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Stock liquidity, financial constraints, and innovation in Chinese SMEs

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Abstract

This study investigates the relationship between stock liquidity and firm innovation for publicly traded growing small and medium-sized enterprises (SMEs) in China using both innovation input and output. We collected samples of 785 SMEs from China's Shenzhen Growth Enterprises Market without the financial industry from 2010 to 2020. The empirical findings demonstrate a significant positive relationship between stock liquidity and both innovation input, as measured by R&D investments, and innovation output, as proxied by patenting activities. A series of robustness tests demonstrate the reliability of our results. Increased liquidity enhances SMEs' innovation mainly by alleviating financial constraints, whereas the mediating effect of mergers and acquisitions (M&A) is not apparent at the firm level. Furthermore, the inhibitory effect of blockholder ownership on firm innovation is weak. Further analysis reveals that this favorable impact can last for at least four years, with manufacturing SMEs benefiting the most. Our study shows that the innovation abilities of SMEs can be enhanced by improving stock liquidity, which is mainly driven by tackling financial constraints.

Keywords: SMEs, Stock liquidity, Firm innovation, Blockholder ownership, Financial constraints

JEL Classification: G10, G12, G34, O31

Introduction

Small and medium-sized enterprises (SMEs) are critical to economic growth because of their contributions to job development, employment, and productivity, especially in developing countries (Ayyagari et al. 2007, 2011; Neagu 2016). SMEs constitute the majority of enterprises worldwide, representing approximately 90% of the world's enterprises and over 50% of employment. In emerging economies, SMEs contribute up to 40% of the national income and create seven out of ten jobs.[1] Cefis and Marsili (2006) argue that innovation is the engine for the survival of small and young firms. Moreover, innovation is one of the most important competitive strategies for both small and large firms, where the limited financing capacity of SMEs is a common problem limiting their innovative activities (Kaufmann and Tödtling 2002).

[1] The statistics are retrieved from The World Bank: https://www.worldbank.org/en/topic/smefinance

Berger and Udell (2006) point out that SMEs' financing options change at all stages of their life cycles. Due to problems such as opaque information, SMEs rely heavily on internal financing during the start-up phase. As SMEs grow and enhance information transparency, they become better positioned to issue securitized loans and publicly listed shares to raise funds (Berger and Udell, 2006; Abdulsaleh and Worthington 2013; Ghak and Zarrouk 2022; Lim et al. 2023). Access to equity markets is a widespread option for national policymakers worldwide to solve financing problems for SMEs. According to the World Federation of Exchanges (WFE) (2018), 37 specialized SME exchanges operated throughout the WFE membership as of December 2019. These exchanges provide financially challenged SMEs with an alternative avenue to raise capital, both during the initial listing and following the initial public offering. Despite having only 13 SME exchanges, the Asia–Pacific region has the most listed SMEs, with the highest market capitalization and capital raised (WFE 2018). Similar to the NASDAQ market in the U.S., China offers a financing platform for growth-oriented SMEs: the Shenzhen Growth Enterprises Market (GEM). As of December 2020, 895 firms were listed on the Shenzhen GEM.[2]

Bulter et al. (2007) state that when market liquidity is low, issuance costs for securities dealers and transaction costs for investors are higher; thus, firms have higher financing costs. Therefore, the higher the liquidity, the more the market resource allocation can be utilized, and the better the access to financing for SMEs. Amihud and Noh (2021) find a positive and significant pricing of the illiquidity factor's conditional risk, which increases during times of financial distress. Innovation requires investment in resources obtained from financing (Peneder 2008; Xiang et al. 2022). Thus, the relationship between stock liquidity and firm innovation has become a widespread concern. Fang et al. (2014) collect samples from the NYSE, AMEX, and NASDAQ markets,[3] and their empirical results show that at the firm level, an increase in liquidity reduces future innovation through two possible mechanisms: (1) heightened risk of hostile takeovers and (2) a greater presence of institutional investors who do not actively obtain or monitor information. Based on the findings of Fang et al. (2014) at the market level, Vo (2014) investigates the relationship between asset liquidity and firm innovation from a macro perspective for all publicly traded firms in the U.S., whose findings contradict those of Fang et al. (2014). Vo (2014) suggests that management shortsightedness does not exist at the market level and that aggregate liquidity can promote firm innovation through two mechanisms. First, increased stock market liquidity reduces the cost of obtaining external financing, making it easier for small firms to issue shares and finance innovations. Second, higher stock market liquidity leads to higher firm value and reduced transaction costs, allowing large firms to acquire innovations from smaller firms through mergers and acquisitions (M&A). Meanwhile, at the firm level, Zhong (2018) also comes to the opposite conclusion of Fang et al. (2014). He examined all Chinese listed firms and found that stock liquidity improves innovation in terms of R&D expenditure by alleviating financial constraints and increasing agency costs.

[2] Statistics retrieved from the Wind Database.

[3] The NYSE is the New York Stock Exchange, AMEX is the American Stock Exchange, and NASDAQ is the National Association of Securities Dealers Automated Quotations.

Wen et al. (2018) and Tang et al. (2022) challenge the findings of Fang et al. (2014) by asserting that the Chinese market, following the Share Splitting Reform[4] aimed to increase share liquidity and improve capital market efficiency, contradicting the conclusion that liquidity impedes firm innovation. Instead, they suggest that reform enhances sustainable innovation capacity and competitiveness. Specifically, Wen et al. (2018) compare the results for state-owned enterprises (SOEs) and private firms from the perspective of ownership of the firm's equity and show that increased liquidity can only promote innovation in SOEs through two mechanisms: (1) the long-term entry and (2) strategic institutional investors in the case of the implementation of Share Splitting Reform. Tang et al. (2022) also emphasize the importance of ownership concentration, arguing that after the Share Splitting Reform in 2005, stock liquidity and firm innovation are positively correlated because blockholders, particularly institutional investors, increased their involvement in regulating and balancing ownership in firms. From the above, the findings at the firm level of Fang et al. (2014), Wen et al. (2018), Zhong (2018), and Tang et al. (2022) are the opposite. The primary reasons for this discrepancy are the different market microstructures in the U.S. market and Chinese markets. Specifically, the proportion of individual investors in the Chinese market is higher than that in the U.S. market, whereas the number of institutional investors (blockholders) in the U.S. market is higher. This may make institutional investors' regulatory effects less pronounced in China. Furthermore, distinct trading systems, as exemplified by up-and- down-price ranges, compel institutional investors in the Chinese market to employ different trading strategies. This study focuses on the Chinese stock market because of its distinct characteristics. First, the role of stock liquidity in fostering innovation in emerging markets such as China has received little attention. China, the world's second largest economy after the U.S., holds significant global economic importance as a representative emerging economy. Second, Pissarides (1999) highlights that SMEs are potentially the most active businesses in emerging economies where access to capital is recognized as a primary barrier to their development, constraining their innovative capacities. Third, in a market driven mainly by retail investors who lack specialized investment knowledge, the impact of liquidity on firms' innovation capabilities is likely to differ substantially from that in developed countries, where institutional investors are dominant.

Driven by these concerns, this study examines the relationship between liquidity and innovation in Chinese listed SMEs. Our study employs all nonfinancial firms traded on the Chinese Shenzhen GEM, a financing platform for growth-oriented SMEs, from 2010 to 2020. The baseline models regress R&D expenditure or the number of granted patents against the Closing Percentage Quoted Spread (*CPQS*) and a set of standard control variables. The empirical results show evidence of a positive relationship between stock liquidity and firm innovation in Chinese-listed SMEs, with a long-term positive impact of at least four years. The positive relationships pass a series of robustness checks using (1) alternative stock liquidity measures, (2) alternative firm innovation measures, (3) alternative estimation methods, (4) industry-specific regressions, and (5) endogeneity tests. It is worth highlighting that the results of industry-specific regressions show that

[4] Established in 2005, the Share Splitting Reform refers to the division of shares of listed companies in the A-share market into tradable and non-tradeable shares.

the role of higher liquidity in promoting firm innovation (innovation input or output) is strongest in SMEs in the manufacturing industry.

Based on existing studies, we propose two mechanisms without an exogenous policy impact that may lead to this positive relationship: (1) reducing financial constraints and (2) the willingness of large firms to buy innovation. Our subsequent tests on mechanisms further show that among SMEs, the positive relationship between liquidity and innovation is mainly caused by the financing difficulties they face. At the firm level, the mediating effect of M&A on stock liquidity and firm innovation, as proposed by Vo (2014), is not evident. Motivated by Fang et al. (2014), we also test the effect of blockholder ownership, showing that both external blockholders, represented by institutions, and internal blockholders can inhibit firm innovation under higher liquidity, but this effect is not strong in SMEs.

Our study contributes to the limited literature on the relationship between stock liquidity and firm innovation in SMEs, especially for SMEs in emerging markets. Browsing through the literature on SMEs innovation is confined to other determinants of firm innovation, which can be grouped as follows: (1) financial factors (Laforet 2011; Xie et al. 2013; Wonglimpiyarat 2015; Yao and Yang 2022), (2) institutional factors (Zhu et al. 2012; Volchek et al. 2013; Donbesuur et al. 2020), (3) management (Alegre et al. 2011; Chereau 2015; Adla et al. 2019; Madison et al. 2022; Timothy 2022), (4) economic factors (North and Smallbone 2000; Kumar and Subrahmanya 2010; Bala Subrahmanya 2013; Gherghina et al. 2020), and (5) culture (Aksoy 2017; Gonzalez-Loureiro et al. 2017).

Many scholars investigated the obstacles that affect the development of large firms. However, little research has been conducted on SMEs, which are critical for their survival. Notably, although Vo (2014) presents a greater role of higher liquidity in promoting innovation in small firms, he focuses mainly on the market and neglects the effects of blockholders at the firm level. Furthermore, it is worth noting that most studies on firm innovation are limited to mature markets, such as the U.S., which makes it doubtful that developing markets dominated by SMEs can draw the same conclusions. Often, SMEs lack external financing. Zhong (2018) emphasizes the problem of financial constraints, whereas Wen et al. (2018) and Tang et al. (2022) neglect it in favor of focusing on ownership concentration in Chinese SMEs because of the Chinese Share Splitting Reform's policy effect. The Chinese Share Splitting Reform was established in 2005 and completed by the end of 2006.[5] The GEM, a market with reduced listing standards for mainly SMEs, was launched on 30th, October 2009, to solve the difficult financing for SMEs, which is already after the implementation of the shareholding reform. It is reasonable to infer that the mechanisms proposed by Wen et al. (2018) and Tang et al. (2022) may not be applicable to SMEs facing financing difficulties without exogenous policy shocks.

Our study addresses these gaps and contributes to existing literature as follows. First, we provide empirical evidence from the Chinese stock market, adding to the growing body of research on the effect of stock liquidity on SME innovation in financial markets. Second, we comprehensively examine all possible mechanisms and propose two ways to enhance innovation in SMEs: (1) resolving financial constraints, and (2) lowering M&A

[5] Information about the Chinese Splitting Share Reform is available from the Chinese Government Website at http://www.gov.cn/ztzl/gclszfgzbg/content_554986.htm.

activity. Third, we complement Wen et al. (2018) and Tang et al. (2022) by showing that liquidity can improve innovation in Chinese listed SMEs without exogenous shocks, primarily by reducing financial constraints. Furthermore, our empirical evidence contradicts those of Vo (2014) and Fang et al. (2014), who focus on the U.S. market. On the one hand, at the firm level, the mediating effect of M&A on stock liquidity and firm innovation is not evident. By contrast, blockholder ownership can inhibit firm innovation under higher liquidity, but this effect is relatively weak in SMEs.

The remainder of this paper is organized as follows. section "theoretical basis for the hypotheses" reviews the relevant literature and develops our hypotheses on stock liquidity and firm innovation based on them. Section "Measurement of variables and model specification" presents the variable measurements and model specifications. Section "The data" describes the data collection and discusses the results of the summary statistics. Section "Baseline results: Stock liquidity and firm innovation" presents the baseline results, and robustness checks are presented in Section "Robustness checks". Section "Potential mechanisms" addresses possible mechanisms that may affect the relationship between stock liquidity and firm innovation. Section "Conclusion and discussions" offers concluding remarks, policy recommendations, limitations, and future research.

Theoretical basis for the hypotheses

Previous studies on the relationship between stock liquidity and firm innovation are restricted to U.S. stock markets and all Chinese A-share stocks (Vo 2014; Fang et al. 2014; Wen et al. 2018; Zhong 2018). Their findings lead to the opposing conclusion that liquidity promotes or inhibits firm innovation. In addition to the Chinese and U.S. markets, recent studies have explored the impact of innovation on other markets using factors such as mediators. Amin et al. (2023) investigate the impacts of a firm's information asymmetry on corporate innovation in the Korean market and find that a firm's innovation activities are positively affected by the quality of its information. Arifin et al. (2022) examine the principal-agent relationship and financing constraints to explain the level of corporate innovation in Indonesia. Zhang (2023) finds that financial constraints can reduce Indian firms' motivation to engage in product innovation. Hanelt et al. (2021) employ panel data regressions to analyze a longitudinal dataset of the top automakers in the world and discover that digital M&As have a positive impact on digital innovation, which is largely mediated through the generation of new digital patents filed by the acquiring firms. Extending the work of Vo (2014), Fang et al. (2014), Wen et al. (2018), and Zhong (2018) on the linear relationship between stock liquidity and firm innovation, we propose the following four perspectives to support our linear relationship hypothesis.

Information asymmetry

According to information asymmetry theory, persons with sufficient information are frequently in a more beneficial position, whereas those with poorer information are in a less favorable position. First, Stein (1989) finds that information asymmetry between managers and investors, coupled with market pressure, compels managers to forfeit long-term investments such as innovation to avert a near-term share price decline and the risk of a hostile takeover. Therefore, managers prefer short-term investments that stabilize stock prices, and forgo long-term innovative investments to avoid threats to their positions if the firm is acquired (Fang et al. 2014).

Second, as shown by Kyle (1984) and Holmström and Tirole (1993), traders with increased liquidity make it easier for well-informed parties to conceal their information and capitalize on it. In pursuit of short-term gains, investors tend to seek undisclosed information, which does not foster innovation. Information asymmetry prompts executives with inside information to engage in speculative behavior when a firm's share price is overvalued, leading to a high cash output of shares for short-term maximization. Third, Graham et al. (2005) argue that Chief Financial Officers (CFOs) are often willing to sacrifice long-term projects to achieve short-term profit goals. Kyle and Vila (1991) show that higher liquidity can exacerbate the myopia of firm management that fails to be aware of the entry of outsiders disguised as hostile takeovers. As innovation activities often do not yield short-term profitability, myopia can prompt management to curtail investment in innovation and overlook potentially disguised hostile actions. Fourth, Porter (1992) indicates that enhanced liquidity reduces transaction costs for institutional investors, thus enabling smoother entry and exit from transactions. However, their trading practices, driven by current earnings news, may result in misvaluation and underinvestment in innovation. Institutional investors tend to prefer investing in firms with higher expected short-term returns (Bushee 2001). Thus, researchers grounded given that information asymmetry argue that liquidity hinders firm innovation (Fang et al. 2014).

Principal-agent relationship

In corporate governance, ownership and operations are often separated, with the business owner retaining residual claims and ceding operating power. First, as a highly liquid market allows shareholders to sell their shares more easily, it is more likely to allow blockholders to continue holding more shares at a lower cost and attract more blockholders to the market (Maug 1998; Edmans 2009). Maug (1998) indicates that increased liquidity encourages blockholders to engage in corporate governance oversight because the benefits of informed trading offset the associated costs. As blockholders, institutional investors effectively discipline concentrated ownership and significantly influence innovation activities (Shleifer and Vishny 1997; Mahmood and Mitchell 2004; Choi et al. 2011; Belloc 2012). Blockholders can discipline a firm's management when the management's compensation is closely related to its share price (Admati and Pfleiderer 2009; Edmans and Manso 2011). Thus, blockholders' monitoring role can inhibit managers' short-sighted behavior and encourage firms to invest in innovation. Consequently, more liquidity stimulates innovation.

Financial constraints

A higher stock liquidity leads to lower transaction costs. Higher liquidity is often accompanied by lower issuance costs because underwriters can maintain a net equity position at a lower cost with high liquidity. Higher stock liquidity lowers financing costs and increases the funds available to a company, thus mitigating financing constraints on innovation activities (Vo 2014; Zhong 2018). Based on these arguments, higher liquidity promotes innovation.

Merger and acquisition

Harford (2005) shows that higher liquidity can reduce transaction costs, creating a wave of M&A. Phillips and Zhdanov (2013) showed that large firms are more likely to buy innovation from small firms to obtain more innovation and avoid competing head-to-head with small firms in an active acquisition market. Higher aggregate liquidity enhances firm valuation and reduces transaction costs, facilitating large firms' acquisition of innovation from small firms, thereby promoting increased innovation investment by small firms (Vo 2014). Zhao (2009) and Bena and Li (2014) document that less-innovative SMEs often acquire more innovative firms which can enhance innovation. Therefore, more liquidity stimulates innovation.

Measurement of variables and model specification

This section briefly introduces the dependent, independent, and control variables used in the analysis. We then specify baseline models to examine the relationships between stock liquidity and firm innovation in listed SMEs. All the variables and their respective data sources are shown in Appendix A.

Dependent variable of firm innovation

Prior studies propose two proxies from the perspectives of input and output to capture firm innovation: (1) R&D investments and (2) patenting activities (Fang et al. 2014). R&D investment represents capital allocated to innovation, whereas patent activities denote innovation output. Both proxies were employed in our models to better capture a firm's innovation activity. On the one hand, the number of granted patents (*INNOV_PAT*) is adopted as the innovation proxy to measure the output of innovation (Sun and Du 2010; Fang et al. 2014; Vo 2014; Zheng and Zhang 2021). On the other hand, Cohen and Klepper (1996) show that R&D efforts increase firm size, leading to product and process innovation. Therefore, we use the natural logarithm of R&D expenditure (*INNOV_EXP*) to measure firms' innovation input (Czarnitzki and Lichi, 2006; Vo 2014; Liu et al. 2021).

Independent variable of stock liquidity

Liquidity, a key determinant of market quality, affects financial instrument pricing, portfolio allocation, and risk management (Amihud and Mendelson 2015). The liquidity-related literature divides liquidity measures into (1) high-frequency data measures (Jarnecic and Snape 2014; Easley et al. 2012) and (2) low-frequency data measures (Lesmond et al. 1999; Amihud 2002; Chung and Zhang 2014; Abdi and Ranaldo 2017). High-frequency liquidity measures were developed from intraday data, whereas low-frequency liquidity proxies were obtained from daily stock returns and volume data (Le and Gregoriou 2020). However, access to high-frequency data is often restricted, especially in emerging markets (Będowska-Sójka 2018). Due to the multifarious character of liquidity, Le and Gregoriou (2020) presented a set of proxies with low-frequency data; therefore, the bid/ask spread is the most popular liquidity estimator (Będowska-Sójka 2018). Some studies aim to determine the best proxy from a variety of low-frequency proxies in different markets (Lesmond 2005; Goyenko et al.

2009; Marshall et al. 2013; Fong et al. 2017; Będowska-Sójka and Echaust 2020). Fong et al. (2017) and Będowska-Sójka and Echaust (2020) show that *CPQS* introduced by Chung and Zhang (2014) outperforms other low-frequency percent-cost proxies. Therefore, *CPQS* is employed in this study to measure liquidity. The choice is based on Fong et al. (2017), who show that *CPQS* is the best daily percentage cost proxy for the Chinese stock market. We exclude an incomplete sample for years in which the firms are not listed for less than one full year.

Thus, *CPQS* is computed using the daily closing ask and bid prices from Thomson Reuters Datastream and is multiplied by 100 to make it easier to calculate (Chia et al. 2020):

$$CPQS_{i,d} = \frac{Closing\ ask_{i,d} - Closing\ bid_{i,d}}{\left(Closing\ ask_{i,d} + Closing\ bid_{i,d}\right)/2} \text{x}100,$$

where $CPQS_{i,d}$ is the Closing Percent Quoted Spread of stock i on day d, $Closingask_{i,d}$ and $Closingbid_{i,d}$ are closing ask and bid prices of stock i on day d, respectively and the multiplication by 100 is for scaling purposes. Annual *CPQS* estimates were generated by averaging daily *CPQS* values over an entire year. Because higher values suggest larger spreads and higher transaction costs for investors, the value of *CPQS* is inversely associated with liquidity.

Control variables

We follow previous studies on firm innovation to control for a set of variables divided into ownership and firm characteristics. Appendix A provides the definitions of all variables. As shown in Table 1, following Choi et al. (2011) and the characteristics of the Chinese stock market, we employ three variables to control for ownership characteristics: *TSHARE*, *SHRHFD5*, and *FREE*. *TSHARE* is the number of shares of listed firms that can be traded on the exchange, whereas *FREE* is the proportion of all tradable shares that exclude blockholders holding more than 5% of the shares. *SHRHFD5* is the sum of the squares of the firm's top five largest owners' shareholdings to measure ownership concentration. Firms with higher *TSHARE* or *SHRFHD5* are expected to show higher firm innovation because blockholders, especially those with institutional and insider ownership, are positively related to firm performance by lowering the agency cost of management ownership (Jensen and Mecking, 1976; McConnell and Servaes 1990; Aghion et al. 2013). Turning to *FREE*, firms with higher *FREE* are expected to be associated with lower firm innovation owing to non-information trading by noise traders. This is due to the dominance of individual investors, who make up over 90% of the Chinese stock market (Yu et al. 2019). Management focuses on controlling public opinion and reducing R&D innovation efforts.

Second, 12 variables were collected to control for firm characteristics and isolate the effect of stock liquidity on firm innovation (Choi et al. 2011; Chang et al. 2015; Fang et al. 2014; Brown et al. 2013): *RET*, *TO*, *VOL*, *EARN*, *INTAN*, *LEV*, *ROE*, *Q*, *BTM*, *CAPITAL*, *SALES*, *AGE*. Firms with higher *RET*, *TO*, *VOL*, *EARN*, *INTAN*, *ROE*, *Q*, *BTM*, *SALES* are associated with higher firm innovation (Hall 1999; Chan et al. 2001; Coad and Rao

Table 1 The classification of control variables

Ownership	Firm characteristics
1. Tradable shares (*TSHARE*), 2. The sum of the square of the top five shareholders' shareholdings (*SHRHFD5*) 3. Free float (*FREE*)	4. Stock return (*RET*) 5. Stock turnover (*TO*) 6. Return volatility (*VOL*) 7. Earnings (*EARN*) 8. Intangibles (*INTAN*) 9. Leverage (*LEV*) 10. Return on equity (*ROE*) 11. Tobin's Q (*Q*) 12. Book to market (*BTM*) 13. Capital expenditures (*CAPITAL*) 14. Sales growth (*SALES*) 15. Firm age (*AGE*)

This table presents the classification of 15 control variables correlated with firm innovation, comprising ownership and firm characteristics

2016; Luoma-aho and Halonen 2010; Piergiovanni and Santarelli 2013; Hirshleifer et al. 2013; Wang and Wang 2012; Setayesha and Daryae 2017; Mahmutaj and Krasniqi 2020).

On the contrary, *LEV* is negatively related to innovation input but positively associated with innovation output because the debt burden robs firms of R&D investment and pushes them to produce more innovative products (Iqbal et al. 2020). Hansen (1992) reported that firm age is inversely related to innovative output because young companies face special challenges in terms of innovation and engage in R&D with greater risks (Coad et al. 2016).

Model specifications

Motivated by Wen et al. (2018), we specify linear models (1) and (2) to assess whether stock liquidity enhances or impedes innovation input and output for Chinese growth-oriented SMEs.

$$\begin{aligned} INNOV\_EXP_{i,t} = {} & \alpha_0 + \alpha_1 CPQS_{it} + \alpha_2 TSHARE_{it} \\ & + \alpha_3 SHRHFD5_{it} + \alpha_4 TO_{it} + \alpha_5 RET_{it} \\ & + \alpha_6 FREE_{it} + \alpha_7 VOL_{it} + \alpha_8 EARN_{it} \\ & + \alpha_9 INTAN_{it} + \alpha_{10} LEV_{it} + \alpha_{11} ROE_{it} + \alpha_{12} Q_{it} \\ & + \alpha_{13} BTM_{it} + \alpha_{14} CAPITAL_{it} + \alpha_{15} SALES_{it} \\ & + \alpha_{16} lnAGE_{it} + \sum_{j=1}^{J-1} \alpha_{17j} IND_j + \sum_{t=1}^{T-1} \alpha_{18t} YR_t + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} INNOV\_PAT_{i,t} = {} & \alpha_0 + \alpha_1 CPQS_{it} + \alpha_2 TSHARE_{it} \\ & + \alpha_3 SHRHFD5_{it} + \alpha_4 TO_{it} + \alpha_5 RET_{it} \\ & + \alpha_6 FREE_{it} + \alpha_7 VOL_{it} + \alpha_8 EARN_{it} \\ & + \alpha_9 INTAN_{it} + \alpha_{10} LEV_{it} + \alpha_{11} ROE_{it} + \alpha_{12} Q_{it} \\ & + \alpha_{13} BTM_{it} + \alpha_{14} CAPITAL_{it} + \alpha_{15} SALES_{it} \\ & + \alpha_{16} lnAGE_{it} + \sum_{j=1}^{J-1} \alpha_{17j} IND_j + \sum_{t=1}^{T-1} \alpha_{18t} YR_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

where *ln* denotes the natural logarithm. The dependent variable is firm innovation, comprising innovation input, proxied by the natural logarithm of R&D expenditures, and innovation output, proxied by the number of patents. The key independent variable Closing Percent Quoted Spread (*CPQS*) is constructed by daily closing ask and bid prices to measure stock liquidity. The control variables are tradeable shares (*TSHARE*), the sum of the square of the top five shareholders' shareholdings (*SHRHFD5*), turnover (*TO*), stock returns (*RET*), free float (*FREE*), return volatility (*VOL*), earnings (*EARN*), intangibles (*INTAN*), leverage (*LEV*), return on equity (*ROE*), Tobin's Q (*Q*), book to market (*BTM*), capital expenditure (*CAPITAL*), sales growth (*SALES*), firm age (*AGE*). Appendix A presents the definitions of all the variables in the models. We control for industry effects using industry dummies, where $IND_j = 1$ if firm i is in industry j and 0 otherwise, and J is the number of industries, following the classifications of the National Bureau of Statistics of China. We control for common shocks by including year dummies, where $YR_t = 1$ for year t and 0 otherwise and t is the number of years. Fixed effects (FE), random effects (RE), and pooled ordinary least squares (OLS) models are typically considered when selecting regression models for panel data. The assumption of the RF model requires that unobservable individual heterogeneity effects cannot be correlated with the explanatory variables. Many corporate finance and accounting studies avoid the RE model because of its challenging assumptions and inability to account for time-invariant omitted variables. Unlike the FE model, the pooled OLS model treats all individuals as homogeneous and ignores firm-specific and temporal effects. To estimate firm-level panel data, we typically use heteroscedasticity-robust standard errors or clustering adjustments across years and firms. Once we applied these controls, the estimation effects of the pooled OLS and FE models became nearly equivalent. The pooled OLS model, with constant coefficients for intercepts and slopes, combines all data for efficient OLS estimation, offering better analytical properties than other econometric models. Based on this, we follow Fang et al. (2014) by using pooled OLS and incorporating year-fixed effects to control for omitted firm characteristics that remain constant over time and intertemporal variation. To consider within-cluster correlations, we estimate liquidity models with standard error adjustments using double clustering (Petersen 2009).

The data

This section discusses how the sample data are constructed using firms listed on the Shenzhen GEM. Subsequently, descriptive statistics and a correlation matrix are presented.

Data collection

The Shenzhen GEM is a platform launched in October 2009 to satisfy the demands of growth-oriented innovative SMEs for funding. As of December 2020, 895 firms were listed on the Shenzhen GEM. After removing firms with insufficient data, delisted firms, and financial firms, our study comprises 785 growth-oriented innovative SMEs from 2010 to 2020. All variables are winsorized at the 1st and 99th percentiles, except for the dummy variables, to reduce the impact of outliers.

Summary statistics

We present summary statistics for all variables in Table 2, with our primary emphasis on stock liquidity and firm innovation. First, the mean *CPQS* for Chinese-listed growth-oriented SMEs is 0.110, significantly lower than the *CPQS* averages of 0.421 and 0.407 reported by Fong et al. (2017) for firms listed on the Shenzhen and Shanghai Stock Exchanges, respectively. *CPQS*, as an inverse measure of stock liquidity, the *CPQS* indicates that high-technology growth-oriented SMEs listed on the Shenzhen GEM have, on average, more liquid stocks than firms listed on the Chinese main board. The main reasons for this are summarized as follows. First, a significant number of GEM listed firms come from emerging industries with strong growth potential, attracting substantial investor interest. Second, the GEM market's trading rules are more permissive than those of the main board market. For instance, they have fewer restrictions on short stock release times and have no circuit breakers. These lenient trading rules provide investors with greater autonomy and flexibility, thereby bolstering their market liquidity. Furthermore, the *CPQS* average of 5.337 reported by Chia et al. (2020) for Malaysian listed firms significantly exceeds the *CPQS* of 0.110 for Chinese SMEs. This discrepancy suggests that the GEM market enjoys substantially higher liquidity than the Bursa Malaysian mainboard market. We conjecture that individual investors who exhibit low confidence and heightened sensitivity to market movements predominantly influence the GEM market. The prevalence of herd-like investment behavior and speculative actions affects stock market liquidity, resulting in market performance distinctions from the more mature mainboard market.

Table 2 Descriptive Statistics

	N	Mean	S.D	Min	Max	Median
INNOV_EXP	4719	17.641	0.955	15.296	20.092	17.614
INNOV_PAT	4778	5.969	18.435	0.000	12.000	0.000
CPQS	4786	0.110	0.059	0.025	0.319	0.096
TSHARE	4786	64.090	21.662	25.000	100.000	63.367
SHRHFD5	4786	64.090	0.079	0.016	0.378	0.111
TO	4786	0.037	0.032	0.004	0.188	0.028
RET	4786	0.015	0.194	− 0.395	0.533	0.003
FREE	4786	46.945	14.417	19.294	83.512	45.660
VOL	4786	3.176	0.824	1.608	5.686	3.084
EARN	4786	0.034	0.085	− 0.417	0.188	0.044
INTAN	4786	0.112	0.117	0.001	0.521	0.064
LEV	4786	0.141	0.133	0.000	0.506	0.104
ROE	4786	0.060	0.114	− 0.598	0.314	0.067
Q	4732	3.325	2.098	1.080	12.607	2.692
BTM	4786	0.311	0.177	0.050	0.878	0.273
CAPITAL	4786	0.054	0.049	0.001	0.241	0.039
SALES	4780	21.393	37.848	− 53.350	186.560	16.005
ln*AGE*	4785	2.721	0.299	1.946	3.332	2.708
INSTITUTION	4761	26.954	20.090	0.061	75.257	22.962

This table presents the descriptive statistics for all the variables in the baseline linear models. The definition and sources for all variables are shown in Appendix A. To control for outliers, all variables are winsorized at the 1st and 99th percentiles. *N* is the number of firm-year observations and *S.D.* is the standard deviation

Second, the mean number of patents is 5.969, whereas the mean R&D expenditure amounts to 17.641. Notably, the former is lower than 31.110 and the latter is higher than the 0.042 reported for all Chinese listed firms from 2006 to 2013 by Wen et al. (2018). This distinction suggests that high-risk growth-oriented SMEs grappling with underfunding intensify their investment efforts in pursuit of greater innovation outcomes, but still grapple with innovation shortfalls. Fong et al. (2017) report an average number of patents of 1.208 ($e^{0.792}$–1) for U.S. public firms, implying that despite the relatively short history of the GEM market, it demonstrates significant innovation output.

The median number of granted patents at zero suggests that a significant portion of the firms in our sample do not generate any innovative output. Figure 1 illustrates the distribution of zero- and non-zero-granted patents, with 1068 in the non-zero category and 7567 in the zero category.

Table 3 presents Pearson correlation matrices for the 18 variables included in the baseline models. The correlations between explanatory variables and firm innovation provide a preliminary view of their univariate relationships. First, *CPQS* is an inverse proxy for liquidity and is negatively associated with both innovation input and output, suggesting that higher liquidity promotes firm innovation. Second, only *TSHARE*, *FREE*, *EARN*, *ROE*, and *BTM* yield the expected positive relationships with firm innovation. Third, *SALES* is positively correlated only with innovation input, whereas *SHRHFD5*, *RET*, *INTAN*, and *CAPITAL* are only positively associated with innovation output. Fourth, both *LEV* and ln*AGE* positively correlate with firm innovation, whereas *TO*, *VOL*, and *Q* show the opposite signs. Next, we explore the explanatory power of *CPQS* and firm innovation in the pooled OLS estimation when controlling for other innovation-related variables. These univariate relationships may change or become insignificant when all competing factors are included in multivariate regression.

Baseline results: stock liquidity and firm innovation

This section discusses the baseline pooled OLS results and the statistical significance of the linear relationship between stock liquidity and firm innovation.

Key variable of firm innovation

In our baseline models, firm innovation is classified into innovation input and output. The former is measured as the natural logarithm of R&D expenditure (*INNOV_EXP*), whereas the latter is proxied by the number of patents granted (*INNOV_PAT*). Baseline

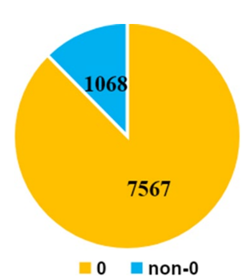

Fig. 1 Number of patents granted. *Notes*: This figure presents the number of zero and non-zero-granted patents

Table 3 Correlation Matrix

	INNOV_EXP	***INNOV_PAT***	***CPQS***	***TSHARE***	***SHRHFD5***	***TO***	***RET***	***FREE***
INNOV_EXP	1.000							
INNOV_PAT	0.202	1.000						
CPQS	– 0.137	– 0.029	1.000					
TSHARE	0.265	0.070	0.100	1.000				
SHRHFD5	– 0.212	0.044	– 0.059	– 0.160	1.000			
TO	– 0.232	– 0.057	– 0.216	– 0.165	0.002	1.000		
RET	0.022	-0.011	– 0.130	0.054	0.020	0.369	1.000	
FREE	0.258	0.023	0.117	0.652	– 0.586	0.001	0.031	1.000
VOL	– 0.042	– 0.035	– 0.196	0.015	– 0.025	0.456	0.417	0.003
EARN	0.005	0.004	– 0.296	-0.207	0.173	0.062	0.196	– 0.223
INTAN	0.198	– 0.024	– 0.046	0.051	– 0.206	– 0.064	– 0.011	0.101
LEV	0.204	0.053	0.158	0.238	– 0.081	– 0.099	– 0.023	0.191
ROE	0.105	0.013	– 0.273	– 0.133	0.127	0.001	0.169	– 0.156
Q	– 0.070	– 0.061	– 0.381	-0.115	0.098	0.249	0.462	– 0.124
BTM	0.065	0.070	0.445	0.079	– 0.092	– 0.263	-0.429	0.108
CAPITAL	– 0.022	0.042	– 0.062	-0.175	0.148	0.077	0.005	– 0.148
SALES	0.066	– 0.012	– 0.176	– 0.160	0.014	0.114	0.165	-0.131
ln*AGE*	0.196	0.029	0.046	0.290	– 0.144	– 0.223	– 0.017	0.232
	VOL	***EARN***	***INTAN***	***LEV***	***ROE***	***Q***	***BTM***	***CAPITAL***
VOL	1.000							
EARN	– 0.057	1.000						
INTAN	– 0.016	– 0.098	1.000					
LEV	– 0.003	– 0.312	0.025	1.000				
ROE	– 0.099	0.722	0.003	– 0.093	1.000			
Q	0.393	0.281	– 0.054	– 0.294	0.187	1.000		
BTM	– 0.381	– 0.193	0.094	0.073	– 0.139	– 0.720	1.000	
CAPITAL	– 0.063	0.153	– 0.146	0.054	0.137	0.028	– 0.025	1.000
SALES	0.007	0.281	0.227	– 0.025	0.350	0.115	– 0.158	0.038
ln*AGE*	0.006	– 0.105	0.089	0.130	– 0.045	– 0.090	0.075	– 0.143
	SALES	ln*AGE*						
SALES	1.000							
ln*AGE*	– 0.117	1.000						

The Pearson correlation coefficients between pairs of variables in the baseline linear model (1) (2) are shown in this table. The definition of all variables is shown in Appendix A

linear models were estimated using white heteroscedastic-robust, firm-clustered, time-clustered, and double-clustered standard errors to control for heteroscedasticity and within-cluster autocorrelation (Petersen 2009). To save space, only the results of the linear relationships between stock liquidity and firm innovation for white heteroscedastic-robust and double-clustered adjustments are reported in Table 4; however, all four within-cluster estimations are considered in the statistical analysis. As Table 4 shows, the coefficient of *CPQS* is negative and significantly associated with both *INNOV_EXP* and *INNOV_PAT* at the 1% level. Because *CPQS* is an inverse proxy for liquidity, the negative and significant results suggest a positive linear relationship between stock liquidity and firm innovation. An increase in *CPQS* is associated with a decrease in *INNOV_EXP* by

Table 4 The Baseline Results between Stock Liquidity and Firm Innovation

	INNOV_EXP		***INNOV_PAT***		**Economic Impact 1**	**Economic Impact 2**
	White	**Double**	**White**	**Double**		
CPQS	− 4.062***	− 4.062***	− 28.561***	− 28.561***	− 0.240	− 1.083
	(0.276)	(0.456)	(5.763)	(9.048)		
TSHARE	0.003***	0.003*	0.050***	0.050*	0.065	1.083
	(0.001)	(0.002)	(0.019)	(0.028)		
SHRHFD5	− 0.627***	− 0.627*	17.405***	17.405***	− 0.050	1.375
	(0.183)	(0.337)	(4.884)	(6.553)		
TO	− 6.193***	− 6.193***	− 22.846**	− 22.846	− 0.198	− 0.731
	(0.499)	(1.333)	(9.622)	(15.881)		
RET	0.832***	0.832***	6.769***	6.769**	0.161	1.313
	(0.107)	(0.250)	(2.484)	(3.279)		
FREE	0.007***	0.007**	0.035	0.035	0.101	0.505
	(0.001)	(0.003)	(0.032)	(0.044)		
VOL	− 0.054***	− 0.054*	0.036	0.036	− 0.044	0.030
	(0.023)	(0.028)	(0.468)	(0.455)		
EARN	0.032	0.032	− 0.395	− 0.395	0.003	− 0.034
	(0.269)	(0.316)	(4.025)	(2.579)		
INTAN	0.873***	0.873***	− 3.614*	− 3.614	0.102	− 0.423
	(0.113)	(0.234)	(2.152)	(3.553)		
LEV	1.195***	1.195***	3.483	3.483	0.159	0.463
	(0.110)	(0.195)	(2.471)	(3.916)		
ROE	0.551***	0.551*	− 1.643	− 1.643	0.063	− 0.187
	(0.207)	(0.281)	(3.560)	(3.144)		
Q	− 0.007	− 0.007	− 0.224	− 0.224	− 0.015	− 0.470
	(0.010)	(0.021)	(0.199)	(0.212)		
BTM	0.785***	0.785***	11.700***	11.700***	0.139	2.071
	(0.110)	(0.167)	(2.605)	(3.408)		
CAPITAL	1.224***	1.224***	16.248***	16.248*	0.060	0.796
	(0.271)	(0.423)	(6.184)	(8.387)		
SALES	0.002***	0.002***	0.002	0.002	0.076	0.076
	(0.000)	(0.000)	(0.007)	(0.006)		
ln*AGE*	− 0.075*	− 0.075	− 0.585	− 0.585	− 0.022	− 0.175
	(0.044)	(0.092)	(1.139)	(1.795)		
CONSTANT	16.792***	16.580***	− 2.791	-2.791		
	(0.228)	(0.448)	(4.37)	(5.366)		
Year dummies	Yes	Yes	Yes	Yes		
Industry dummies	Yes	Yes	Yes	Yes		
N	4664	4664	4719	4719		
Adj.R^2	0.355	0.355	0.028	0.028		

This table presents the pooled OLS estimation results for the linear relationship between stock liquidity and firm innovation. The independent variable is *CPQS* as a liquidity proxy, whereas the dependent variables are *INNOV_EXP* and *INNOV_PAT*, respectively. The natural logarithm of R&D expenditures (*INNOV_EXP*) is used to measure the innovation input, whereas the number of granted patents (*INNOV_PAT*) is the innovation output. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed, and only white and double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

4.062 points and *INNOV_PAT* by 28.561 points. These results suggest that stock liquidity is more sensitive to a firm's innovation outputs.

First, the positive linear relationship between stock liquidity and innovation input is comparable to that reported in previous studies. Zhong (2018) attributes improvements in innovation inputs to reduced financing constraints through increased equity liquidity in listed Chinese firms. Wen et al. (2018) find that this positive relationship exists solely in state-owned enterprises (SOEs) and is negative in private firms, primarily because of the higher likelihood of takeovers compared to SOEs in China. Our findings support their results, confirming the existence of a positive relationship between stock liquidity and firm innovation in high-technology SMEs following the split-share structural reform.[6]

Second, considering innovation output as the dependent variable, the positive relationship between stock liquidity and the number of granted patents suggests that increased stock liquidity is associated with higher innovation output for SMEs. Our results contradict those reported by Fang et al. (2014) and Wen et al. (2018). Fang et al. (2014) suggest that increased liquidity reduces future innovation output through two mechanisms: (1) greater vulnerability to hostile takeovers and (2) increasing participation of institutional investors who do not actively obtain information or monitor. Moreover, Wen et al. (2018) show that higher liquidity impedes the innovation output of Chinese listed private firms because of the risk of a hostile takeover. Our main findings are consistent with those of Vo (2014) and Tang et al. (2022). Thus, we posit that growth-oriented SMEs face a reduced risk of hostile takeovers due to their inherently unstable investment risk.

Following Boubaker et al. (2019), we report the economic impacts of all explanatory variables on *INNOV_EXP* and *INNOV_PAT* in the last two columns of Table 4 (Economic Impact 1 and Economic Impact 2), computed by multiplying one standard deviation of the variable by its corresponding coefficient estimate from the results of the double-clustered regression. In terms of economic magnitude, a one-standard-deviation increase in *CPQS* leads to a 0.240 decrease in *INNOV_EXP* and a 1.083 decrease in *INNOV_PAT*. Given that the coefficient impacts of *CPQS* of *INNOV_PAT* and *INNOV_EXP* differ by a factor of 4.513, it is evident that *CPQS* has a greater influence on *INNOV_PAT*.

Control variables

Only five control variables are significant across both the innovation input and innovation output models within the double-clustered standard errors in Table 4: *TSHARE*, *SHRHFD5*, *RET*, *BTM*, and *CAPITAL*. In terms of *INNOV_EXP*, the coefficients of *TSHARE*, *SHRHFD5*, *RET*, *BTM*, and *CAPITAL* are 0.003, -0.627, 0.832, 0.785, 1.224, whereas their coefficients of 0.050, 17.405, 6.769, 11.700, 16.248 in *INNOV_PAT*. This finding suggests that an increase in *TSHARE* (*RET*, *BTM*, and *CAPITAL*) is associated with an increase of 0.003 (0.832, 0.785, and 1.224) points in *INNOV_EXP* and an increase of 0.050 (6.769, 11.700, and 16.248) points in *INNOV_PAT*. Moreover, the regression results of *SHRHFD5* suggest that an increase in *SHRHFD5* is associated with a decrease in *INNOV_EXP* by 0.627 points and an increase in *INNOV_PAT* by 17.405 points.

[6] China's government proposed the split-share structure reform to change non-tradable shares into tradable shares. The reform was nearly complete at the end of 2006. Our samples from 2010-2020 are all tradable shares and are not shocked by this reform.

First, *TSHARE* is positively and significantly related to firm innovation, supporting the following empirical evidence: China's GEM has a significant share of institutional investors,[7] particularly institutional blockholders in the Chinese market, who hold substantial tradeable shares. We posit that their active monitoring and discipline positively influence firm performance, and consequently, firm innovation (Choi et al. 2011; Aghion et al. 2013). Second, *SHRHFD5* exhibits a negative and significant relationship with innovation input but a positive association with innovation output. However, the coefficient representing the impact of *SHRHFD5* on innovation input is relatively small, indicating a weak influence. Typically, a firm's top five stockholders have substantial internal ownership, often comprising individuals closely related to the firm's management such as its founders, family members, affiliates, managers, and executive directors (Xu and Wang 1999; Chang et al. 2006). Our result is consistent with Fang et al. (2014), who report that internal owners prefer short-term investments to stabilize stock prices and potentially forgo long-term innovative investments to mitigate threats to their positions in the case of a firm acquisition. However, maintaining a firm's image and preventing abnormal share price fluctuations from damaging its profits may ensure that its existing innovative investments achieve good results. Third, *RET* has the expected positive coefficient, which is consistent with Hirshleifer et al. (2013). Fourth, the positive coefficient of *BTM* indicates that higher *RET* leads to improved firm innovation, supporting Hall's (1999) findings that apply to manufacturing firms. This suggests that the larger market value of growth-oriented SMEs can augment their innovation activities. Fifth, *CAPITAL* demonstrates a positive relationship with firm innovation, consistent with the findings of Piergiovanni and Santarelli (2013) who suggest that capital expenditure involving equipment inputs can enhance the efficiency of innovation efforts.

Turning to the economic impacts of the control variables in Table 4, the largest effect comes from *BTM*. More precisely, a one standard deviation increase in *BTM* was related to a increase of 0.139 and 2.071 in *INNOV_EXP* and *INNOV_PAT*. Closely followed by *RET*, a one-standard-deviation increase resulted in an increase of 0.161 in *INNOV_EXP* and 1.313 in *INNOV_PAT*.

Further analysis

Blockholders ownership and firm innovation

Fang et al. (2014) and Wen et al. (2018) point out that the regulatory role of blockholders has a disincentive effect on firm innovation. To identify whether this inhibiting effect exists in SMEs, we conduct the following analysis.

In China, since the 2005 equity share reform, all shares listed on the GEM have been tradable. However, some blockholders' shareholdings are required to be tradable under certain conditions. For example, the regulations require the shares held by the beneficial owner to be listed for three years before they can be transferred. All shares held by institutional holders are freely tradable. According to Xu and Wang (1999) and Chang et al. (2006), the top five stockholders of a firm are often those with a large percentage of internal ownership. These individuals are often closely associated with the

[7] The average proportion of institutional shareholdings of China's GEM is 26.877%, 27.926%, 26.954%, 33.756%, 31.994%, 31.814%, 30.451%, 28.097%, 30.743%, 30.935%, and 29.905% from 2010 to 2020, respectively, according to data from the WIND database.

firm's management, including its founders and their families, affiliates, managers, and executive directors. Therefore, *TSHARE* includes external blockholders represented by institutional blockholders, whereas *SHRHFD5* includes internal blockholders. Higher

Table 5 Blockholders Ownership and Firm Innovation

	INNOV_EXP			*INNOV_PAT*		
	(1)	(2)	(3)	(4)	(5)	(6)
CPQS	− 3.920***	− 4.037***	− 4.048***	− 27.501***	− 28.135***	− 27.764***
	(0.431)	(0.456)	(0.456)	(8.614)	(8.844)	(8.678)
INSTITUTION	0.005***			0.020		
	(0.001)			(0.023)		
SHRHFD5		− 0.526			19.001***	
		(0.334)			(6.619)	
TO	− 5.820***	− 6.457***	− 6.435***	− 24.580	− 27.133*	− 27.632*
	(1.364)	(1.309)	(1.304)	(15.706)	(15.901)	(15.979)
RET	0.758***	0.869***	0.869***	7.093**	7.357**	7.356**
	(0.265)	(0.252)	(0.253)	(3.525)	(3.397)	(3.335)
FREE	0.012***	0.010***	0.012***	0.024	0.082*	0.023
	(0.002)	(0.002)	(0.002)	(0.041)	(0.044)	(0.040)
VOL	− 0.046*	– 0.054*	− 0.051*	− 0.141	0.040	− 0.055
	(0.028)	(0.029)	(0.029)	(0.438)	(0.449)	(0.443)
EARN	0.009	0.014	0.004	− 0.355	− 0.669	− 0.285
	(0.315)	(0.318)	(0.320)	(2.701)	(2.678)	(2.733)
INTAN	0.856***	0.857***	0.901***	− 5.631	− 3.870	− 5.485
	(0.229)	(0.241)	(0.239)	(3.622)	(3.556)	(3.599)
LEV	1.183***	1.217***	1.204***	4.234	3.823	4.258
	(0.196)	(0.202)	(0.203)	(3.924)	(3.940)	(3.930)
ROE	0.524*	0.548*	0.537*	− 1.335	− 1.653	− 1.252
	(0.281)	(0.278)	(0.277)	(3.139)	(3.162)	(3.127)
Q	− 0.009	− 0.008	− 0.008	− 0.236	− 0.245	− 0.235
	(0.020)	(0.021)	(0.021)	(0.214)	(0.218)	(0.216)
BTM	0.843***	0.796***	0.803***	11.745***	11.907***	11.603***
	(0.153)	(0.170)	(0.169)	(3.311)	(3.400)	(3.347)
CAPITAL	1.131***	1.166***	1.142***	15.947*	15.292*	16.181*
	(0.432)	(0.417)	(0.417)	(8.403)	(8.387)	(8.459)
SALES	0.001***	0.001***	0.002***	− 0.002	0.001	− 0.001
	(0.000)	(0.001)	(0.000)	(0.007)	(0.007)	(0.007)
ln*AGE*	− 0.065	− 0.070	− 0.074	− 0.271	− 0.501	− 0.380
	(0.091)	(0.092)	(0.091)	(1.824)	(1.789)	(1.822)
CONSTANT	16.399***	16.831***	16.698***	0.933	− 1.838	2.744
	(0.438)	(0.447)	(0.438)	(5.271)	(5.386)	(5.141)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	4640	4664	4664	4695	4719	4719
Adj.R^2	0.360	0.352	0.351	0.023	0.026	0.023

This table presents the pooled OLS estimation results for the linear relationship between stock liquidity and firm innovation. We substitute *TSHARE* with institutional shareholdings (*INSTITUTION*) in the baseline models. The independent variable is *CPQS* as a liquidity proxy, whereas the dependent variables are *INNOV_EXP* and *INNOV_PAT*. The natural logarithm of R&D expenditures (*INNOV_EXP*) is used to measure the innovation input, whereas the number of granted patents (*INNOV_PAT*) is the innovation output. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed, and only white and double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively liquidity can allow blockholders to hold more shares at a lower cost, attracting larger shareholders to the market (Maug 1998; Edmans 2009). Hence, to analyze the effects of institutional and internal blockholders, we replace *TSHARE* with the shareholdings of institutions (*INSTITUTION*) and then exclude *INSTITUTION* and *SHRHFD5* in our baseline models to regress the models again; the results are shown in Table 5.

The results without *SHRHFD5* are shown in columns 1 and 4; the results without *INSTITUTION* are shown in columns 2 and 5; and columns 3 and 6 present the results without both *SHRHFD5* and *INSTITUTION*. Compared to the results in Table 4, the coefficient between *CPQS* and *INNOV_EXP or INNOV_PAT* increases. *CPQS* is an inverse proxy for liquidity, which means that the impact of liquidity on firm innovation diminishes when controlling for *INSTITUTION* or *SHRHFD5* in our baseline models. This indicates that blockholders can weaken firm innovation, and that the weakening effect of internal blockholders (*SHRHFD5*) is stronger.

We can explain the results as follows. Under higher liquidity, blockholders can continue to hold more shares at a lower cost, facilitating the entry of more blockholders (Maug 1998; Edmans 2009). External blockholders, represented by institutional investors, tend to invest in projects with higher expected short-term returns rather than choosing innovative projects in the long term (Bushee 2001). Internal blockholders are also often related to a firm's management, including founders and their families, affiliates, managers, and executive directors (Xu and Wang 1999; Chang et al. 2006). Therefore, managers prefer short-term investments that can stabilize stock prices, and forgo long-term innovative investments to prevent challenges to their positions (Fang et al. 2014). Hence, blockholders have a negative effect on firm innovation as stock liquidity increases. However, this inhibition is not obvious in SMEs.

Long-term effect

We specify the innovation input and output in one-to eight-year lags and one five-year lag for the baseline models, respectively, and re-estimate the models with a double-clustered estimation. The results in Appendices B (a) and (b) show that the coefficient of *CPQS* is negative and significant for both seven-lag-year innovation input and four-lag-year innovation output. Specifically, the positive linear relationships between stock liquidity and innovation input or between stock liquidity and innovation output are highly significant at the 1% level in a one-to three-lag year, implying that higher stock liquidity promotes long-term firm innovation, especially in the first three years.

Robustness checks

This section presents the results of a series of robustness checks to ensure that the baseline models are reliable.

Alternative innovation measures

We replace *INNOV_EXP* in the baseline model (1) using the ratio of R&D expenditures to total revenue (*EXP_REVENUE*) and the ratio of R&D expenditures to total assets (*EXP_REVENUE*) to measure the input of firm innovation (Zhong 2018; Liu et al. 2021). The number of applied patents is used to replace *INNOV_PAT* as the output of firm innovation in the baseline model (2) (Zheng and Zhang 2021). Following Wen et al. (2018), we also adopt innovation efficiency (*Efficiency*) as an alternative innovation proxy by deflating the number of granted patents with the natural logarithm of R&D expenditures. Table 6 shows that the linear relationship between *CPQS* and these four

Table 6 Robustness checks with alternative innovation measures

	EXP_REVENUE	*EXP_ASSET*	*APPLIED_PAT*	*Efficiency*
CPQS	− 15.590***	− 0.041***	− 53.999***	− 1.323***
	(2.974)	(0.010)	(13.190	(0.447)
TSHARE	0.004	0.000*	0.061*	0.003*
	(0.007)	(0.000)	(0.033)	(0.001)
SHRHFD5	− 4.123**	− 0.019***	10.595	0.874***
	(1.877)	(0.007)	(8.180)	(0.319)
TO	− 13.394***	− 0.029*	− 30.303	− 1.142
	(4.082)	(0.017)	(24.380)	(0.803)
RET	− 1.927*	− 0.011***	4.847	0.323*
	(1.071)	(0.004)	(6.040)	(0.165)
FREE	0.030**	0.000	0.120	0.002
	(0.014)	(0.000)	(0.073)	(0.002)
VOL	0.176	0.001	− 0.142	0.003
	(0.166)	(0.001)	(0.865)	(0.023)
EARN	2.155	0.012***	− 11.635*	− 0.015
	(1.411)	(0.005)	(6.283)	(0.126)
INTAN	5.627***	− 0.002	− 5.954	− 0.170
	(1.960)	(0.006)	(4.758)	(0.186)
LEV	− 7.771***	− 0.018**	6.355	0.138
	(0.988)	(0.004)	(4.498)	(0.200)
ROE	− 13.982***	− 0.018***	5.612	− 0.112
	(2.583)	(0.004)	(4.588)	(0.163)
Q	0.472***	0.002***	− 0.086	− 0.011
	(0.084)	(0.000)	(0.399)	(0.011)
BTM	− 2.687***	− 0.021***	9.618***	0.573***
	(0.852)	(0.003)	(3.058)	(0.170)
CAPITAL	7.428***	0.031***	29.187**	0.831***
	(2.317)	(0.009)	(14.760)	(0.410)
SALES	− 0.014***	0.000	0.007	0.000
	(0.003)	(0.000)	(0.008)	(0.000)
ln*AGE*	− 0.704	0.002	− 4.585*	− 0.031
	(0.546)	(0.002)	(2.762)	(0.091)
CONSTANT	7.331***	0.014*	9.832	− 0.168
	(1.994)	(0.007)	(7.592)	(0.284)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	4664	4662	4727	4664
Adj.R^2	0.296	0.297	0.045	0.028

This table presents the pooled OLS estimation results for linear relationships between the alternative firm innovation proxies and stock liquidity. The ratio of R&D expenditures and revenue (*EXP_REVENUE*) and the ratio of R&D expenditures and total assets (*EXP_ASSET*) are the proxies of innovation input, respectively, whereas the number of applied patents (*APPLIED_PAT*) is the innovation output. Innovation efficiency (*Efficiency*) is calculated by using the number of patents divided by the natural logarithm of R&D expenditures. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively alternative innovation measures are significantly positive at the 1% level, which reinforces our main findings.

Alternative liquidity measures

The *CPQS* can capture the costs incurred by investors for immediate transactions. According to Fong et al. (2017), the Closing Percent Quoted Spread Impact (*CPQSIM*) and Amihud's (2002) illiquidity ratio (*ILLIQ*) have good performances in measuring liquidity in the Chinese market. *CPQSIM* is calculated as the ratio of *CPQS* scaled by trading volume, whereas *ILLIQ* is computed as the ratio of absolute stock returns scaled by trading volume. Both price impact measures are inverse liquidity indicators, with higher values indicating greater illiquidity. We reestimate the baseline models (1) and (2) and provide the regression results for both *CPQSIM* and *ILLIQ* in Table 7. The linear relationships among *CPQSIM*, *ILLIQ*, and *INNOV_EXP* are highly significant at the 1% level, whereas both the price impact measures and *INNOV_PAT* are significant at the 5% level.

Alternative estimation methods

Our baseline models are estimated using pooled OLS with standard errors adjusted for within-cluster correlations. To ensure the robustness of our findings, we re-estimate baseline model (1) using the Fama–MacBeth two-step regression and quantile regression, and baseline model (2) was re-estimated with the Fama-MachBeth two-step regression and Tobit regression. The Fama–MacBeth two-step regression averages the coefficients from yearly cross-sectional regressions across time (Fama and MachBeth 1973), whereas the quantile regression determines whether there is a linear relationship between stock liquidity and firm innovation over the entire range of the firm's innovation conditional distribution, especially at the extreme upper and lower tails (Koenker and Bassett 1978; Koenker and Hallock 2001). We exclude year dummies in the two-step Fama–MacBeth regression because of its cross-sectional nature.

A Tobit regression is used to estimate the linear relationship between variables when there is a left or right subsumption in the dependent variable. Most patents as innovation output fall into the value of 0; thus, a Tobit regression is more appropriate than a quantile regression for our baseline model (2) (Zheng and Zhang 2021). However, the Tobit model can only fix the concentrated distribution of zero patents, and except for the 0 value, the other patent values belong to count samples (Wen et al. 2018; Tang et al. 2022). Therefore, we also conducted a Poisson regression and negative binomial regression (*NBR*) with robust standard error adjustments to regress the models with patents as the dependent variable. Because the Poisson regression requires that the expected and variance of the explanatory variables be equal, the results of *NBR* are more persuasive in Table 9. Tables 8 and 9 show that both R&D expenditure as the innovation input and the number of patents as the innovation output are highly positively significant with stock liquidity across different estimation methods, which is consistent with our main findings drawn from the pooled OLS estimator.

Table 7 Robustness Checks with Alternative Liquidity Measures

	INNOV_EXP		*INNOV_PAT*	
CPQSIM	− 3.164***		− 17.486**	
	(0.724)		(7.465)	
ILLIQ		− 4.222***		− 20.996**
		(1.235)		(8.829)
TSHARE	0.002	0.002	0.045*	0.044
	(0.002)	(0.002)	(0.027)	(0.027)
SHRHFD5	− 0.557*	− 0.593*	17.737***	17.503***
	(0.321)	(0.323)	(6.519)	(6.462)
TO	− 5.955***	− 5.140***	− 19.941	-15.409
	(1.297)	(1.278)	(15.412)	(15.170)
RET	0.734***	0.805***	5.884*	6.170*
	(0.250)	(0.225)	(3.344)	(3.494)
FREE	0.005*	0.003	0.019	0.009
	(0.003)	(0.003)	(0.043)	(0.043)
VOL	− 0.098**	− 0.061	− 0.165	0.049
	(0.039)	(0.038)	(0.482)	(0.559)
EARN	0.263	0.158	1.665	1.147
	(0.344)	(0.371)	(2.862)	(2.882)
INTAN	0.816***	0.867***	− 3.754	− 3.420
	(0.219)	(0.221)	(3.554)	(3.684)
LEV	1.048***	0.989***	2.444	2.187
	(0.186)	(0.179)	(3.834)	(3.806)
ROE	0.680**	0.642**	− 0.668	-0.823
	(0.277)	(0.305)	(3.089)	(3.050)
Q	− 0.003	-0.006	− 0.198	− 0.205
	(0.020)	(0.018)	(0.211)	(0.210)
BTM	0.670***	0.660***	10.614***	10.434***
	(0.147)	(0.165)	(3.235)	(3.242)
CAPITAL	1.481***	1.541***	18.324**	18.665**
	(0.428)	(0.440)	(8.045)	(7.921)
SALES	0.002***	0.002***	0.004	0.003
	(0.000)	(0.000)	(0.006)	(0.007)
ln*AGE*	− 0.103	− 0.100	− 0.768	-0.747
	(0.090)	(0.088)	(1.781)	(1.780)
CONSTANT	16.977***	16.960***	− 3.447	− 3.422
	(0.488)	(0.515)	(5.514)	(5.436)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	4664	4664	4719	4719
Adj.R^2	0.361	0.373	0.027	0.027

This table presents the pooled OLS estimation results for linear relationships between the firm innovation and *CPQS* Impact (*CPQSIM*) and Amihud's (2002) illiquidity ratio (*ILLIQ*). The dependent variable is *INNOV_EXP* and *INNOV_PAT* respectively. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 8 R&D Expenditure as Innovation Proxy with Alternative Estimation Methods

	INNOV_EXP					
	Fama–Macbeth	**Quantile Regression**				
		10th	**25th**	**50th**	**75th**	**90th**
CPQS	− 6.972***	− 3.1166***	− 3.3109***	− 3.991***	− 4.571***	− 4.551***
	(2.086)	(0.4446)	(0.3906)	(0.411)	(0.328)	(0.316)
TSHARE	− 0.002	0.0023**	0.0042***	0.004***	0.004***	0.004***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
SHRHFD5	− 1.218*	− 0.829***	− 0.334	− 0.411	− 0.600***	− 0.600*
	(0.655)	(0.256)	(0.251)	(0.250)	(0.206)	(0.350)
TO	− 8.254***	− 5.769***	− 6.120***	− 5.752***	− 6.811***	− 6.328***
	(2.091)	(0.979)	(0.713)	(0.564)	(0.688)	(0.701)
RET	0.191	0.928***	0.910***	0.797***	0.768***	0.683***
	(0.452)	(0.177)	(0.112)	(0.097)	(0.117)	(0.113)
FREE	0.004	0.002	0.004**	0.008***	0.011***	0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
VOL	− 0.042	0.004	0.017	− 0.048	− 0.062	− 0.109**
	(0.072)	(0.026)	(0.029)	(0.033)	(0.039)	(0.047)
EARN	0.413	0.546	0.196	− 0.542	− 0.312	0.360
	(2.688)	(0.356)	(0.286)	(0.368)	(0.272)	(0.321)
INTAN	1.029**	0.472***	0.987***	0.902***	1.135***	0.682***
	(0.355)	(0.151)	(0.145)	(0.134)	(0.176)	(0.197)
LEV	1.172***	0.846***	1.266***	1.275***	1.155***	1.524***
	(0.272)	(0.229)	(0.163)	(0.111)	(0.170)	(0.152)
ROE	− 0.135	1.148***	0.953***	1.008***	0.506***	0.078
	(0.609)	(0.369)	(0.294)	(0.246)	(0.167)	(0.280)
Q	0.060	− 0.045**	− 0.025	− 0.003	0.008	0.008
	(0.036)	(0.018)	(0.018)	(0.012)	(0.016)	(0.014)
BTM	0.281	0.944***	0.945***	0.869***	0.546**	0.672***
	(0.948)	(0.155)	(0.157)	(0.133)	(0.215)	(0.160)
CAPITAL	0.640	0.825**	1.129***	1.053***	1.741***	1.666***
	(0.627)	(0.321)	(0.260)	(0.328)	(0.312)	(0.464)
SALES	0.003**	0.002***	0.001***	0.001**	0.002**	0.002**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
ln*AGE*	− 0.032	− 0.033	− 0.112*	− 0.128**	− 0.046	− 0.063
	(0.032)	(0.074)	(0.066)	(0.060)	(0.069)	(0.068)
CONSTANT	17.409***	15.588***	16.235***	17.360***	17.950***	18.910***
	(0.812)	(0.309)	(0.361)	(0.200)	(0.427)	(0.383)
Year dummies	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	4664	4664	4664	4664	4664	4664
R^2/Pseudo R^2	0.371	0.203	0.202	0.211	0.222	0.244

This table presents the results of Fama–MacBeth and Quantile regressions of the baseline model (1), where R&D expenditures are the dependent variable. The definition of all variables is presented in Appendix A. Coefficients for the year and industry dummies are not reported for brevity. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 9 Patents as Innovation Proxy with Alternative Estimation Methods

	INNOV_PAT			
	Fama–Macbeth	**Tobit**	**Poisson**	***NBR***
CPQS	− 29.826***	− 80.986**	− 4.720***	− 5.682***
	(4.990)	(38.300)	(1.070)	(0.997)
TSHARE	0.043	0.211**	0.006***	0.004
	(0.034)	(0.101)	(0.002)	(0.003)
SHRHFD5	21.048***	82.374***	2.365***	3.189***
	(5.047)	(28.111)	(0.642)	(0.709)
TO	− 53.083**	− 113.338	− 5.174**	− 5.785***
	(18.774)	(69.183)	(2.231)	(1.905)
RET	10.125*	22.891**	1.057***	1.513***
	(4.604)	(10.308)	(0.387)	(0.402)
FREE	0.069*	0.135	0.007	0.010**
	(0.034)	(0.190)	(0.005)	(0.005)
VOL	1.128*	1.522	0.024	0.023
	(0.556)	(2.539)	(0.082)	(0.091)
EARN	31.919	37.788	− 0.066	0.254
	(29.826)	(28.340)	(0.928)	(1.030)
INTAN	− 6.052	− 18.050	− 0.533	0.588
	(3.490)	(17.763)	(0.404)	(0.500)
LEV	− 0.973	− 2.240	0.225	0.244
	(2.491)	(17.189)	(0.373)	(0.412)
ROE	− 11.448	− 25.277	− 0.211	− 0.523
	(14.551)	(23.090)	(0.721)	(0.641)
Q	− 1.006**	− 0.430	− 0.059	− 0.060*
	(0.404)	(1.175)	(0.037)	(0.035)
BTM	7.947*	48.242***	1.526***	2.329***
	(4.344)	(15.080)	(0.335)	(0.449)
CAPITAL	23.366***	84.600**	2.318***	3.088***
	(4.687)	(35.920)	(0.807)	(0.999)
SALES	− 0.009	− 0.001	− 0.000	− 0.001
	(0.008)	(0.034)	(0.001)	(0.002)
ln*AGE*	− 1.336	1.863	− 0.064	− 0.109
	(1.016)	(8.078)	(0.172)	(0.164)
CONSTANT	0.443	− 111.958***	0.700	0.839
	(5.041)	(36.974)	(0.770)	(0.830)
Year dummies	No	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	4719	4719	4727	4727
R^2/Pseudo R^2	0.124	0.020	0.086	0.013
/lnalpha				2.935
alpha				18.818

This table presents the results of Fama–MacBeth and Tobit regressions or the baseline model (2), where the number of patents is the dependent variable. The definition of all variables is presented in Appendix A. Coefficients for the year and industry dummies are not reported for brevity. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

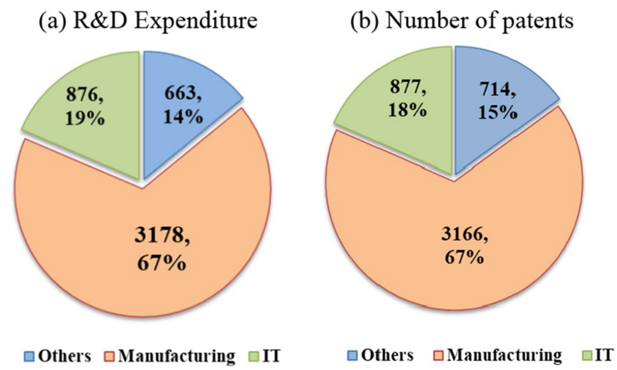

Fig. 2 Percentage of firms by industry in the total sample. *Notes*: The figures present the number of the firms from each of the Manufacturing industry, IT industry, and other 13 industries as a percentage of our total sample, respectively.[8] R&D expenditures are the input of innovation as the dependent variable in Fig. 2(a), whereas the number of patents is the output of the innovation as the dependent variable in Fig. 2(b)

Industry-specific regressions

Based on the classifications of the National Bureau of Statistics of China, we classify the listed growth-oriented SMEs into 16 industries: (1) agriculture; (2) construction; (3) culture, sports, and entertainment; (4) education; (5) environmental sports; (4) education; (5) environment protection; (6) finance; (7) IT; (8) leasing and business service; (9) manufacturing; (10) mining; (11) public health; (12) research & development; (13) residence service; (14) transportation; (15) utilities; and (16) wholesales & retail. Among them, only the manufacturing and IT industries have a sample of firms larger than 200, accounting for approximately 67% and 19% of the total sample size, respectively, as shown in Figs. 2(a) and (b). The remaining 14 industries, excluding the manufacturing and IT sectors, account for only 15% of the total sample.

We reestimate the baseline models, including those for the financial industry, to check whether the existence of a mutually offsetting relationship between different industries has a net effect. 14 other industries are combined into one category, namely "others," together with manufacturing and IT as the other two categories for regression estimation. The regression results in Table 10 show that the positive relationship between stock liquidity and R&D expenditure remains intact across industries. However, a highly significant relationship between stock liquidity and the number of patents as the output of firm innovation appears only in the manufacturing industry.

Endogeneity

In examining the endogeneity of stock liquidity and innovation in listed Chinese firms, Wen et al. (2018) and Tang et al. (2022) explore the impact of exogenous shocks on the Splitting Share Reform on this positive relationship. However, Chinese SMEs listed on the GEM board are not affected by this policy shock because it ended in

[8] Our samples are divided into 16 industries according to the industry classification of China Securities Regulatory Commission. Excluding the finance industry, we have 15 industries: (1) agriculture; (2) construction; (3) culture, sports and entertainment; (4) education; (5) environmental protection; (6) IT; (7) leasing and business service; (8) manufacturing; (9) mining; (10) public health; (11) research & development; (12) resident service; (13) transportation; (14) utilities; and (15) wholesale & retail.

Table 10 Innovation-liquidity relationships by industry

Industry	*INNOV_EXP*		*INNOV_PAT*	
	CPQS	Adjusted R^2	*CPQS*	Adjusted R^2
Manufacturing	− 4.636*** (0.537)	**0.333**	− 40.688*** (12.967)	**0.024**
IT	− 4.141*** (0.819)	**0.367**	− 15.735 (14.321)	**0.002**
Others	− 2.463* (1.362)	**0.211**	9.581 (12.109)	**0.064**

This table shows the pooled OLS estimation results where the dependent variables are R&D expenditures and the number of patents, respectively. The sample period is from 2010 to 2020, focusing on industries with a minimum of 200 firm-year observations. Estimates for control variables, constants, and year dummies have been suppressed for brevity, but are available upon request. Double-clustered standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

2006. Thus, the endogeneity in this study is mainly due to unobserved heteroscedasticity-omitted variables and reverse-causality problems. The extant literature on liquidity fails to locate a precise instrumental variable, and policy shocks are not the focus of this study.

For these reasons, as shown in Table 11 and 12, five robustness checks are conducted to address endogeneity; however, we are aware that this issue is not completely avoidable. First, we lagged all independent variables by one year to exclude the impact of the current period and re-estimated the baseline models using pooled OLS (Ali et al. 2016). The results in Columns 1 of both Table 11 and 12 strengthen our main finding that stock liquidity is highly positively correlated with firm innovation. Second, we conduct a one-year change regression for the dependent and independent variables to remove long-term effects (Chung et al. 2010). The results presented in Column 2(a) show that the relationship between *CPQS* and *INNOV_EXP* is significantly negative at the 1% level. The coefficients of *CPQS* and *INNOV_PAT* are statistically significant at the 10% level, and the explanatory power weakens. Third, Gormley and Matsa (2014) show that a fixed-effects estimator can address time-invariant unobserved heterogeneity. The presence of an unobservable factor correlating with both stock market liquidity and firm innovation may lead to biased coefficient estimates. For example, high-quality managers tend to manage highly liquid firms, which results in improved firm innovation. The significant positive relationship between stock liquidity and firm innovation remains intact, as shown in columns 3 (1) and (2), ruling out the possibility that unobserved firm factors simultaneously determine stock liquidity and firm innovation at the same time. Fourth, the system generalized method of moments (GMM) estimator is used to address the problems of reverse causation due to the difficulties in locating a strictly exogenous external instrument and correcting for unobserved heteroskedasticity problems, omitted variable bias, and measurement error (Wintoki et al. 2012). To capture the dynamic relationship between stock liquidity and firm innovation, we modify the baseline models by including the lagged dependent variable of *Innovation* as a regressor. The estimation results in columns 4 (a) and (b) provide further evidence of a significant and positive relationship between stock liquidity and firm innovation.

Fifth, two-stage least squares are used to control for endogeneity, which deals with unobservable factors that do not have to be constant over time. According to Fang et al.

Table 11 Endogeneity Checks on Innovation Input (R&D Expenditures)

	INNOV_EXP			
	Lag in Variables (1)	**Changes in Variables (2)**	**Firm Fixed Effects (3)**	**System GMM (4)**
CPQS	− 4.042***	− 0.981***	− 2.694***	− 2.633***
	(0.513)	(0.180)	(0.288)	(0.758)
TSHARE	0.005***	0.001*	− 0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
SHRHFD5	-0.719**	-0.910**	− 1.149**	− 0.147
	(0.326)	(0.435)	(0.461)	(0.645)
TO	− 5.252***	− 2.202***	− 5.674***	-3.325
	(1.080)	(0.420)	(0.483)	(2.578)
RET	0.738**	0.030	0.274***	0.118
	(0.296)	(0.030)	(0.079)	(0.171)
FREE	0.004**	− 0.002**	− 0.000	− 0.004
	(0.002)	(0.001)	(0.001)	(0.003)
VOL	− 0.055*	0.007	0.022	-0.052
	(0.033)	(0.015)	(0.015)	(0.074)
EARN	− 0.366	− 0.334***	− 0.377**	− 1.267**
	(0.319)	(0.052)	(0.181)	(0.559)
INTAN	0.829***	0.359**	0.459***	0.772**
	(0.243)	(0.149)	(0.160)	(0.310)
LEV	1.127***	0.381***	0.769***	0.321
	(0.210)	(0.127)	(0.159)	(0.953)
ROE	1.297***	0.243**	0.428***	0.184
	(0.298)	(0.097)	(0.163)	(0.412)
Q	− 0.011	− 0.004	− 0.017*	0.023
	(0.025)	(0.006)	(0.009)	(0.049)
BTM	0.817***	− 0.005	0.346***	− 0.183
	(0.180)	(0.079)	(0.121)	(0.406)
CAPITAL	1.251***	0.636***	0.839***	− 1.942
	(0.429)	(0.127)	(0.225)	(1.424)
SALES	0.001**	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
ln*AGE*	− 0.078	0.285	− 0.061	− 0.059
	(0.094)	(0.218)	(0.292)	(0.217)
$INNOV\_EXP_{t-1}$				0.627***
				(0.120)
CONSTANT	16.807***	0.196***	18.574***	2.548
	(0.430)	(0.048)	(0.846)	(10.116)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	No	Yes
N	3901	3875	4664	3888
Adj.R^2	0.360	0.130	0.626	
Hansen test (*p*-value)				21.300 (0.128)
AR (1) (*p*-value)				− 5.470 (0.000)
AR (2) (*p*-value)				− 1.400 (0.162)

Columns (1) and (2) estimate the baseline model for R&D expenditures as the innovation proxy but specify the independent variables in one-year lagged (*t*-1) and annual changes (△). Columns (3) and (4) re-estimate the model with the firm fixed effects estimator and system GMM, respectively. The diagnostic tests for system GMM are presented: the Hansen test

Table 11 (continued)

of over-identification with the null that all instruments are valid. AR (1) and AR (2) tests are under the null of no first-order and second-order serial correlation, respectively, in the first-differenced residuals. The definition of all variables is presented in Appendix A. Coefficients for the year and industry dummies are not reported for brevity and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

(2009), one lag of *CPQS* ($CPQS_{t-1}$) and the mean *CPQS* of the two firms in firm *i*'s industry, which has the closest size (market value of equity) to firm *i* (*MCPQS*), are exogenous variables because $CPQS_{t-1}$ and *MCPQS* are correlated with liquidity but uncorrelated with the error term. The lag in *CPQS* can mitigate concerns that an unobservable in fiscal year *t* is correlated with both stock liquidity and firm innovation at time *t*. Compared to its liquidity, *MCPQS* is less likely to be connected with an unobservable that influences firm *i*'s innovation. The outcomes in Table 13 for 2SLS are consistent with our baseline results.

Potential mechanisms

This section analyzes the potential mechanisms that may account for the positive relationship between stock liquidity and firm innovation in Chinese SMEs.

Stock liquidity, firm size, and financing

SMEs tend to finance R&D using cash flows and external equity (Brown et al. 2009). SMEs face greater issues when raising capital than large firms, and Butler et al. (2005) indicate that increased stock liquidity can reduce flotation costs and investment bank fees, thereby increasing the possibility of raising more external capital. Mancusi and Vezzulli (2020) show that financial constraints have a markedly unfavorable impact on R&D operations. We infer that SMEs may face more serious financing difficulties than large firms. We further explore whether financing constraints can be relieved by improving the stock liquidity of SMEs, which in turn can enhance innovation inputs, and whether this facilitation mechanism is more evident in SMEs than in large firms. First, we collected data on 3,010 large firms from 2010 to 2020[9] from the CSMAR database as the control group. Following Cotter (1996), net cash flows from financing activities (*CFF*) are used to measure the ability of external financing, which represents net cash receipts and disbursements resulting from a reduction or increase in issuing bonds and shares and repaying debts or dividends and cash. The following model is used to investigate the effects of financing:

$$\begin{aligned}CFF_{i,t} =&\alpha_0 + \alpha_1 CPQS_{it} + \alpha_2 TSHARE_{it}\\ &+ \alpha_3 SHRHFD5_{it} + \alpha_4 TO_{it} + \alpha_5 RET_{it}\\ &+ \alpha_6 FREE_{it} + \alpha_7 VOL_{it} + \alpha_8 EARN_{it}\\ &+ \alpha_9 INTAN_{it} + \alpha_{10} LEV_{it} + \alpha_{11} ROE_{it} + \alpha_{12} Q_{it}\\ &+ \alpha_{13} BTM_{it} + \alpha_{14} CAPITAL_{it} + \alpha_{15} SALES_{it}\\ &+ \alpha_{16} lnAGE_{it} + \sum_{j=1}^{J-1} \alpha_{17j} IND_j + \sum_{t=1}^{T-1} \alpha_{18t} YR_t + \varepsilon_{it}\end{aligned} \tag{3}$$

[9] The "Statistical Classification of Large, Small, Medium and Micro Enterprises (2017)" National Statistics [2017] No. 213, which consider the aspects of business income, employees, and total assets.

Table 12 Endogeneity Checks on Innovation Output (Patents)

	INNOV_PAT			
	Lag in Variables (1)	**Changes in Variables (2)**	**Firm Fixed Effects (3)**	**System GMM (4)**
CPQS	− 30.414***	− 19.925**	− 26.040***	− 38.651***
	(10.009)	(8.742)	(9.088)	(13.525)
TSHARE	0.063**	0.040***	0.013	0.059*
	(0.027)	(0.013)	(0.022)	(0.032)
SHRHFD5	18.437***	− 1.362	5.510	4.149
	(6.943)	(14.453)	(13.219)	(17.094)
TO	− 16.691	− 11.332	− 23.995	− 25.560
	(14.214)	(15.335)	(18.736)	(36.296)
RET	5.170	− 1.522	2.450	0.091
	(3.791)	(1.975)	(2.196)	(2.726)
FREE	0.037	− 0.022	− 0.003	0.034
	(0.053)	(0.029)	(0.051)	(0.079)
VOL	0.018	− 0.292	− 0.435	− 0.416
	(0.484)	(0.428)	(0.577)	(0.871)
EARN	− 2.741	− 0.157	3.259	0.363
	(3.876)	(2.767)	(4.262)	(7.970)
INTAN	-2.230	4.331*	-2.099	1.119
	(3.505)	(2.338)	(4.066)	(5.435)
LEV	1.783	1.836	4.351	4.307
	(4.342)	(3.752)	(4.692)	(5.950)
ROE	0.444	− 4.550**	− 3.391	− 7.241*
	(5.615)	(2.081)	(3.425)	(4.299)
Q	− 0.247	0.337	0.301	0.387
	(0.251)	(0.270)	(0.283)	(0.339)
BTM	10.300***	4.217*	10.313**	8.228
	(3.520)	(2.342)	(4.049)	(5.412)
CAPITAL	18.820**	3.302	9.691	8.046
	(8.739)	(5.601)	(6.990)	(11.466)
SALES	0.001	− 0.001	− 0.004	− 0.000
	(0.008)	(0.003)	(0.007)	(0.010)
ln*AGE*	− 0.903	− 4.628	− 15.596*	1.706
	(1.913)	(5.302)	(8.017)	(3.252)
$INNOV\_PAT_{t-1}$				0.194***
				(0.066)
CONSTANT	− 2.199	− 0.477	52.373**	− 31.568
	(5.741)	(5.263)	(24.683)	(30.756)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	No	Yes
N	3948	3927	4719	3941
Adj.R^2	0.030	0.002	0.022	
Hansen test (*p*-value)				546.740 (0.210)
AR (1) (*p*-value)				4.390 (0.000)
AR (2) (*p*-value)				0.790 (0.432)

Columns (1) and (2) estimate the baseline model for the number of patents as the innovation proxy but specify the independent variables in one-year lagged (*t*-1) and annual changes (△). Columns (3) and (4) re-estimate the model with the firm fixed effects estimator and system GMM, respectively. The diagnostic tests for system GMM are presented: the

Table 12 (continued)

Hansen test of over-identification with the null that all instruments are valid. AR (1) and AR (2) tests are under the null of no first-order and second-order serial correlation, respectively, in the first-differenced residuals. The definition of all variables is presented in Appendix A. Coefficients for the year and industry dummies are not reported for brevity and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

where $CFF_{i,t}$ is the net cash flow from the financing activities of firm i in year t. Appendix A presents the definitions of all the variables in the models. We controlled for industry and year effects.

The results for large firms and SMEs are listed in Table 14, respectively. The coefficient of *CPQS* for SMEs is much smaller than that for large firms, which means that higher liquidity is more sensitive to raising external financing for SMEs because *CPQS* is an inverse proxy for stock liquidity. Therefore, our conclusion complements and strengthens the findings of Vo (2014) finding that the firm-level effect of stock liquidity on external financing is stronger for innovative SMEs than for large firms. According to Hall et al. (2010), firms tend to finance their innovative projects through cash flow or equity; hence, our evidence suggests that SMEs rely on external financing to invest more in their R&D expenditures.

Stock liquidity, M&As, and innovation

SMEs with more innovative abilities tend to be acquired by large firms, and large firms optimally choose to purchase innovation from small firms rather than invest more in R&D (Cremers et al. 2009; Phillips and Zhdanov 2013). Zhao (2009) and Bena and Li (2014) document that less innovative SMEs tend to acquire more innovative firms which can enhance large firms' innovation. Motivated by these findings, we further explore whether acquisitions by large firms affect SMEs' innovation. Dass et al. (2016) and Massa and Xu (2013) show that more liquid targets are more likely to be acquired, which can increase an acquirer's stock value. Accordingly, our study examines whether a mediating mechanism from M&A facilitates the innovation output when stock liquidity increases.

In China, M&A for firms encompasses broad concepts, such as mergers, acquisitions, trusteeships, equity transfers, and asset swaps. The concept of M&A for Chinese listed firms is that a listed firm becomes the controlling shareholder of another listed firm by acquiring shares or becoming the actual controller through investment relationships, agreements, and so on.[10] Based on this concept, SMEs can be considered acquired if a transfer of equity occurs. We extracted data from the CSMAR database related to asset restructuring events based on the date of the first announcement: (1) occurrence of equity transfer events (*MA*) and (2) number of equity transfer events per year (*NMA*). *MA* is a dummy variable that takes the value of 1 for M&As and 0 for not occurring for the entire year. Next, we use the procedures recommended by Baron and Kenny (1986) to test the mediation of M&A, as it is the most popular method to test for mediation effects. The three-step approach to testing for mediating effects has yielded good results in many studies (see the example of Alesina et al. 2011). Therefore, we choose a three-step approach to facilitate our understanding and perform manipulation and statistical analysis. Figure 3 and models (4)–(6) show the regression procedures, and the results

[10] See the "Measures for the Administration of Takeover of Listed Companies" by the China Securities Regulatory Commission, at: http://www.csrc.gov.cn/csrc/c106256/c1653983/content.shtml.

Table 13 Two-stage Least Squares (2SLS) Regression Result

	First-stage	**Two-stage least squares**	
	CPQS	***INNOV_EXP***	***INNOV_PAT***
FIT-CPQS		− 6.761***	− 29.046*
		(0.803)	(15.536)
$CPQS_{t-1}$	0.599***		
	(0.026)		
MCPQS	0.006**		
	(0.025)		
TSHARE	0.004	0.002	0.030
	(0.007)	(0.001)	(0.026)
SHRHFD5	− 4.123**	− 1.151***	11.938
	(1.877)	(0.296)	(7.678)
TO	− 13.394***	− 6.867***	− 16.228
	(4.082)	(0.804)	(14.274)
RET	− 1.927*	0.859***	1.224
	(1.071)	(0.186)	(3.532)
FREE	0.030**	0.004*	0.028
	(0.014)	(0.002)	(0.050)
VOL	0.176	− 0.021	− 0.113
	(0.166)	(0.042)	(0.828)
EARN	2.155	− 0.025	9.682*
	(1.411)	(0.542)	(5.338)
INTAN	5.627***	0.635***	− 1.820
	(1.960)	(0.191)	(3.701)
LEV	− 7.771***	1.285***	3.037
	(0.988)	(0.204)	(3.931)
ROE	− 13.982***	0.574	− 4.513
	(2.583)	(0.387)	(4.823)
Q	0.472***	− 0.008	− 0.237
	(0.084)	(0.017)	(0.290)
BTM	− 2.687***	0.846***	8.085**
	(0.852)	(0.208)	(3.842)
CAPITAL	7.428***	2.056***	24.837**
	(2.317)	(0.499)	(10.575)
SALES	− 0.014***	0.001*	0.010
	(0.003)	(0.001)	(0.011)
ln*AGE*	− 0.704	− 0.098	0.188
	(0.546)	(0.076)	(1.656)
CONSTANT	0.074***	18.191***	− 1.267
	(0.017)	(0.413)	(6.966)
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
N	1538	1538	1538
Adj.R^2	0.675	0.350	0.022

This table presents the pooled 2SLS estimation results for the relationships between the alternative firm innovation proxies and stock liquidity. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 14 Liquidity, firm size, and financing

	CFF	
	Large firms	**SMEs**
CPQS	− 0.841*	− 118.329***
	(9.572)	(24.316)
TSHARE	0.047	− 0.048
	(0.035)	(0.037)
SHRHFD5	2.300**	− 39.843***
	(7.039)	(8.101)
TO	− 57.802	− 65.964***
	(39.354)	(16.559)
RET	0.484*	27.281***
	(3.055)	(7.420)
FREE	0.015	− 0.089
	(0.048)	(0.063)
VOL	0.123	− 3.900***
	(0.696)	(1.052)
EARN	− 3.080	13.931
	(19.514)	(10.583)
INTAN	1.850	6.861
	(12.280)	(7.846)
LEV	− 6.243*	64.109***
	(3.492)	(9.763)
ROE	− 3.835	− 11.539
	(7.838)	(8.276)
Q	− 0.545*	− 2.741***
	(0.529)	(0.683)
BTM	− 7.583**	2.617
	(3.633)	(5.090)
CAPITAL	− 0.683	95.699***
	(3.896)	(22.934)
SALES	0.001*	0.168***
	(0.002)	(0.026)
ln*AGE*	− 1.159	− 1.877
	(2.140)	(1.573)
CONSTANT	16.695*	− 111.958***
	(11.068)	(36.974)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
N	11,838	4,719
Adj.R^2	0.124	0.020

This table presents the pooled OLS estimation results for the relationship between stock liquidity and cash flow from financing activities (*CFF*) for large firms and SMEs, respectively with double-clustered adjustments. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

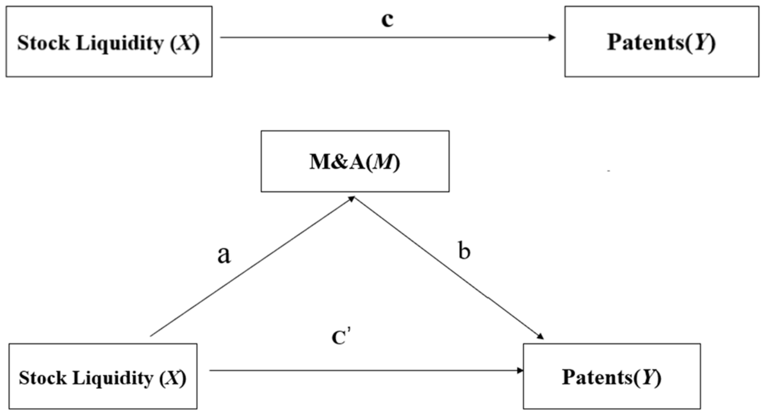

Fig. 3 Mediating effect test process for M&As

are presented in Table 15, 16 and 17. From Table 15 and 16 and the last three columns in Table 17, we find that stock liquidity (*CPQS*, *CPQSIM*, *ILLIQ*), M&As (*MA* and *NMA*), patents (*INNOV_PAT*) are both significantly correlated.

$$Y = cX + e_1 \tag{4}$$

$$M = aX + e2 \tag{5}$$

$$Y = cX + bM + e3, \tag{6}$$

where M&A(M) is measured by the *MA* and *NMA* of firm i in year t. Y is proxied by the number of granted patents, and X is proxied by *CPQS*. The definitions for all variables in the models are presented in Appendix A. Tobit is used for the regression when MA is the dependent variable, and OLS is used for the remaining models.

We include M&As (*MA* and *NMA*) in our models to control for their effects, and the results are presented in Table 17. Compared to the outcomes without control variables, we observe little variation in the liquidity coefficient. The coefficients of *MA* and *NMA* are not significant except for the significant coefficient at 10% for *NMA* under the *ILLIQ* measure of liquidity. We can conclude that under firm stock liquidity, an improvement in liquidity promotes firm innovation, with little mediating effect from M&As.

To further confirm our conclusions, we introduce M&As (*MA* and *NMA*) as control variables in our baseline models. The regression results are presented in Table 18. The change in the coefficient of *CPQS* increases slightly compared with the results without control variables, but the overall magnitude of the change is not evident. We infer that the interaction of M&As with the other control variables has a modest negative impact on innovation. Our findings add to VO (2014) by indicating that the M&A effect does not significantly promote innovation by SMEs when stock liquidity is increased.

Table 15 M&As (*MA*, *NMA*) and Stock Liquidity (*CPQS*, *ILLIQ*, *CPQSIM*)

	CPQS		***ILLIQ***		***CPQSIM***	
	MA	***NMA***	***MA***	***NMA***	***MA***	***NMA***
CPQS	0.065*	1.058*				
	(0.112)	(0.500)				
CPQSIM					− 0.774***	− 3.014***
					(0.077)	(0.346)
ILLIQ			− 1.169***	− 4.688***		
			(0.098)	(0.439)		
CONSTANT	0.691	1.768***	0.771***	2.175***	0.739***	2.042***
	(0.014)	(0.062)	(0.009)	(0.040)	(0.008)	(0.035)
N	4786	4786	4786	4786	4786	4786
R^2/Pseudo R^2	0.000	0.001	0.023	0.023	0.016	0.015

This table presents the Tobit estimation results for the relationship between stock liquidity and M&As for SMEs, respectively. Stock liquidity is denoted by *CPQS*, *ILLIQ*, and *CPQSIM*, respectively. M&As are measured by *MA* and *NMA*. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 16 M&As (*MA*, *NMA*) and Innovation Output (Patents)

	MA	***NMA***
INNOV_PAT	3.417***	0.600***
	(0.277)	(0.076)
CONSTANT	2.047	2.757***
	(0.174)	(0.158)
N	8635	8635
Adj.R^2	0.017	0.023

This table presents the pooled OLS estimation results for the relationship between M&As and innovation output (*INNOV_PAT*) for SMEs, respectively. M&As are measured by *MA* and *NMA*, whereas innovation output is measured by the number of granted patents. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 17 Stock Liquidity (*CPQS*, *CPQSIM*, *ILLIQ*) and Innovation Output (Patents) under Controlled and Uncontrolled M&As (*MA*, *NMA*)

	MA			***NMA***			***Without MA/NMA***		
CPQS	− 5.392*			− 5.272*			− 5.393*		
				(3.891)			(3.889)		
CPQSIM		− 7.2573***			− 7.578***			− 7.103***	
		(2.7422)			(2.735)			(2.714)	
ILLIQ			− 15.531***			− 16.003***			− 15.076***
			(3.503)			3.492			(3.452)
MA	− 0.001	− 0.199	− 0.390						
	(0.502)	(0.507)	(0.509)						
NMA				− 0.114	− 0.158	− 0.198*			
				(0.113)	(0.113)	(0.114)			
CON-STANT	6.111***	6.036***	6.750	6.311	6.210***	6.880***	6.110***	5.889***	6.450***
	(0.597)	(0.462)	(0.502)	(0.525)	(0.356)	(0.399)	(0.486)	(0.271)	(0.314)
N	4786	4786	4786	4786	4786	4786	4786	4786	4786
Adj.R^2	0.000	0.001	0.004	0.000	0.001	0.004	0.001	0.001	0.004

This table presents the pooled OLS estimation results for the relationship between stock liquidity (*CPQS*, *CPQSIM*, *ILLIQ*) and innovation output (*INNOV_PAT*) for SMEs, respectively. *MA* is controlled in the first three columns, whereas *NMA* is controlled in the 4–6 columns, and M&As (*MA*, *NMA*) are not controlled in the last three columns. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 18 Stock Liquidity (*CPQS*, *CPQSIM*, *ILLIQ*) and Innovation Output (Patents) under Controlled and Uncontrolled M&As (*MA*, *NMA*) in our Baseline Models

	MA			*NMA*			*Without MA/NMA*		
CPQS	− 23.300***			− 23.197***			− 28.561***		
	(7.785)			(7.764)			(9.048)		
CPQSIM		− 14.582**			− 14.597**			− 17.486**	
		(6.375)			(6.362)			(7.465)	
ILLIQ			− 17.524			− 17.627**			− 20.996**
			(7.499)			(7.452)			(8.829)
MA	− 0.140	− 0.174	− 0.260						
	(0.751)	(0.731)	(0.729)						
NMA				− 0.149	− 0.161	− 0.173			
				(0.213)	(0.205)	(0.204)			
TSHARE	0.045*	0.042*	0.041*	0.047*	0.043*	0.042*	0.050*	0.045*	0.044
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.028)	(0.027)	(0.027)
SHRHFD5	14.629***	14.894***	14.657***	14.153**	14.395***	14.157**	17.405***	17.737***	17.503***
	(5.476)	(5.448)	(5.402)	(5.576)	(5.540)	(5.496)	(6.553)	(6.519)	(6.462)
TO	− 21.347	− 19.110	− 15.389	− 21.491	− 19.281	− 15.518	− 22.846	− 19.941	− 15.409
	(13.828)	(13.574)	(13.363)	(13.790)	(13.546)	(13.321)	(15.881)	(15.412)	(15.170)
RET	5.859**	5.157*	5.392*	5.913**	5.223*	5.470*	6.769**	5.884*	6.170*
	(2.900)	(3.000)	(3.122)	(2.937)	(3.037)	(3.158)	(3.279)	(3.344)	(3.494)
FREE	0.026	0.013	0.005	0.026	0.014	0.005	0.035	0.019	0.009
	(0.038)	(0.037)	(0.037)	(0.039)	(0.038)	(0.037)	(0.044)	(0.043)	(0.043)
VOL	0.080	− 0.090	0.095	0.122	− 0.048	0.135	0.036	− 0.165	0.049
	(0.392)	(0.415)	(0.462)	(0.393)	(0.411)	(0.453)	(0.455)	(0.482)	(0.559)
EARN	-0.746	0.944	0.503	-0.992	0.667	0.200	− 0.395	1.665	1.147
	(2.262)	(2.519)	(2.521)	(2.221)	(2.529)	(2.503)	(2.579)	(2.862)	(2.882)
INTAN	− 2.785	− 2.912	− 2.624	− 2.663	− 2.787	− 2.499	− 3.614	− 3.754	− 3.420
	(3.196)	(3.195)	(3.310)	(3.203)	(3.200)	(3.310)	(3.553)	(3.554)	(3.684)
LEV	2.359	1.518	1.307	2.416	1.582	1.369	3.483	2.444	2.187
	(3.425)	(3.377)	(3.353)	(3.441)	(3.395)	(3.370)	(3.916)	(3.834)	(3.806)
ROE	− 1.238	− 0.494	− 0.612	− 1.145	− 0.403	− 0.519	− 1.643	− 0.668	− 0.823
	(2.664)	(2.610)	(2.582)	(2.716)	(2.655)	(2.621)	(3.144)	(3.089)	(3.050)
Q	− 0.204	− 0.183	− 0.189	− 0.198	− 0.177	− 0.183	− 0.224	− 0.198	− 0.205
	(0.181)	(0.182)	(0.181)	(0.183)	(0.183)	(0.183)	(0.212)	(0.211)	(0.210)
BTM	9.725***	8.855***	8.702***	9.697***	8.836***	8.691***	11.700***	10.614***	10.434***
	(2.818)	(2.672)	(2.674)	(2.817)	(2.671)	(2.676)	(3.408)	(3.238)	(3.242)
CAPITAL	14.787**	16.476**	16.781***	14.924**	16.606**	16.902***	16.248*	18.324**	18.665**
	(6.837)	(6.521)	(6.412)	(6.861)	(6.539)	(6.426)	(8.387)	(8.045)	(7.921)
SALES	0.001	0.002	0.002	0.001	0.003	0.002	0.002	0.004	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
ln*AGE*	− 0.445	− 0.596	− 0.582	− 0.472	− 0.624	− 0.610	− 0.585	− 0.768	− 0.747
	(1.569)	(1.560)	(1.556)	(1.564)	(1.555)	(1.552)	(1.795)	(1.781)	(1.780)
Constant	− 2.712	− 2.591	− 2.999	− 2.690	− 2.549	− 2.945	− 2.791	− 3.447	− 3.422
	(5.013)	(5.192)	(4.990)	(5.019)	(5.200)	(4.987)	(5.366)	(5.514)	(5.436)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4727	4727	4727	4727	4727	4727	4719	4719	4719
Adj.R^2	0.029	0.028	0.028	0.029	0.028	0.029	0.028	0.027	0.027

This table presents the pooled OLS estimation results within double-clustered adjustments for the relaionship between stock liquidity (*CPQS*, *CPQSIM*, *ILLIQ*) and innovation output (*INNOV_PAT*) for SMEs, respectively. *MA* is controlled in the first three columns, whereas *NMA* is controlled in the 4–6 columns, and M&As (*MA*, *NMA*) are not controlled in the last three columns. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Conclusion and discussions

This section presents the study's findings and policy recommendations and discusses the limitations and potential future research.

Conclusion

This study explores the relationship between stock liquidity and firm innovation (innovation input and output) in Chinese publicly traded growth-oriented SMEs. Stock liquidity is proxied by the Closing Percentage Quoted Spread (*CPQS*), innovation input is captured by R&D expenditures, and innovation output is measured by the number of patents granted. Our results indicate that higher liquidity can promote both the innovation input and innovation output of SMEs in emerging markets at the firm level.

Based on existing studies, we propose two mechanisms without exogenous policy shocks for this positive relationship: (1) reducing financial constraints, and (2) the willingness of large firms to buy innovation. Our subsequent tests on mechanisms further show that among SMEs, the positive relationship between liquidity and innovation is mainly caused by the financing difficulties they face. Increased stock liquidity lowers the cost of acquiring external capital, encouraging SMEs to inject more money into R&D expenditures by issuing more equity and debt. The mediating role of M&A between stock liquidity and firm innovation at the firm level, as put forth by Vo (2014), is not readily apparent. Following Fang et al. (2014), we evaluate the impact of blockholder ownership. The findings indicate that, under the condition of increasing liquidity, both internal and external blockholders, represented by institutions, can impede firm innovation, but this effect is not strong in SMEs.

Our research also examines the long-term influence, and the results show that a positive relationship between stock liquidity and firm innovation has at least a four-year effect. The results of the industry-specific regressions show that higher liquidity can alleviate financing problems for SMEs in all sectors, prompting more investment in innovation. However, innovation output only achieves good results in the manufacturing industry.

Policy recommendations

Our study supplements the existing research on the relationship between stock liquidity and firm innovation in SMEs in emerging markets such as China. SMEs play a vital role in economic growth, and our findings have significant implications for SMEs, especially for managers, such as those in the manufacturing industry. First, our findings provide evidence that SME management can enhance firm innovation in terms of both input and output by improving stock liquidity. Management can improve disclosure for greater market transparency and investor confidence, while the government should tighten regulations to prevent manipulative behavior and boost trading activities. Second, addressing SMEs' financial constraints of SMEs is crucial for boosting investment in innovation, highlighting the importance of prioritizing financing solutions for SMEs. Therefore, SMEs must establish robust internal financial management systems and diversify their financing channels. Finally, the creation of a supportive innovation ecosystem is essential. To stimulate innovation in SMEs, the government should consider providing specific policy subsidies to facilitate talent recruitment and advanced equipment acquisition.

Limitations and future research

This study has two main limitations. First, while Tang et al. (2022) examine the impact of the exogenous shocks of the Share Splitting Reform on stock liquidity and firm innovation in Chinese listed firms, our study's samples from the GEM board remain unaffected, as this regulation ended in 2006. We do not investigate exogenous shocks in this study; instead, we construct a current period model for firm innovation based on Wen et al. (2018). The long-term effects on innovation are not the primary focus of this study, but we can explore them in the presence of other exogenous shocks in future research.

Second, further research should investigate SMEs in both developed and developing countries. As China represents an emerging economy, the findings may not be universally applicable to SMEs in other developing countries because of their varying economic structures. Moreover, although the sample of Vo (2014) comprises developed countries represented by the U.S. market, its concentration on aggregate stock liquidity and the evidence provided at the firm level for SMEs are not sufficient.

Appendix

See Table 19, 20 and 21.

Table 19 Variable definitions and data sources

Variables	Definition	Data Sources
INNOV_EXP	The natural logarithm of R&D expenditures is used to measure the innovation input	WIND Database
INNOV_PAT	The number of granted patents is used in the baseline model to measure the innovation output	CSMAR Database
EXP_REVENUE	The ratio of R&D expenditures and revenue as an alternative proxy for innovation input is used in robustness checks	WIND Database
EXP_ASSET	The ratio of R&D expenditures and total assets used in robustness checks, which is an alternative proxy for innovation input	WIND Database
APPLIED_PAT	The number of applied patents is an alternative proxy for innovation output in robustness tests	CSMAR Database
CPQS	Chung and Zhang (2014) proposed that the low-frequency liquidity proxy is the Closing Percent Quoted Spread (*CPQS*). *CPQS* is an inverse measure of liquidity, calculated as the ratio of the difference between the closing ask and bid prices over the midpoint of these prices. The *CPQS* is initially estimated daily, and then all daily estimates are averaged across the year to give yearly values for each stock and each year	Refinitiv Datastream
CPQSIM	The *CPQS* Impact is calculated as the daily ratio of the *CPQS* divided by the local currency trading volume, and it is utilized as an alternate liquidity proxy in our robustness assessment. The yearly *CPQSIM* estimates for each stock are calculated by averaging the estimated daily ratios over all the trading days in each year	Refinitiv Datastream

Table 19 (continued)

Variables	Definition	Data Sources
ILLIQ	Amihud's (2002) illiquidity ratio is calculated as the daily ratio of absolute stock returns to local currency trading volume, and it is utilized as an alternate liquidity metric in our robustness assessment. The yearly *ILLIQ* values for each stock are calculated by averaging the computed daily ratios over all the trading days in a given year	Refinitiv Datastream
TSHARE	Tradable shares are the number of shares of listed firms that can be traded in the exchange. In the Chinese market, it can be divided into individual investors and blockholdings	WIND Database
SHRHFD5	*SHRHFD5* is the Herfindahl–Hirschman Index, the sum of the squared shareholding ratios of the top five shareholders	WIND Database
TO	Stock turnover is defined as the number of shares trading divided by the number of outstanding shares. The yearly value for each stock is calculated by taking the time-series averages of daily turnover ratios over each year	Refinitiv Datastream
RET	The daily stock return is calculated as the natural logarithm of price and then averaged over the year to get the annual stock return for each stock and year	Refinitiv Datastream
FREE	Free float is the portion of *TSHARE* that excludes blockholders with more than 5% of the shares	WIND Database
VOL	The standard deviation of daily stock returns over the year is used to calculate annual return volatility	Refinitiv Datastream
EARN	Earnings are calculated by dividing operating income by the book value of total assets	Refinitiv Datastream
INTAN	The ratio of intangible assets divided by the book value of total assets is used to calculate intangibles	Refinitiv Datastream
LEV	Leverage is the book value of debts scaled by the book value of assets at year's end	Refinitiv Datastream
ROE	The ratio of operating income divided by the book value of equity is used to calculate return on equity	Refinitiv Datastream
Q	Tobin's Q ratio is a measure of firm value that is the market value of assets divided by the book value of assets at the end of the year	Refinitiv Datastream
BTM	Book-to-market is computed as the ratio of the book value of equity divided by the market value of equity	Refinitiv Datastream
CAPITAL	Capital is the ratio of capital expenditures over the book value of assets measured at year-end	Refinitiv Datastream
SALES	Sales growth is defined as the annual percentage change in sales	Refinitiv Datastream
ln*AGE*	Natural logarithm of firm age, measured by taking the number of whole years which covers 365 or 366 days from the establishment date to the end of 2020	WIND Database
INSTITUTION	*INSTITUTION* is the ratio of institutional shareholdings to the total shares of SMEs listed on GEM	WIND Database
CFF	*CFF* is the cash flow from financing activities, measured by the difference between cash inflows from debt and equity issuance and outflows from share repurchases, debt repayments, and dividend payments	Refinitiv Datastream
MA	*MA* is a dummy variable that takes the value of 1 for M&A occurring and 0 for not occurring based on the date of the first announcement for the whole year	CSMAR Database
NMA	The number of M&A over the year is based on the date of the first announcement for the whole year	CSMAR Database

Table 20 Long-term innovation effect on R&D expenditures

	INNOV_EXP						
	T+1	***T+2***	***T+3***	***T+4***	***T+5***	***T+6***	***T+7***
CPQS	− 4.378***	− 4.457***	− 4.158***	− 3.172***	− 2.285**	− 1.974**	− 2.170**
	(0.532)	(0.749)	(1.200)	(1.108)	(0.949)	(0.776)	(0.935)
TSHARE	0.003**	0.003**	0.002	0.003*	0.003**	0.004*	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
SHRHFD5	− 0.729**	− 0.622*	− 0.461	− 0.398	− 0.302	− 0.429	− 0.412
	(0.337)	(0.361)	(0.385)	(0.423)	(0.467)	(0.509)	(0.521)
TO	− 4.296***	− 2.521**	− 1.021	0.438	0.967	1.855	2.397
	(1.129)	(0.985)	(1.042)	(0.918)	(1.167)	(1.280)	(1.855)
RET	0.980***	0.912***	0.929***	0.447**	0.122	0.001	0.149
	(0.291)	(0.295)	(0.352)	(0.208)	(0.347)	(0.525)	(0.759)
FREE	0.005*	0.004	0.003	0.002	0.001	− 0.002	− 0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
VOL	− 0.092***	− 0.115***	− 0.116***	− 0.115***	− 0.124**	− 0.168*	− 0.230*
	(0.030)	(0.029)	(0.029)	(0.037)	(0.057)	(0.102)	(0.134)
EARN	0.058	0.659	4.319***	4.934***	4.965***	4.355***	4.930***
	(0.331)	(0.863)	(1.080)	(1.174)	(1.316)	(1.287)	(1.779)
INTAN	1.000***	0.862***	0.803***	0.769*	0.999***	0.937**	1.134**
	(0.234)	(0.238)	(0.294)	(0.398)	(0.335)	(0.441)	(0.571)
LEV	1.066***	0.872***	0.892***	0.884**	0.877**	0.892*	1.050
	(0.190)	(0.198)	(0.253)	(0.348)	(0.344)	(0.459)	(0.664)
ROE	1.252***	1.402***	0.551	0.382	− 0.089	− 0.107	− 1.926*
	(0.277)	(0.370)	(0.683)	(0.804)	(0.500)	(0.998)	(1.001)
Q	− 0.011	− 0.014	− 0.035*	− 0.026	− 0.003	0.052	0.066
	(0.024)	(0.027)	(0.018)	(0.020)	(0.024)	(0.041)	(0.062)
BTM	0.778***	0.697**	0.529	0.311	0.071	0.246	0.131
	(0.210)	(0.293)	(0.3787)	(0.314)	(0.318)	(0.335)	(0.354)
CAPITAL	1.204**	1.483***	1.679***	1.624**	1.340*	0.977*	0.489
	(0.471)	(0.521)	(0.609)	(0.826)	(0.707)	(0.548)	(0.718)
SALES	0.002***	0.002***	0.003***	0.003***	0.002***	0.003**	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ln*AGE*	− 0.101	− 0.104	− 0.097	− 0.105	− 0.112	− 0.149	− 0.123
	(0.096)	(0.099)	(0.109)	(0.122)	(0.140)	(0.148)	(0.159)
CONSTANT	17.227***	17.092***	17.025***	17.241***	17.352***	17.330***	17.934***
	(0.459)	(0.481)	(0.518)	(0.537)	(0.573)	(0.687)	(0.660)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3907	3195	2511	1963	1494	1113	780
Adj.R^2	0.349	0.311	0.280	0.220	0.170	0.152	0.139

This table presents the long-term relationship between stock liquidity and firm innovation proxied by R&D expenditures. We lag the dependent variable for one to seven-year, respectively. The estimation method is pooled OLS. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed, and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 21 Long-term Innovation Effect on the Patents

	INNOV_PAT				
	T+1	***T+2***	***T+3***	***T+4***	***T+5***
CPQS	− 26.521***	− 32.044***	− 42.603***	− 50.408**	− 20.697
	(8.754)	(10.176)	(12.008)	(20.552)	(18.156)
TSHARE	0.046	0.051	0.053	0.066	0.123**
	(0.030)	(0.032)	(0.036)	(0.043)	(0.050)
SHRHFD5	18.441**	17.765	22.118*	23.652	20.192
	(8.110)	(11.004)	(11.616)	(14.770)	(14.905)
TO	− 26.389*	− 13.872	− 14.732	-13.559	− 23.508
	(15.114)	(12.964)	(13.753)	(18.610)	(24.343)
RET	10.429**	7.733*	13.038***	3.057	− 8.851**
	(4.378)	(4.041)	(3.644)	(5.286)	(4.092)
FREE	0.050	0.048	0.031	− 0.018	− 0.032
	(0.056)	(0.065)	(0.063)	(0.089)	(0.084)
VOL	1.028	0.629	− 0.792	− 1.865*	0.800
	(0.804)	(0.771)	(0.612)	(0.958)	(0.935)
EARN	0.939	− 2.609	− 15.377	3.240	15.082
	(5.082)	(7.026)	(25.841)	(31.808)	(48.701)
INTAN	-4.939	− 7.018**	− 13.983***	− 22.075***	− 20.794***
	(3.172)	(3.560)	(4.612)	(4.536)	(5.274)
LEV	− 0.390	− 6.484	− 11.449**	− 12.020*	− 12.399*
	(4.124)	(4.415)	(5.344)	(6.415)	(7.175)
ROE	5.856	14.920*	23.160	21.615	26.602
	(5.028)	(8.081)	(18.408)	(20.080)	(23.859)
Q	− 0.690**	− 0.924**	− 1.202***	− 1.000***	− 0.484
	(0.300)	(0.393)	(0.383)	(0.370)	(0.443)
BTM	9.261***	7.544**	7.236*	8.092	4.622
	(2.679)	(3.408)	(3.822)	(5.973)	(7.647)
CAPITAL	13.633	16.231	18.244	17.079	23.194
	(10.691)	(13.234)	(15.921)	(17.349)	(20.230)
SALES	0.002	0.005	0.025*	0.047*	0.045*
	(0.008)	(0.010)	(0.015)	(0.024)	(0.025)
ln*AGE*	0.224	0.890	0.948	2.325	3.025
	(2.061)	(2.434)	(2.929)	(3.509)	(3.703)
CONSTANT	− 3.459	− 5.003	5.486	0.009	− 17.658
	(5.954)	(7.849)	(8.391)	(9.453)	(10.827)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
N	3950	3228	2535	1980	1505
Adj.R^2	0.028	0.028	0.033	0.037	0.032

This table presents the long-term relationship between stock liquidity and firm innovation proxied by the number of patents. We lag the dependent variable for one to five years, respectively. The estimation method is pooled OLS. The definition of all variables is provided in Appendix A. For brevity, year and industry dummies are suppressed, and only double-clustered adjustments are reported in parentheses. *N* is the number of firm-year observations. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Abbreviations

FE	Fixed effects
GEM	Shenzhen Growth Enterprises Market
GMM	System generalized method-of-moments
M&A	Mergers and acquisitions
NBR	Negative binomial regression
OLS	Ordinary least squares
RE	Random effects
SMEs	Small and medium-sized enterprises
SOEs	State-owned enterprises
WFE	World Federation of Exchanges

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Author contributions
WL: Design of the work, Formal analysis, Interpretation of data Validation, Methodology, Software, Writing-original draft, Writing-review & editing. YS: Validation, Supervision, Writing-review & editing.

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Availability of data and materials
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Declarations

Competing interests
The authors declare that they have no competing interests.

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