects are controlled for.

IA Table 1 reports the summary statistics. Both $NCF\ ratio$ and ROA were right-skewed, with means of 0.045 and 0.082, respectively (see Panel A). For other key fundamental variables, the distribution characteristics are similar to Table 1. Panel B of IA Table 1 reports the statistics on key variables for SOEs and non-SOEs, respectively. Consistent with Panel B of Table 1, non-SOEs not only had higher innovation output but also achieved a higher level of profitability. We therefore infer that non-SOEs possess higher patent-to-earnings transfer efficiency (Hypothesis 2).

Table 6 reports a sharp contrast in the coefficient on $Innov$ between SOEs and non-SOEs from the panel regressions specified in Equation (1). We first use ROA as the dependent variable. In columns 1 and 2, for non-SOEs, $Innov$ is positively related to future profitability with a coefficient of 0.232 and a t-stat of 1.75, while for SOEs, the coefficient on $Innov$ is negative and insignificant, suggesting that non-SOEs sucessfully transfer innovation output into profitability while SOEs do not.

We then examine the relationship between $Innov$ and $NCF\ ratio$ in columns 3 and 4 of Table 6. As shown, the coefficient on $Innov$ is positive (0.287) and significant (t-stat = 1.91) for non-SOEs, and it is negative (-0.096) and insignificant (t-stat = -0.56) for SOEs. Regardless of whether ROA or $NCF\ ratio$ is used to measure a firm's profitability, the results are consistent: patent-to-earnings transfer efficiency exists only in non-SOEs. This finding is consistent with our assumption that SOE managers have little incentive to transfer innovation output into profits, while non-SOE managers are well motivated to do so. Combining the results in Tables 3 and 6, we conclude that the difference in the patent-return relationship between SOEs and non-SOEs is rooted in their different patent-to-earnings transfer effciency (i.e., Hypothesis 2).

[Insert Table 6 Here]

5.2 CEO duration and transfer efficiency

Our story implies that when the mechanism is well designed and top management reacts appropriately, patent-to-earnings transfer efficiency will be achieved. One assumption is that the transfer efficiency relies on the incentives that top managers perceive. Even among non-SOEs, if a CEO has little incentive to improve patent-to-earnings efficiency, the transfer efficiency should also be low.

To directly test this hypothesis, we examine how differing ages of CEOs might result in heterogeneous transfer efficiency among non-SOEs. When CEOs know that they will retire soon, they are likely to conclude that improving transfer efficiency will not yield any personal benefits for them. They may therefore choose to make only limited effort to improve efficiency. To test this hypothesis, we include one-year-lagged CEO age dummy ($CEOAgeDum$)as well as its interaction with $Innov$ and conduct the following panel regressions:

$$OP_{i,t} = \alpha + \beta_1 Innov_{i,t-1} + \beta_2 CEOAgeDum_{i,t-1} + \beta_3 Innov_{i,t-1} * CEOAgeDum_{i,t-1}$$
$$+\gamma X_{i,t-1} + YearFE + FirmFE + \varepsilon_{i,t}\ , \qquad (2)$$

where the CEO age dummy ($CEOAgeDum$) equals one if the CEO is aged 58 or above, and zero otherwise. Generally, CEO terms are three years and the retirement age of a male is 60 in China. We thus expect that when a CEO is aged 58 or above, it is very likely the CEO's last term before retirement (Tzioumis, 2008; Kang, 2015). Among non-SOEs, if CEOs lose interest in working hard in their last years in the position, one should expect the interaction effect to be significantly negative.

Table 7 presents the estimates of the CEO age effect. Consistent with our expectation, we find that the coefficient on the interaction term is significantly negative among non-SOEs (columns 1 and 3). More importantly, its magnitude is comparable to the coefficient on $Innov$, indicating that the incentive to transfer innovation into profits diminishes when non-SOEs' CEOs are in their remaining tenure. As a counterfactual study, we also rerun the regressions among SOEs and find the coefficient on the interaction term statistically insignificant (columns 2 and 4).

[Insert Table 7 Here]

6. Firm Innovation, Value Uncertainty, and Future Stock Returns among non-SOEs

The previous tests in Section 4 have confirmed the return predictability of firm innovation among non-SOEs. In this section, we examine why firm innovation could predict future stock returns among non-SOEs. We then investigate the evolution of market efficiency of the Chinese stock market by rerunning the monthly FM cross-sectional regressions for non-SOEs using four rolling periods.

Hard-to-value stocks usually place a greater cognitive burden on investor attention, which can cause market under-reaction (Hirshleifer et al., 2013). To test whether the positive relationship between firm innovation output and future stock returns among non-SOEs is driven by valuation uncertainty, we rerun the Fama-MacBeth cross-sectional regressions with non-SOEs split by different proxies for valuation uncertainty. Specifically, we consider analyst forecast inaccuracy and institutional ownership to measure the extent of valuation uncertainty. Following Capstaff et al. (1998) and Kothari (2001), we calculate analyst forecast inaccuracy as the mean or the median of analyst forecast errors in a given year. Analyst forecast errors are defined as the absolute value of the difference between a forecast and realized earnings, scaled by the absolute value of actual EPS.[4] We refer to these forecast errors as inaccuracy since the difficulty for analysts to assimilate information increases analysts' forecast errors for hard-to-value firms. We expect the positive innovation-return relationship to be more pronounced among non-SOEs with higher analyst forecast inaccuracy.

We perform monthly Fama-MacBeth cross-sectional regressions in subsamples divided by the median value of analyst forecast inaccuracy. Panel A of Table 8 presents the average slopes and corresponding Newey-West (1987) t-stat. As shown in columns 1 and 3, among non-SOEs with higher analyst forecast inaccuracy, the coefficients on $Innov$ are positive and significant at the 5% level. In contrast, among non-SOEs with low analyst forecast inaccuracy, these coefficients are smaller and insignificant. It is intuitive as the higher accuracy of analysts' forecasts is associated with higher valuation efficiency, and the value of firm innovation is thus well explored.

Institutional investors are often considered to have information advantages, which in turn transmit firm-specific information into stock prices promptly (Piotroski and Roulstone, 2004; Boehmer and Kelly, 2009). Higher institutional ownership is usually associated with greater management disclosure and more analyst following, resulting in lower information asymmetry (Boone and White, 2015). Regarding institutional ownership, we employ three measures. First, we take all types of institutional investors into account, and calculate institutional ownership as the proportion of the firm's outstanding shares that are owned by institutional investors at the year end. Then, we consider specific types of institutional investors since studies have documented that

[4] The existing literature argues that cross-sectional comparisons of forecast errors using the stock price deflator may lead to spurious results (Mian and Teo, 2004; Hribar and McInnis, 2012). Among stocks with similar market prices, the ones with larger earnings-to-price ratios are more likely to exhibit larger absolute forecast errors when scaled by price, simply because the forecasts involve larger numbers. Thus, we do not scale by stock price in this study.

"independent" institutional investors, such as mutual funds and QFIIs (Qualified Foreign Institutional Investors), tend to collect information and carry out active monitoring (Chen et al., 2007; Bena et al., 2015; Luong et al., 2015; Rong et al., 2017). Accordingly, we define fund ownership and QFII ownership as the proportion of a firm's outstanding shares that are owned by mutual funds and QFIIs at the year end, respectively.

Panel B of Table 8 presents the results of FM regressions in subsamples by the median value of institutional ownership. As shown, among non-SOEs with lower institutional ownership, $Innov$ is significant in predicting future stock returns with a coefficient of 0.543 and a t-stat of 1.91. In contrast, the return predictive power of innovation is ignorable among non-SOEs with higher institutional ownership. Similar results are obtained when we consider specific types of institutional investors in columns 3 to 6. Specifically, the coefficient on $Innov$ is positive and significant at the 1% level among non-SOEs with lower mutual fund or QFII ownership, while there is a substantial decrease in its magnitude among firms with higher mutual fund or QFII ownership, further confirming that the predictability power is more pronounced among non-SOEs with lower institutional ownership. Overall, the results of Table 8 support Hypothesis 3 that the return predictability of innovation is more pronounced among hard-to-value stocks, and the $Innov$-return relationship reflects market inefficiency driven by valuation uncertainty.

[Insert Table 8 Here]

Our results also support the notion that China's stock market displays a weak form of efficiency, and that financial institutions are poorly developed (Groenewold et al., 2004; Rong et al., 2017). However, China's stock market has recently received increasing attention from international investors and regulators, and stock market efficiency is expected to rise (Carpenter et al., 2021). To confirm this argument, we rerun the monthly FM cross-sectional regressions for non-SOEs using four rolling periods (i.e., 2004-2015, 2006-2017, 2008-2019, 2010-2021). As shown in IA Table 2, the coefficient on $Innov$ decreases gradually over time from 0.515 to 0.110. The drop is relatively substantial, suggesting that the efficiency of the Chinese stock market was gradually improving during our examination period.

7. Conclusion

In contrast to related studies in developed countries, this paper documents that in China a simple innovation measure, patent counts normalized by total assets, has significant and positive predictive power on subsequent stock returns among non-SOEs but not among SOEs. Further exploration reveals that such a difference is rooted in differences in patent-to-earnings transfer efficiency: patent counts are associated with higher future profitability among non-SOEs but not among SOEs. Last, we find that the predictive power of patent counts on stock returns is more pronounced among non-SOEs with higher forecast inaccuracy and among non-SOEs with lower institutional ownership, which are supposed to have higher valuation uncertainty.

Our findings have two policy implications. First, our results suggest that in developing countries like China, investors might lack information on how capable firms are of transferring innovation output into profitability. Policymakers could enhance investors' awareness of the link between innovation and financial performance. By providing investors with clearer insights into this relationship, the undervaluation of innovation output could be mitigated. Second, given the contrasting outcomes between SOEs and non-SOEs, policy measures could be tailored to bolster the transfer efficiency of innovation output among SOEs. Encouraging mechanisms that facilitate transfer efficiency could enhance the attractiveness of SOEs to investors. This involves enhancing CEO professionality within SOEs to better align innovation output with shareholder value.

Appendix Table 1. Variable definitions

Variable	Definition
ER	Excess return, a firm's stock return in a given month minus the risk-free interest rate.
Patent	The number of a firm's invention and utility patents that are granted in a given year.
Innov	*Patent* over total assets at the year end.
Patent_sub	The number of subsidiary firms' invention and utility patents that are granted in a given year.
Innov_sub	*Patent_sub* over total assets at the year end.
STRev	Short-term reversal, defined as the stock return of the prior month.
Mom	Momentum, defined as the previous 11-month returns (with a one-month gap between the holding period and the current month).
Ins	Institutional ownership, defined as the fraction of a firm's outstanding shares that are owned by institutional investors at the year end.
BM	The ratio of book equity to market value at the year end.
Size	The log of market value at the end of June.
LR	Leverage ratio, defined as the ratio of total debts to total assets at the year end.
SIZE	The log of market value at the year end.
TR	The ratio of shares traded to total shares outstanding at the end of June.
Turn	The ratio of shares traded in a given year to total shares outstanding at the year end.
CapEx	Capital expenditure divided by total assets at the year end.
ROA	Income before extraordinary items plus interest expenses divided by one-year lagged total assets at the year end.
NCF ratio	Net profits plus depreciation expenses divided by one-year lagged total assets at the year end.
△ROA	Annual change in *ROA*.
△NCF ratio	Annual change in *NCF ratio*.
R&D	The ratio of R&D expenditures to total assets at the year end.
Miss_RD	A dummy variable indicating whether the R&D value is missing.
CEOAgeDum	A dummy variable taking the value of one if the CEO is aged 58 or above, and zero otherwise.

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Table 1. Summary statistics for the monthly sample

This table reports the time-series averages of the monthly cross-sectional summary statistics. *ER* is a firm's stock return in a given month minus the risk-free rate. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* is the number of a firm's invention and utility patents that are granted in year t-1. *ROA* is income before extraordinary items plus interest expenses divided by total assets at the end of year t-1. *BM* is the ratio of book equity to market value at the end of year t-1. *Size* is the log of market value at the end of June of year t. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Mom* is the previous 11-month returns (with a one-month gap between the holding period and the current month). *STRev* is the stock return of the prior month. *TR* is the ratio of shares traded to total shares outstanding at the end of June of year t. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The return data are from July 2004 to June 2021. We winsorize all financial variables at the 1% and 99% levels.

Panel A. Full sample

	Mean	S.D.	Min.	P25	P50	P75	Max.
ER	0.011	0.128	-0.038	-0.066	-0.0003	0.077	0.431
Innov	0.002	0.007	0.000	0.000	0.000	0.001	0.435
ROA	0.055	0.063	-0.117	0.018	0.043	0.081	0.297
BM	0.817	0.708	0.083	0.346	0.594	1.040	3.972
Size	22.399	1.121	19.749	21.739	22.381	23.073	25.439
CapEx	0.056	0.052	0.000	0.017	0.040	0.077	0.252
Mom	0.166	0.618	-0.661	-0.225	-0.001	0.354	2.833
STRev	0.010	0.130	-0.310	-0.067	-0.001	0.077	0.436
TR	0.004	0.004	0.000	0.001	0.002	0.005	0.020
Ins	0.536	0.212	0.022	0.397	0.559	0.694	0.926
Observations	219533						

Panel B. Non-SOEs vs. SOEs

	Non-SOEs		SOEs	
	Mean	S.D.	Mean	S.D.
ER	0.010	0.129	0.011	0.128
Innov	0.003	0.009	0.001	0.004
ROA	0.062	0.067	0.049	0.057
BM	0.666	0.557	0.952	0.797
Size	22.406	1.015	22.392	1.208
CapEx	0.055	0.051	0.056	0.053
Mom	0.165	0.601	0.011	0.128
STRev	0.010	0.130	0.011	0.129
TR	0.004	0.004	0.004	0.004
Ins	0.457	0.228	0.606	0.167
Observations	103760		115773	

Table 2. Return predictive power of firm innovation, full sample

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. The dependent variable *ER* is a firm's stock return in a given month minus the risk-free interest rate. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* is the number of a firm's invention and utility patents that are granted in year t-1. *ROA* is income before extraordinary items plus interest expenses divided by one-year lagged total assets at the end of year t-1. *BM* is the ratio of book equity to market value at the end of year t-1. *Size* is the log of market value at the end of June of year t. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Mom* is the previous 11-month returns (with a one-month gap between the holding period and the current month). *STRev* is the stock return of the prior month. *TR* is the ratio of shares traded to total shares outstanding at the end of June of year t. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The return data are from July 2004 to June 2021. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Sample	All	All	All
	(1)	(2)	(3)
Innov	0.2485***	0.2445***	0.2360***
	(3.56)	(3.58)	(3.34)
ROA		0.0104	0.0062
		(0.93)	(0.63)
BM		0.0005	0.0005
		(0.63)	(0.61)
Size		-0.0018	-0.0028**
		(-1.42)	(-2.14)
CapEx		0.0015	0.0027
		(0.18)	(0.34)
Mom		-0.0056	0.0008
		(-1.41)	(0.20)
STRev			-0.0536***
			(-8.23)
TR			-1.1414***
			(-6.56)
Ins			-0.0001
			(-0.05)
Industry FE	Yes	Yes	Yes
Observations	219533	219533	219533
Adjusted R^2	0.108	0.158	0.176

Table 3. Return predictive power of firm innovation, non-SOEs vs. 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 within two subsamples, non-SOEs and SOEs. The dependent variable *ER* is a firm's stock return in a given month minus the risk-free interest rate. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in year t-1. *ROA* is income before extraordinary items plus interest expenses divided by one-year lagged total assets at the end of year t-1. *BM* is the ratio of book equity to market value at the end of year t-1. *Size* is the log of market value at the end of June of year t. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Mom* is the previous 11-month returns (with a one-month gap between the holding period and the current month). *STRev* is the stock return of the prior month. *TR* is the ratio of shares traded to total shares outstanding at the end of June of year t. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The return data are from July 2004 to June 2021. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Sample	Non-SOEs		SOEs	
	(1)	(2)	(3)	(4)
Innov	0.4769***	0.3719***	0.1657	0.1530
	(3.00)	(3.04)	(1.51)	(1.41)
ROA		0.0124		0.0057
		(1.04)		(0.49)
BM		0.0016		0.0007
		(1.37)		(0.68)
Size		-0.0028*		-0.0028**
		(-1.76)		(-2.23)
CapEx		0.0126		-0.0114
		(1.15)		(-1.42)
Mom		0.0018		-0.0014
		(0.44)		(-0.35)
STRev		-0.0551***		-0.0586***
		(-7.60)		(-8.19)
TR		-1.3353***		-1.0867***
		(-6.66)		(-4.92)
Ins		0.0024		-0.0025
		(0.91)		(-0.73)
Industry FE	Yes	Yes	Yes	Yes
Observations	103760	103760	115773	115773
Adjusted R^2	0.073	0.142	0.140	0.211

Table 4. Portfolio formations, 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. Besides, non-SOEs and SOEs with no patents are assigned to a separate portfolio, respectively. We hold these portfolios over the next 12 months (July of year t to June of year t+1). We calculate the average monthly equally weighted portfolio returns and alphas over the next 12 months. Raw return is the average monthly equally weighted portfolio return. Excess return is the average monthly equally weighted portfolio return in excess of the one-month Treasury bill rate. To adjust for risk, we consider the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model.

	Panel A. Non-SOEs				
Equal-weighted portfolios sorted by *Innov*	Non-patent	Low	Middle	High	High-Low
Raw return	1.456*	1.456*	1.689**	2.017***	0.561**
	(1.94)	(1.91)	(2.34)	(2.75)	(2.17)
Excess return	1.261*	1.262*	1.494**	1.823**	0.561**
	(1.68)	(1.76)	(2.07)	(2.48)	(2.17)
FF3 α	-0.080	-0.053	0.203	0.551**	0.604***
	(-0.53)	(-0.26)	(1.05)	(2.54)	(2.71)
CH4 α	-0.095	-0.073	0.145	0.459**	0. 532**
	(-0.63)	(-0.36)	(0.77)	(2.04)	(2.17)
FF5 α	-0.167	-0.126	0.022	0.307	0.432*
	(-0.91)	(-0.52)	(0.10)	(1.37)	(1.93)
	Panel B. SOEs				
Equal-weighted portfolios sorted by *Innov*	Non-patent	Low	Middle	High	High-Low
Raw return	1.362*	1.456**	1.550**	1.659**	0.204
	(1.88)	(2.02)	(2.06)	(2.23)	(0.88)
Excess return	1.168	1.261*	1.356*	1.465*	0.204
	(1.61)	(1.75)	(1.80)	(1.97)	(0.88)
FF3 α	-0.056	0.146	0.125	0.211	0.065
	(-0.35)	(0.76)	(0.62)	(1.06)	(0.40)
CH4 α	-0.012	0.206	0.140	0.241	0.036
	(-0.08)	(1.07)	(0.71)	(1.20)	(0.23)
FF5 α	-0.030	0.234	0.185	0.221	-0.013
	(-0.17)	(1.13)	(0.82)	(1.03)	(-0.08)

Table 5. Return predictive power of firm innovation, non-SOEs vs SOEs, controlling for other innovation-related factors

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 R&D or subsidiary innovation within two subsamples, non-SOEs and SOEs. The dependent variable *ER* is a firm's stock return in a given month minus the risk-free interest rate. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in year t-1. *R&D* is the ratio of R&D expenditures over book value of equity in year t-1. *Miss_RD* is a dummy variable indicating whether the R&D value is missing. We define *Innov_sub* as *Patent_sub* over total assets at the end of year t-1; *Patent_sub* denotes the number of a subsidiary firm's invention and utility patents that are granted in year t-1. The return data are from July 2004 to June 2021. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A. Control for R&D expenditures

	All	All	Non-SOEs	SOEs
	(1)	(2)	(3)	(4)
Innov	0.2485***	0.1988***	0.3026**	0.1220
	(3.56)	(2.83)	(2.60)	(1.12)
R&D		0.1766***	0.1926***	0.1604*
		(4.78)	(4.29)	(1.79)
Miss_RD		0.0003	0.0003	0.0008
		(0.34)	(0.20)	(0.92)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	219533	219533	103760	115773
Adjusted R^2	0.108	0.177	0.144	0.212

Panel B. Control for subsidiary innovation

	All	All	Non-SOEs	SOEs
	(1)	(2)	(3)	(4)
Innov	0.2485***	0.2378***	0.3723***	0.1507
	(3.56)	(3.33)	(3.08)	(1.36)
Innov_sub		0.0178	0.1274	-0.0074
		(0.18)	(0.90)	(-0.06)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	219533	219533	103760	115773
Adjusted R^2	0.108	0.176	0.143	0.212

Table 6. Firm Innovation and future profitability

This table presents annual panel regressions of operating performance in year t on firm innovation (*Innov*), control variables, and firm dummies for non-SOEs and SOEs in year t-1, respectively. We measure profitability by *ROA* and *NCF ratio*. *ROA* is income before extraordinary items plus interest expenses divided by one-year lagged total assets at the end of year t. *NCF ratio* is net profits plus depreciation expenses divided by one-year lagged total assets at the end of year t. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in year t-1. △*ROA* is the change in *ROA* from year t-1 to year t. △*NCF ratio* is the change in *NCF ratio* from year t-1 to year t. *BM* is the ratio of book equity to market value at the end of year t-1. *SIZE* is the log of market value at the end of year t-1. *LR* is the ratio of total debts to total assets at the end of year t-1. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Turn* is the ratio of shares traded to total shares outstanding at the end of year t-1. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The sample period is from 2004 to 2020. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the yearly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	ROA		*NCF ratio*	
Sample	Non-SOEs	SOEs	Non-SOEs	SOEs
	(1)	(2)	(3)	(4)
Innov	0.2324*	-0.0721	0.2865*	-0.0963
	(1.75)	(-0.51)	(1.91)	(-0.56)
lagged ROA	0.4026***	0.4303***		
	(15.36)	(22.52)		
△*ROA*	-0.0494***	-0.0479***		
	(-2.76)	(-3.24)		
lagged NCF ratio			0.3773***	0.4425***
			(15.01)	(24.12)
△*NCF ratio*			-0.0368**	-0.0423***
			(-2.11)	(-3.01)
BM	-0.0310***	-0.0178***	-0.0382***	-0.0222***
	(-11.45)	(-13.35)	(-12.60)	(-13.86)
SIZE	-0.0095***	-0.0079***	-0.0120***	-0.0110***
	(-4.49)	(-5.25)	(-4.99)	(-6.18)
LR	-0.0175*	-0.0521***	-0.0294***	-0.0718***
	(-1.92)	(-9.03)	(-2.85)	(-10.45)
CapEx	-0.0246	-0.0140	-0.0327	-0.0251*
	(-1.30)	(-1.10)	(-1.50)	(-1.75)
Turn	-0.0177	0.0755***	-0.0092	0.0831***
	(-0.57)	(3.30)	(-0.27)	(3.08)
Ins	0.0389***	0.0408***	0.0373***	0.0340***
	(4.62)	(6.10)	(3.95)	(4.15)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8495	9688	8495	9688
Adjusted R^2	0.496	0.525	0.526	0.585

Table 7. Firm innovation, CEO retirement, and future profitability

This table presents annual panel regressions examining how CEO retirement influences the relationship between firm innovation and operating performance for non-SOEs and SOEs, respectively. We measure operating performance by *ROA* and *NCF ratio*. *ROA* is income before extraordinary items plus interest expenses divided by one-year lagged total assets at the end of year t. *NCF ratio* is net profits plus depreciation expenses divided by one-year lagged total assets at the end of year t. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in year t-1. *CEOAgeDum* is a dummy variable taking the value of one if a CEO's age is above 58, and zero otherwise. △*ROA* is the change in *ROA* from year t-1 to year t. △*NCF ratio* is the change in *NCF ratio* from year t-1 to year t. *BM* is the ratio of book equity to market value at the end of year t-1. *SIZE* is the log of market value at the end of year t-1. *LR* is the ratio of total debts to total assets at the end of year t-1. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Turn* is the ratio of shares traded to total shares outstanding at the end of year t-1. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The sample period is from 2004 to 2020. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the yearly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	ROA		*NCF ratio*	
Sample	Non-SOEs	SOEs	Non-SOEs	SOEs
	(1)	(2)	(3)	(4)
Innov	-0.5169***	-0.2844	-0.5833**	-0.0074
** CEOAgeDum*	(-2.60)	(-0.45)	(-2.52)	(-0.01)
Innov	0.5646***	-0.0425	0.6620***	-0.0461
	(2.95)	(-0.30)	(2.90)	(-0.26)
CEOAgeDum	0.0009	0.0025	0.0024	0.0031
	(0.26)	(1.35)	(0.61)	(1.39)
lagged ROA	0.3995***	0.4266***		
	(15.10)	(22.14)		
△*ROA*	-0.0473***	-0.0476***		
	(-2.62)	(-3.18)		
lagged NCF ratio			0.3739***	0.4354***
			(14.75)	(23.56)
△*NCF ratio*			-0.0347**	-0.0405***
			(-1.97)	(-2.85)
BM	-0.0307***	-0.0179***	-0.0378***	-0.0224***
	(-11.32)	(-13.32)	(-12.44)	(-13.85)
SIZE	-0.0094***	-0.0082***	-0.0118***	-0.0112***
	(-4.40)	(-5.45)	(-4.87)	(-6.24)
LR	-0.0170*	-0.0525***	-0.0289***	-0.0729***
	(-1.85)	(-9.02)	(-2.78)	(-10.51)
CapEx	-0.0262	-0.0180	-0.0336	-0.0309**
	(-1.37)	(-1.40)	(-1.53)	(-2.13)
Turn	-0.0238	0.0725***	-0.0157	0.0796***
	(-0.77)	(3.15)	(-0.46)	(2.94)
Ins	0.0387***	0.0415***	0.0374***	0.0358***
	(4.58)	(6.18)	(3.94)	(4.35)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8412	9515	8412	9515
Adjusted R^2	0.495	0.527	0.525	0.586

Table 8. Heterogeneous return predictive power 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 corresponding measure (*Analyst forecast inaccuracy, Institutional ownership, Fund ownership, QFII ownership*) among non-SOEs. To assess a firm's analyst forecast inaccuracy, we use the mean and the median of all analyst forecasts' errors in year t-1, respectively. An analyst forecast's error is defined as the absolute value of the difference between the forecasted earnings and realized earnings, scaled by the absolute value of realized earnings. *Institutional ownership* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. *Fund ownership* is the fraction of firm shares outstanding that are owned by mutual funds at the end of year t-1. *QFII ownership* is the fraction of firm shares outstanding that are owned by QFIIs at the end of year t-1. The dependent variable, *ER* is a firm's stock return in a given month minus the risk-free interest rate. *Innov* is *Patent* over total assets at the end of year t-1; *Patent* is the number of a firm's invention and utility patents that are granted in year t-1. The return data are from July 2004 to June 2021. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Newey-West adjusted t-stat are presented in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A. Analyst forecast inaccuracy

	The mean of analyst forecast errors		The median of analyst forecast errors	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Innov	1.0977**	0.2275	0.8524**	0.0688
	(2.33)	(0.45)	(2.00)	(0.13)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	40089	40177	40089	40177
Adjusted R^2	0.136	0.189	0.137	0.190

Panel B. Institutional ownership

	All institutions		Mutual funds		QFIIs	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Innov	0.1220	0.5432*	0.3069**	0.6763**	-0.0916	0.4088***
	(0.52)	(1.91)	(2.09)	(2.44)	(-0.11)	(2.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51837	51923	51831	51929	11001	92759
Adjusted R^2	0.168	0.117	0.180	0.113	0.206	0.139

Internet Appendix of
"Patents, Profitability, and Stock Returns: Evidence from China"

IA Table 1. Summary statistics for the annual sample

This table reports the time-series averages of the annual cross-sectional summary statistics. *ROA* is the income before extraordinary items plus interest expenses divided by one-year lagged total assets at the end of year t. *NCF ratio* is the net profits plus depreciation expenses divided by one-year lagged total assets at the end of year t. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in year t-1. △*ROA* is the change in *ROA* from year t-1 to year t. △*NCF ratio* is the change in *NCF ratio* from year t-1 to year t. *BM* is the ratio of book equity to market value at the end of year t-1. *SIZE* is the log of market value at the end of year t-1. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *LR* is the ratio of total debts to total assets at the end of year t-1. *Turn* is the ratio of shares traded to total shares outstanding at the end of year t-1. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. We winsorize all financial variables at the 1% and 99% levels.

Panel A. Full sample

	Mean	S.D.	Min.	P25	P50	P75	Max.
ROA	0.045	0.070	-0.219	0.014	0.038	0.074	0.281
NCF ratio	0.082	0.083	-0.181	0.039	0.072	0.119	0.381
Innov	0.002	0.007	0.000	0.000	0.000	0.001	0.435
△*ROA*	-0.003	0.061	-0.259	-0.019	-0.001	0.014	0.241
△*NCF ratio*	-0.003	0.142	-0.579	-0.036	-0.001	0.029	0.646
BM	0.781	0.682	0.076	0.328	0.564	0.993	3.794
LR	0.481	0.192	0.075	0.339	0.490	0.627	0.876
SIZE	22.334	1.154	19.717	21.679	22.358	23.039	25.391
CapEx	0.054	0.052	0.000	0.016	0.038	0.075	0.251
Turn	0.047	0.035	0.004	0.021	0.036	0.062	0.170
Ins	0.534	0.207	0.026	0.397	0.554	0.688	0.922
N	18183						

Panel B. Non-SOEs vs. SOEs

	Non-SOEs		SOEs	
	Mean	S.D.	Mean	S.D.
ROA	0.048	0.079	0.042	0.062
NCF ratio	0.084	0.090	0.081	0.077
Innov	0.002	0.008	0.001	0.004
△*ROA*	-0.005	0.067	-0.001	0.055
△*NCF ratio*	-0.005	0.075	-0.001	0.064
BM	0.622	0.524	0.920	0.769
LR	0.447	0.190	0.511	0.188
SIZE	22.346	1.035	22.324	1.248
CapEx	0.053	0.051	0.131	0.144
Turn	0.049	0.035	0.045	0.034
Ins	0.456	0.222	0.055	0.053
N	8495		9688	

IA Table 2. Return predictive power of firm innovation for rolling period 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 a rolling period among non-SOEs. The dependent variable *ER* is a firm's stock return in a given month minus the risk-free interest rate. We define *Innov* as *Patent* over total assets at the end of year t-1; *Patent* denotes the number of a firm's invention and utility patents that are granted in a given year. *ROA* is income before extraordinary items plus interest expenses divided by one-year lagged total assets. *BM* is the ratio of book equity to market value at the end of year t-1. *Size* is the log of market value at the end of June of year t. *CapEx* is capital expenditure divided by total assets at the end of year t-1. *Mom* is the previous 11-month returns (with a one-month gap between the holding period and the current month). *STRev* is the stock return of the prior month. *TR* is the ratio of shares traded to total shares outstanding at the end of June of year t. *Ins* is the fraction of firm shares outstanding that are owned by institutional investors at the end of year t-1. The return data are from July 2004 to June 2021. The reported adjusted R^2 is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Newey-West adjusted t-stat 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)
Innov	0.5151***	0.2428**	0.1430**	0.1079**
	(2.86)	(2.37)	(2.35)	(2.35)
ROA	0.0111	-0.0023	-0.0045	-0.0017
	(0.62)	(-0.15)	(-0.51)	(-0.18)
BM	0.0018	0.0004	0.0010	0.0008
	(1.20)	(0.26)	(0.67)	(0.57)
Size	-0.0040**	-0.0053***	-0.0050**	-0.0030
	(-2.28)	(-2.72)	(-2.50)	(-1.50)
CapEx	0.0001	-0.0039	-0.0031	0.0187
	(0.01)	(-0.29)	(-0.24)	(1.39)
Mom	0.0007	-0.0043	-0.0046	0.0023
	(0.12)	(-0.82)	(-0.84)	(0.54)
STRev	-0.0666***	-0.0665***	-0.0629***	-0.0462***
	(-8.27)	(-9.50)	(-7.68)	(-5.16)
TR	-1.2086***	-1.3856***	-1.3422***	-1.4548***
	(-4.40)	(-5.06)	(-5.39)	(-7.49)
Ins	0.0031	0.0014	0.0025	0.0003
	(0.82)	(0.41)	(0.96)	(0.15)
Industry FE	Yes	Yes	Yes	Yes
Observations	46113	55675	68581	85394
Adjusted R^2	0.146	0.143	0.142	0.140