1. Introduction

A growing number of studies investigate how the managers' real decisions are affected by financial markets (e.g., Goldstein, Ozdenoren, and Yuan (2013), Edmans, Goldstein, and Jiang (2012, 2015), Dow, Goldstein, and Guembel (2017), Edmans, Jayaraman, and Schneemeier (2017)).[1] For example, firms with liquid stocks enjoy a lower cost of equity (Butler, Grullon, and Weston (2005)), suggesting that corporate investment is sensitive to stock market liquidity through the channel of equity issuance. However, the ability of secondary market liquidity, i.e., trading between investors in the absence of a capital flow to firms, to influence the efficiency of corporate investment decisions is unexplored.[2] In this paper, we examine the following question: is the investment efficiency of a firm affected by its liquidity in the stock market? An optimal level of corporate investment can have real consequences to the economy by efficiently allocating capital and labour and by ensuring that firms neither ignore profitable investment opportunities nor invest excessively in unprofitable projects. To the extent that stock liquidity leads to efficient investment decisions, financial markets can mitigate the boom and bust nature of business cycles; thus, the effect of stock liquidity on investment decisions deserves more attention from policymakers.

Using Chinese listed companies and exploiting the passage of a 2005 reform (split-share structure reform) as a quasi-natural experiment, we investigate the effect of an increase in stock liquidity on subsequent investment efficiency. To understand why firms may invest inefficiently, prior work has offered various explanations, such as agency costs, financial constraints, and information asymmetry. Shirking managers enjoying a quiet life can cause under-investment problems for their firms (Bertrand and Mullainathan (2003)). Firms with

[1] Bond, Edmans, and Goldstein (2012) provide a comprehensive survey of literature examining the real effects of financial markets.

[2] Becker-Blease and Paul (2006) find that firms when facing an increase in liquidity through index additions are able to invest more, as their cost of capital is lowered, thus increasing the opportunity set of investments available to them.

higher free cash flow are subject to over-investment problems to the detriment of shareholders (Richardson (2006)). Past studies have identified factors that can mitigate investment inefficiency, such as financial reporting quality (Biddle, Hilary, and Verdi (2009), Gomariz and Ballesta (2014)), accounting conservatism (Lara, Osma, and Penalva (2016)), and the expertise and the quality of analysts' coverage (Chen, Xie, and Zhang, 2017). Meanwhile, Chen et al. (2011) find that government intervention distorts investment behaviour and lowers investment efficiency. However, whether secondary market trading can influence investment efficiency is still unexamined.

Stock liquidity can affect investment efficiency in various ways. First, proponents of 'feedback effect' suggest that managers learn from stock prices to make more informed corporate decisions. When a speculator invests without any information, the manager assumes the higher stock price as validation and exhibits a higher propensity to over-invest (Goldstein and Guembel (2008)). Similarly, large selling without any negative information can give rise to under-investment that can benefit a short-seller, thus setting up a vicious cycle. Dow, Goldstein, and Guembel (2017) argue that traders' incentives to produce information are dependent on the ex ante probability of investment choice, and therefore when managers are less influenced by stock prices, any shock to fundamentals of the firm can be amplified, leading to a large discontinuous drop in investment; this suggests that investment is sensitive to stock trading, irrespective of the manager's attitude to incorporate feedback. At the other extreme, Khanna and Sonti (2004) argue that informed traders also weigh the prospect that their large trades will affect firm decisions and use exaggerated trading behaviour to signal managers on their choices of investment. In summary, prior work using feedback theory suggests that stock market liquidity and prices convey valuable information to managers and influence their choice of investments. To the extent that enhanced stock liquidity lowers the information costs of speculators and strengthens their incentives for information production, we should expect stock liquidity to mitigate any investment inefficiency. Additionally, an increase in stock liquidity increases the effectiveness of managerial incentive compensation and thus encourages managers to follow stock prices more closely, thus enhancing the feedback effect.

Even in the absence of any feedback effect from stock trading on managerial real decisions, incentive theories suggest that stock liquidity can still influence investment efficiency. Fishman and Hagerty (1989) propose that efficient stock prices can lead to efficient investment because stock illiquidity and the unobservability of managers' investment choices lead to under-investment. Thus, when stock liquidity increases, the demand for stock specific information increases, providing the incentives for managers to provide more disclosure and, in the process, mitigating the under-investment problem. Monitoring by the financial markets has a social value through its enhancement of the effectiveness of both concentrated shareholder's governance and managerial incentive compensation (Holmstrom and Tirole (1993), Faure-Grimaud and Gromb (2004)). If a large shareholder can observe the effect of their efforts to improve governance, their incentives to improve monitoring are strengthened. This suggests that higher stock liquidity can ensure better monitoring and more managerial effort, all of which can lead to optimal investment.

However, the effect of stock liquidity on investment efficiency need not be similar for under-investment and over-investment problems because their underlying causes and enabling environments are starkly different (Edmans, Goldstein, and Jiang (2011)). For example, a weak governance mechanism, speculative trading, and short-sale constraints allow over-investment to thrive, while all these factors have an opposite or weaker effect on under-investment behaviour. Specifically, over-investment has the following antecedents. Managers in firms with large free cash flow show a greater propensity to engage in wasteful expenditure (Jensen (1986), Stulz (1990)). Additionally, when external monitoring by activist institutions or the takeover market is weak, such over-investment can persist (Gompers, Ishii, and Metrick (2003), Larcker, Richardson, and Tuna (2005)). Stock liquidity, while lowering the monitoring costs by facilitating both block formation and the ease of takeover, can also decrease the costs of exit (selling), thus weakening the incentives of external monitors (Appel, Gormley, and Keim, (2016), Schmidt and Fahlenbrach (2017)). As long as monitoring costs are related to the seriousness of governance lapses, institutional investors can choose to exit from firms having over-investment problems, while continuing to monitor firms with under-investment problems. Given these opposing arguments, the effect of stock liquidity on over-investment is ex ante unclear and remains an open empirical question.

To understand the channels through which stock liquidity can affect investment efficiency, we propose the following arguments. First, institutional ownership can play an important role in the investment efficiency of firms. Institutional owners, by having large blocks of shares, have strong incentives to monitor the firm and encourage firm decisions that achieve higher investment efficiency (i.e., use their 'voice'). Institutional ownership can affect company policies through shareholder voting, through trading on private information (Edmans (2009)), and through informal communication with the management. However, when institutional owners do not agree with management decisions, they can sell or threaten to sell their entire stake ('exit'). Previous studies (Hartzell and Starks (2003), Edmans (2014)) have shown that when managerial compensation is closely tied to shareholder returns, such exit behaviour can discipline managers. However, when stock liquidity increases, due to the lower price impact of large trades targeted at disciplining the management, exit becomes a less effective strategy. Furthermore, among under- and over-investing firms, the governance lapses are also contrasting in nature. Under-investing firms often do not pursue value-increasing projects, due to inexperience, lack of capital, or poor management strategy. On the other hand, over-investing firms are overcome by optimism or overconfidence in pursuing value-decreasing projects. Therefore, institutional ownership can play different roles in mitigating such contrasting firm behaviours. In the former case, voice strategies can be quite effective in encouraging management to undertake more investments, while in the latter case, only exit strategies hold the potential to influence managerial decisions. Any increase in stock liquidity further weakens exit strategies, thus weakening the effect of institutional ownership on over-investment. However, voice strategies become more plausible and effective due to the positive spillover of liquidity on the cost of capital and the access to finance (Amihud and Mendelson (1989), Butler, Grullon, and Weston (2005)). Therefore, we hypothesize that an exogenous increase in stock liquidity increases (decreases) institutional ownership among firms that are prone to under-investment (over-investment).

Second, the threat that a firm making inefficient investment decisions may be acquired can be a significant deterrent for managers. The possible termination of the employment of target managers post-acquisition implies that the prospect of job loss can encourage somewhat efficient investment behaviour. Therefore, to the extent that an increase in stock liquidity increases the risk of being acquired, investment efficiency will consequently increase.

Third, financially constrained firms might avoid undertaking positive NPV projects, suggesting that investment efficiency is simply a function of the firm's access to capital markets. Therefore, to the extent that stock liquidity relaxes financial constraints (Butler, Grullon, and Weston (2005), Amihud et al. (2015), Brogaard, Li, and Xia (2017)), firms will be able to improve investment efficiency by not having to forego any positive NPV investment projects due to the lack of external financing.

Chinese publicly listed companies provide an ideal empirical setting to examine the relationship between stock liquidity and investment efficiency because a combination of short-sale constraints and lower investor protection allow much larger deviations from optimal investment decisions (Guarigilia and Yang (2016)). Thus, an exogenous increase in stock liquidity, such as the one resulting from the 2005 split-share structure reform, allows us to conduct a quasi-natural experiment to examine the effect of stock liquidity on firms with ex ante poor investment efficiency.

Our major findings support the hypothesis that stock liquidity has a causal effect on investment efficiency for firms prone to under-investment problems. A one standard deviation increase in stock liquidity reduces under-investment by 8.6% relative to the sample mean. This is consistent with both the feedback and incentive arguments that managers learn from stock prices, and that is, that managers, along with blockholders, are better incentivized to make optimal real decisions when their stocks are liquid. However, we find that stock liquidity is not able in any significant manner to mitigate over-investment problems. Our baseline findings are robust to different measures of stock liquidity and investment efficiency and to different model specifications.

To address endogeneity concerns between stock liquidity and investment efficiency (i.e., reverse causality and omitted variables bias), we employ various methods. First, we make use of instrumental variables, including the lagged average industry liquidity and an indicator for split-share structure reform. Both instrumental variables are significantly associated with stock liquidity but are unlikely to affect investment efficiency, except through the effect on stock liquidity, thus satisfying both the exclusion and relevance criteria for instrumental variables. Our finding that investment efficiency improves with stock liquidity for under-investing firms remains robust to using a two-stage least squares estimation. Using the split-share structure reforms as a quasi-natural experiment, we also estimate a change regression and a difference-in-differences (DiD) estimation and still find similar results. The average treatment effect of stock liquidity on under-investment is 0.025, which is equivalent to a 36% increase in investment efficiency relative to the sample mean of under-investing firms.

To understand the channels through which stock liquidity affects investment efficiency, we conduct further tests. We find that stock liquidity improves the investment efficiency of under-investing firms by increasing the takeover risk and through the relaxation of financial constraints. Specifically, we find that institutional ownership does not change significantly among under-investing firms with respect to the split-share structure reform. However, we find that institutional ownership decreases significantly when over-investing firms undergo the reform, consistent with the view that institutional investors prefer exit strategies to voice strategies, when governance problems are severe. Next, we find that the takeover probability increases among under-investing firms that undergo the reform, suggesting that managers at under-investing firms face greater pressure to invest efficiently because of the threat of unemployment post-acquisition. However, we do not find any such effect on over-investing firms with respect to the reform. Finally, we find that in both our full sample and subsamples related to investment efficiency, the reform coincides with a relaxation of financial constraints, as measured by the Hadlock and Pierce index (Hadlock and Pierce (2010)), suggesting that the firms in the post-reform period have the ability to increase investments. In summary, all these results suggest that there is a strong motivation for under-investing firms to improve their investment efficiency when there is an increase in stock liquidity, while over-investing firms do not appear to alter their investment efficiency in any significant manner.

We contribute to the literature in several ways. First, we provide additional evidence on the effect of financial markets on real decisions. Using theories on feedback effect and incentives, we argue that stock liquidity modifies the investment efficiency of firms and therefore has real consequences on the economy. Our evidence supports our argument and adds to the growing literature that supports this view (Morck, Shleifer, and Vishny (1990), Dow and Gorton (1997), Shleifer and Vishny (2003), Goldstein and Guembel (2008), Bond, Edmans, and Goldstein, (2012), He and Tian (2015)). Second, we contribute to studies that examine the various factors that influence the investment efficiency of firms (Biddle, Hilary, and Verdi (2009), Gomariz and Ballesta (2014), Lara, Osma, and Penalva (2016), Chen et al. (2011), Chen, Xie, and Zhang (2017)). Prior studies have typically focused on firm choices, such as disclosure policies and accounting conservatism, as determinants of investment efficiency. We add to this literature by examining whether a variable related to financial markets can be a plausible determinant. Third, by using the split-share structure reform as a quasi-natural experiment, we contribute to the growing number of studies that examine the consequences of this massive reform, also called China's second wave of privatization (Li et al. (2011), Liu and Tian (2012), Liao, Liu, and Wang (2014), Xiao (2015), Michaely and Qian (2017)). Through this study, we show that the increase in stock liquidity brought on incidentally by this reform has managed to improve the investment efficiency for those firms that were lagging in investments, which is a significant result given the high level of investment inefficiency prevalent among Chinese listed companies (Guarigilia and Yang (2016)).

This paper proceeds as follows. In Section 2, we explain the various measures used in this study, our research design, baseline regression specification, and our methods to overcome endogeneity concerns. In Section 3, we describe our sample, present the empirical findings, and discuss additional robustness tests. We conclude in Section 4.

2. Methodologies

2.1. Variable Definitions

Measures of Stock Liquidity

To investigate the effect of stock liquidity on investment efficiency, we use the Amihud (2002) liquidity measure as our key explanatory variable. The Amihud measure is widely used in prior studies and performs well in capturing the price impact of trading (Acharya and Pedersen (2005), Goyenko, Holden, and Trzcinka (2009)). As a low frequency price impact proxy, the Amihud measure is easily computed and is reliably available for the majority of the Chinese publicly listed firms. We compute the annual Amihud liquidity measure (*LIQ_A*) as shown below. The negative sign allows the measure to be increasing in stock liquidity and a logarithm transforms the distribution to be closer to a normal distribution.

$$LIQ\_A_{it} = -\log(1 + \frac{1}{D_{it}}\sum_{d=1}^{D_{it}}\frac{|R_{idt}|}{Dvol_{idt}}) \quad (1)$$

where R_{idt} is the daily return on stock *i* in year *t* and $DVol_{idt}$ is the daily dollar volume in millions for stock *i* in year *t*. In additional tests, we use alternative measures of stock liquidity, namely, turnover and trading volume, and find that our main findings are still supported.

Measures of Investment Efficiency

Following Biddle, Hilary, and Verdi (2009), we compute investment efficiency |*I_DEV*| as the absolute value of the residuals ϵ_{it} obtained from industry-year cross sectional regressions of investment on lagged sales growth, as below:

$$INV_{it} = \alpha_0 + \alpha_1 SalesGrowth_{it-1} + \epsilon_{it} \quad (2)$$

where *INV* is defined as the change in net fixed assets divided by lagged total assets. Using the sign of *I_DEV*, we identify under-investing (over-investing) firms as those with a negative (positive) value of *I_DEV*. We also repeat our tests with alternative definitions of *INV* and find that our results are unchanged. For the additional tests, these alternative measures and the findings using them are reported in Section 3.6.

Other Measures

To examine the underlying channels through which stock liquidity affects investment efficiency, we test for changes in institutional monitoring, takeover risk, and financial constraints. To perform this, we use measures of institutional ownership, the probability of takeover, and financial constraints. Specifically, we measure institutional ownership as the proportion of shares held by investors categorized as qualified foreign institutional investors, insurers, banks, and pension funds, by the Wind database.[3] Next, to examine the takeover channel, we define an indicator variable *Target* that takes the value of one if a firm receives a takeover proposal in a given year and the value zero otherwise. To identify takeover proposals, we use Thomson Reuters SDC database to identify either Shanghai or Shenzhen exchange listed Chinese firms that have received a takeover bid in an M&A transaction. Finally, to examine the financial constraints channel, we compute the Hadlock and Pierce (2010) index (or HP index) as:

$$HP\ Index_{it} = -0.737 Log\left(Assets_{i,t}\right) + 0.043\ Log(Assets_{i,t})^2 + 0.04\ Firm\ age_{it} \quad (3)$$

2.2. Research Design

To examine the effect of stock liquidity on investment efficiency, we follow the below empirical approaches. First, we examine the conditional relationship between stock liquidity and investment efficiency, following the empirical framework used in Biddle, Hilary, and Verdi (2009). Using a pooled OLS specification with *INV* as the dependent variable, we interact a measure of stock liquidity with ex ante proxies for a firm's under-investment propensity, while controlling for various firm characteristics as well as internal and external governance mechanisms. For a more direct test of the level of investment efficiency, we also

[3] Among the other categories of investors identified by Wind, we exclude shares owned by securities companies and those sold as financial products from institutional ownership, as these are likely to be non-discretionary holdings.

examine the effect of stock liquidity on the absolute value of deviations from expected investment levels (*I_DEV*), using both a pooled OLS specification and a multinomial logit specification.

Second, the relationship between investment (investment efficiency) and stock liquidity can also arise because of endogeneity due to omitted variables. For example, financially unconstrained firms with better access to equity markets can have higher stock liquidity because of their frequent equity issuances that result in higher free float tradable shares. At the same time, these firms exhibit a greater propensity to over-invest because of the excess cash from previous equity issuances. This would give rise to a spurious positive correlation between stock liquidity and investment. To overcome this, we use an instrumental variable approach in examining the (conditional) relationship between investment efficiency (investment) and stock liquidity. We use two instrumental variables for stock liquidity, including lagged industry average liquidity and a post-split share reform indicator. The relevance and exclusion criterion for these instrumental variables are discussed in Section 2.3.2.

Third, to further overcome endogeneity concerns, we make use of a quasi-natural experiment based on the firm level adoption of the split-share reform. The institutional information about the reform and how it affects stock liquidity is discussed in Section 2.3.1. Using this exogenous shock to stock liquidity, we perform two kinds of analyses. Following Edmans, Fang, and Zur (2013), we estimate a change regression to examine investment efficiency in the post-split-share reform period, using key explanatory and control variables expressed as changes from one year before the adoption of the split-share reform to one year after. Next, following Fang, Tian, and Tice (2014), we perform a difference-in-difference analysis on the split-share reform to examine how firm investment decisions are affected by an increase in stock liquidity, using a sample of propensity-score matched firms, in which treated firms experience large liquidity shocks, while control firms face smaller changes in liquidity with respect to the reform.

Finally, in order to examine the channels through which stock liquidity influences investment decisions, we use the change regression framework of Edmans, Fang, and Zur (2013) to examine the post-split-share reform level of institutional ownership, takeover probability, and financial constraints.[4]

Regression Analysis

To examine the relationship between stock liquidity and investment efficiency, we use two types of baseline specifications. First, we regress investment on stock liquidity, ex ante investment propensity, their interaction terms, and several control variables (Eq. (4)). Second, we regress the absolute value of abnormal investment (*I_DEV*) on *LIQ_A* and several control variables (Eq. (5)).

$$INV_{i,t+1} = a + bLIQ\_A_{i,t} + cUNDER\_PROP_{i,t} + dLIQ\_A_{i,t} x UNDER\_PROP_{i,t} + e'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}. \quad (4)$$

where *UNDER_PROP* is measured at the firm level as a proxy for the firm's ex ante under-investment propensity. This measure is computed as the average of a ranked measure of cash and leverage deciles, in which cash is multiplied by minus one to allow both variables to be increasing in the likelihood of under-investment (Biddle, Hilary, and Verdi (2009)). However, this measure can be endogenously correlated with stock liquidity because of omitted variables. For example, by frequently engaging in seasoned-equity offerings, firms with liquid stock and better access to equity markets can have higher levels of cash and lower leverage. To overcome this concern, following Biddle, Hilary, and Verdi (2009), we use alternative plausibly exogenous measures to capture a firm's under-investment propensity. *UNDER_*

[4] Due to a limited sample of propensity-score matched firms, to examine the different channels in a meaningful manner, we are not able to perform the differences-in-differences analysis as in Fang, Tian, and Tice (2014).

AGGPROP (*UNDER_ INDPROP*) is a ranked variable computed at the aggregate economy (industry-year) level as residuals from regressing *INV* on all firm-year lagged sales-growth (on firm-year lagged sales growth in each industry-year). Both the residuals are multiplied by minus one to allow these measures to be increasing in the likelihood of under-investment.

Although, as discussed above, examining the conditional relationship between investment and stock liquidity can allow us to test investment efficiency, it is possible that our results could be driven alone by the relationship between under-investing (over-investing) firms and stock liquidity. To isolate which of these subgroups' investment behaviour is more affected by stock liquidity, using the absolute level of *I_DEV* as the dependent variable, we also perform OLS regressions. We conduct such a regression on our full sample and then on subsamples of under-investing and over-investing firms, respectively. Firms with positive (negative) values of contemporaneous *I_DEV* are identified as over-investing (under-investing) firms.

$$|I\_DEV|_{i,t+1} = a + bLIQ\_A_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}. \quad (5)$$

In examining the effect of liquidity on investment efficiency, we control for various firm characteristics that can influence firm investment behaviour, as included in Biddle, Hilary, and Verdi (2009). Specifically, we control for the volatility of cash flow, sales, and investment to mitigate the effect of accruals, cost of capital, and investment mean reversion, respectively (Liu and Wysocki (2007), Biddle, Hilary, and Verdi (2009)). To account for the effect of the business cycle on investment behaviour, we include firm age, length of operating cycle, and an indicator for loss (Dechow (1994), Dechow, Kothari, and Watts (1998), Dechow and Dichev (2002)). Additionally, we include controls for firm size, growth opportunities, leverage at the firm and industry levels, tangibility, financial slack, cash, and bankruptcy risk, as these firm characteristics can have a pronounced effect on firm investment. Finally, we also control for governance variables that can affect investment, including the number of analysts tracking the firm, an indicator for state ownership, and an indicator for Chairman-CEO duality. The analysts in China play a crucial external monitoring role, as they have the potential to mitigate twin agency problem, i.e., when faced with political uncertainty, firms modify their cash policies to discourage expropriation (Stulz (2005)). Fan and Wong (2005) show that Chinese state ownership is associated with weaker governance mechanisms. Although guidelines issued by the China Securities Regulatory Commission (CSRC) in 2001 encouraged the separation of ownership and control among listed Chinese firms, Chen, Ezzamel, and Cai (2011) show that CEO-chair duality became more frequent with time and is also associated with poor governance, such as an increase in executive compensation. Detailed definitions of all the control variables are reported in Table 1.

In estimating both Eq. (4) and Eq. (5), we use a pooled OLS specification with robust standard errors clustered at the firm level (Petersen (2009)). We also include year and industry fixed effects to control for time and industry-specific trends in investment behaviour. We use the 32 CSRC industry classification codes as our industry definition.

Alternatively, following Biddle, Hilary, and Verdi (2009), we also estimate a multinomial logistic regression to test the likelihood that a firm might be in the extreme quartile of *INV* compared to being in the middle two quartiles, as a function of stock liquidity. Sorting firms on the value of *I_DEV* (estimated in Eq. (2)), we define a categorical variable *INV_CHOICE* that takes the value of one and three for firms in the bottom and top quartiles of *I_DEV*. The benchmark firms in the two middle quartiles are assigned a value of two for *INV_CHOICE*. We use the same explanatory and control variables as in previous regression analyses.

$$Pr(INV\_CHOICE = 1 \text{ or } 3) = a + bLIQ\_A_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t} \quad (6)$$

2.3. Endogeneity

Although stock liquidity is a significant determinant of investment and financing policies, there remain major empirical challenges in identifying a causal relationship between stock liquidity and firm policies. For example, as discussed earlier, an omitted variable, such as financial constraints, can affect both the stock liquidity and investment behaviour. Firms with poor access to external capital markets are likely to have lower stock liquidity and to forgo profitable investment opportunities. Additionally, firms with higher levels of information asymmetry will be illiquid when measured using conventional liquidity variables and face significant difficulty in raising external capital. Furthermore, the relationship between stock liquidity and investment efficiency is also affected by reverse causality. For example, investors, such as mutual funds, can avoid firms that regularly under-invest, whereas uninformed investors, such as retail investors, can trade excessively in firms that over-invest, to capitalize on the news about their investment projects. This can lead to under-investment (over-investment) decreasing (increasing) stock liquidity. In this section, we discuss our different empirical approaches to overcome unobservable omitted variable bias and reverse causality in our study. We begin with the institutional description of the split-share structure reform, which we exploit in both empirical approaches.

2.3.1. The Split-Share Structure Reform

Jiang, Ma, and Shi (2017) document that the split-share structure reform resulted in a significant and permanent shock to stock liquidity, causing an average increase in liquidity of 35.6% in the post-reform period. Following Michaely and Qian (2017) and Jiang, Ma, and Shi (2017), we exploit the exogenous shock to stock liquidity from the implementation of the split-share reform in Chinese stocks that was initiated in 2005, through an instrumental variable regression and a difference-in-differences analysis.

Since the establishment of the Shanghai and Shenzhen Stock Exchanges in 1990 as part of China's share issue privatization reforms, a dual split-share structure was permitted which allowed the non-tradability of approximately two-thirds of domestically listed A shares (Li et al. (2011)). The dual split-share structure was equally prevalent among both state-owned enterprises (SOEs) and non-SOEs. The holders of such non-tradable shares (NTS) (usually central and local governments and their affiliated agencies) received similar voting and cash-flow rights as accorded to holders of tradable shares (TS). Although the split-share structure fastened the pace of privatization by allowing many state-owned enterprises to privatize, it weakened corporate governance mechanisms, encouraged speculation, and discouraged an active mergers and acquisitions market (Liao, Liu, and Wang (2014)). Therefore, in 2005, the split-share structure reform was initiated to convert all the NTS to TS, effectively leading to the second wave of privatization reforms in China. An important feature of the reform was that the holders of NTS had to negotiate and complete a compensation plan for the holders of TS who were likely to be adversely affected by the increased supply of shares in the market (Li et al. (2011)).

Before making the reform compulsory for all firms, the CSRC chose two sets of pilot firms to assess the reform's impact (Michaely and Qian (2017)). Thereafter, the reforms were made mandatory and firms had to seek the CSRC approval, which was being given in weekly batches. Finally, to implement the reform, each firm sought the approval of the holders of TS for a compensation plan to accommodate the conversion of NTS to TS (Li et al. (2011)). These institutional details ensured that the split-share structure reform was conducted in a staggered manner. For example, 96.82% of the firms in our sample underwent the split-share reform in the first four years after 2005. This kind of a staggered adoption combined with the pre-reform prevalence of split-shares across different ownership structures provides us with a large cross-sectional sample that allows us to efficiently investigate the effect of stock liquidity on investment efficiency.

The adoption of the split-share structure reform increased the supply of shares at the firm level and hence consequently the stock liquidity, while keeping all other firm characteristics fixed because the two classes of shares had the same voting and cash flow rights, even prior to the reform (Jiang, Ma, and Shi (2017), Michaely and Qian (2017)). Some studies (e.g., Chen et al. (2011)) find that the reform improved corporate governance, while other studies, such as Liao, Liu, and Wang (2014), document only an immediate boost to output and profits but no lasting effect on corporate governance or operating efficiency. Therefore, to mitigate the effect on investment efficiency through the reform's potential to improve corporate governance, we control for observable corporate governance variables.

2.3.2. Unobservable Omitted Variables and Instrumental Variables Regression

To mitigate the concerns regarding omitted variables, we adopt a two-stage least squares approach, as in Fang, Noe, and Tice (2009). The first instrument we use, *IND_AVG_LIQ*, is the lagged average liquidity of all firms in the same industry-year as the sample firm. The fraction of a firm's stock liquidity correlated with its industry average is less likely to be correlated with firm-specific unobservable variables that can affect investment efficiency in our study. The second instrument we use is an indicator *POST*, which takes the value one if a firm has adopted split-share structure reform that, as argued earlier, provides an exogenous shock to stock liquidity. Both of our instrument variables are highly correlated with stock liquidity, thus satisfying the relevance criteria for instrumental variables. However, both lagged industry average liquidity and the passage of split-share structure reform are unlikely to be influenced by firm decisions, thereby satisfying the exclusion criteria for instrumental variables.

Using these two instrumental variables, we estimate the two-stage least squares regression. Specifically, we express the stock liquidity, *LIQ_A*, and the interaction between *LIQ_A* and *UNDER_PROP*, in its reduced form in Eq. (7). We estimate both these equations with OLS and the fitted values, *FIT_LIQ* and *FIT_LIQ*x*UNDER_PROP*, are used as instrumented variables for stock liquidity and the interact term, respectively, in Eq. (8) and Eq. (9).

$$LIQ\_A_{i,t}\ (or\ LIQ\_A_{i,t}\text{x}UNDER\_PROP_{i,t}) = a + bIND\_AVG\_LIQ_{i,t-1} + cPOST_{i,t} + dUNDER\_PROP_{i,t} + eUNDER\_PROP_{i,t}\text{x}IND\_AVG\_LIQ_{i,t-1} + fUNDER\_\ PROP_{i,t}\text{x}POST_{i,t} + g'Controls_{i,t} + IND_i + \varepsilon_{i,t}. \quad (7)$$

$$INV_{i,t+1} = a + bFIT\_LIQ_{i,t} + cUNDER\_PROP_{i,t} + dFIT\_LIQ_{i,t}\text{x}UNDER\_PROP_{i,t} + e'Controls_{i,t} + IND_i + \varepsilon_{i,t}. \quad (8)$$

$$|I\_DEV|_{i,t+1} = a + bFIT\_LIQ_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}. \quad (9)$$

2.3.3. Reverse Causality and Difference-in-difference estimation

To overcome reverse causality concerns, for example, investors seeking out (avoiding) over-investing (under-investing) firms, we perform a change regression and a Difference-in-Differences (DiD) estimation using the split-share structure reform, as described below.

Change Regression

The change in stock liquidity caused by the implementation of the split-share structure reform can help us identify the causal effect of stock liquidity on investment efficiency. Following Fang, Noe, and Tice (2009) and Edmans, Fang, and Zur (2013), we estimate the effect of a change in stock liquidity with respect to the split-share structure reform on investment efficiency. Specifically, we examine the probability of over- and under-investing, using a multinomial logit regression (Biddle, Hilary, and Verdi (2009)), and then examine the level of investment efficiency measured by *I_DEV* in the full sample and subsamples of under- and over-investing firms. In our estimation, we omit year and industry fixed effects, as all the variables, including the controls, are computed for all the firms as changes with respect to the split-shock structure reform initiated in 2005 for the majority of the firms and thus are unlikely to have any explanatory power. The specifications are shown below:

$$Pr(INV\_CHOICE=1or3) = a+b\Delta LIQ\_A_{i,(t+1)-(t-1)}+c'Controls_{i,(t+1)-(t-1)} + \varepsilon_{i,t}. \quad (10)$$

$$|I\_DEV|_{i,t+2} = a + b\Delta LIQ\_A_{i,(t+1)-(t-1)} + c'Controls_{i,(t+1)-(t-1)} + \varepsilon_{i,t}. \quad (11)$$

Difference-in-difference Estimation

Further exploiting this exogenous increase in stock liquidity caused by the split-share structure reform, following the methodology of Fang, Tian, and Tice (2014), we perform a DiD analysis. This involves the following three steps.

Step 1. Defining the Treatment Effect: China Split-Share Reform

For all Chinese publicly listed firms on the Shanghai and Shenzhen stock exchanges, we identify the fiscal year in which each firm transitions from a split-share structure to a single class of shares. Following Fang, Tian, and Tice (2014), considering all firms that undergo the split-share reform, we split our sample firms into those that experience a large change in liquidity and those that do not. Next, we build a propensity-score matched sample of firms by matching each treated firm (large change in liquidity) with a control firm (small change in liquidity). We create terciles of firms based on the change in average liquidity (*ΔLIQ_A*) in the three years before and after the adoption of the split-share structure reform. We define the treatment group as the firms in the top tercile, i.e., the firms that experience the largest change in stock liquidity during the reform period. We use the firms in the bottom and middle tercile as the control group. Because of a small sample of firms, including the middle tercile to the list of control firms allows our matching to be precise, by allowing more control firms to match with each treatment firm.

Step 2. Estimating the Treatment Effect: Difference-in-Differences Estimation

To obtain a consistent estimate of the treatment effect, we follow the standard econometric techniques used in economics to study the effectiveness of any new regulation or policy (Rubin (1973 a, b), Rosenbaum (1989, 1995), Dehejia and Wahba (1999), Colak and Whited (2007), Roberts and Whited (2012)). First, we define L as a binary treatment variable that is equal to one if the firm has a large increase in stock liquidity with respect to the split-share reform (being in the top tercile of liquidity change) (Fang, Tian, and Tice (2014)) and is equal to zero otherwise. Setting up our treatment outcome, namely, investment efficiency $I_i(L)$ as a function of treatment variable L for firm i, the expected value of the treatment effect for treated firms can be expressed as $E[I_i(1)|L = 1]$. In contrast, $E[I_i(0)|L = 1]$ is the counterfactual investment efficiency (i.e., hypothetical and unobservable) unaffected by the treatment, given that treatment actually occurs. To perform a DiD estimation of an average treatment effect with respect to the split-share reform, we compute $\Delta I_i(L)$ relative to its value before treatment. The average treatment effect on the treated (ATT) firms that witness a large increase in stock liquidity with respect to the split-share structure reform is given by:

$$ATT = \mathrm{E}[\Delta I_i(1) - \Delta I_i(0)|L = 1] \tag{12}$$

As $\mathrm{E}[\Delta I_i(0)|L = 1]$, the counterfactual is unobservable, and we estimate it by averaging $\Delta I_i(0)$ over the control observations.

Step 3. Matching Estimators: Propensity Score Matching Estimator

As long as the assignment to treatment is random among the population, the above proposed method to estimate the treatment effect can give a consistent estimate of the average treatment effect. Additionally, to minimize the difference in observable control variables before treatment, we construct a matched sample of treated and control firms. We employ a propensity-score matching algorithm as used in past studies (Colak and Whited (2007), Roberts and Whited (2012), Edmans, Fang, and Zur (2013), and Fang, Tian, and Tice (2014)). The propensity score models the probability of receiving treatment conditional on a set of observable covariates $\boldsymbol{Z}$,

$$pscore(\boldsymbol{Z}) = \Pr(L = 1|\boldsymbol{Z}) = \hat{\beta}\boldsymbol{Z} \tag{13}$$

where $\hat{\beta}$ is the maximum likelihood estimate of the baseline covariates and $\boldsymbol{Z}$ is the vector of covariates included in the model.[5] We estimate the propensity score by running the following probit regression of the indicator L for treatment.

$$pscore(\boldsymbol{Z}) = probit(\Pr(L = 1|\boldsymbol{Z})) = \widehat{\beta_0} + \widehat{\beta_1} LIQ\_A_{t-1} + \boldsymbol{X}'\,\widehat{\boldsymbol{\beta}} \tag{14}$$

where the vector of control variables, $\boldsymbol{X}$, includes stock liquidity, firm size, Tobin's *Q*, cash flow volatility, sales volatility, investment volatility, financial distress, tangibility, leverage, industry leverage, the ratio of cash to PPE, the operating cycle, the ratio of cash to assets, an indicator for dividend, an indicator for loss, and the pre-split-share structure reform changes in *I_DEV* and *INV*. The last two variables help satisfy the parallel trends assumption, as the DiD estimator will then be immune to any firm or industry characteristic (Fang, Tian, and Tice (2014)). We perform the propensity score matching with the nearest neighbourhood algorithm without replacement. We report our estimation results in Section 3.4.3.

3. Empirical Results

3.1. Data and Summary Statistics

[5] The propensity score matching estimator is parametric: if the assignment of treatment is assumed to be unconfounded (random) conditional on the set of observable pre-treatment variables ($\boldsymbol{Z}$), then one must only match the propensity score instead of $\boldsymbol{Z}$ (Rosenbaum and Rubin (1983)).

Our sample consists of 11,305 firm-year observations of non-financial Chinese firms listed in the Shanghai and Shenzhen stock exchanges between the years 2002 and 2015. We exclude firms with missing data in the China Stock Market and Accounting Research (CSMAR) and Wind databases. We also exclude firms that are relegated to the special treatment (ST) category by the CSRC due to having consecutive operational losses for two years or for accounting irregularities. We obtain daily return and annual financial data from CSMAR and supplement it with data on institutional equity ownership from Wind. We use the Thomson Reuters SDC database for obtaining data on mergers and acquisitions involving Chinese firms as targets.

To lessen the effect of outliers on our findings, we winsorize all continuous variables at the 1% and 99% levels. We report the definitions and summary statistics of our key variables in Tables 1 and 2, respectively. The mean/median values of our key dependent variables *INV* and *I_DEV* are 3.1% / 0.4% and 5.7% / 3.5%, with standard deviations of 9.8% and 7.6%, respectively, across all firm-years in our sample. The mean (median) measure of stock liquidity (*LIQ_A*) is -0.124 (-0.056), with a standard deviation of 0.192. The mean (median) value of total assets is 3.179 (2.820) billion RMB. Overall, our variables are consistent with other studies examining Chinese firms (Li et al. (2011), Liao, Liu, and Wang (2014), Michaely and Qian (2017)).

3.2. Effect of Stock Liquidity on Investment Efficiency

Table 3 reports the results of OLS regressions of stock liquidity on investment efficiency. Columns (1)–(3) examine the conditional relationship between investment and stock liquidity, i.e., conditional on a firm being more prone to under-invest, the way in which stock liquidity affects the firm's investments (Biddle, Hilary, and Verdi (2009)). To proxy for the under-investment propensity, we use a firm level measure, an economy level measure, and an industry-year level measure, in columns (1)–(3), respectively. The latter two measures offer plausibly exogenous measures of a firm's propensity to under-invest, as discussed earlier. In all the three columns, the interaction between *LIQ_A* and the propensity to under-invest is significant at the 1% level, indicating that conditional on being more prone to under-investment (over-investment), stock liquidity is positively (negatively) associated with investment. In terms of economic significance, the results in columns (1)–(3) suggests that a combined one-standard deviation increase in *LIQ_A* (0.192) and under-investment propensity measured by a firm level measure, an economy level measure, and an industry-year level measure (2.362; 2.874; 2.885) increases *INV* by 0.50, 0.44, and 0.44 percentage points, respectively, over and above the individual effect of these variables on *INV*. Given that the mean value of *INV* in our sample is 3.1%, this effect is economically meaningful.

To examine whether under-investing or over-investing firms drive the findings in columns (1)-(3), we examine the effect of stock liquidity on the absolute value of deviations for our full sample and subsamples of under- and over-investing firms in columns (4)–(6). Consistent with our hypothesis, we find that stock liquidity is significantly negatively associated with the deviation of expected investments only for the subsample of under-investing firms, as seen from the significantly negative coefficient in column (5). In terms of economic significance, a one standard deviation increase in *LIQ_A* (0.192) lowers |*I_DEV*| by 8.6% from the subsample mean. In column (6), we find that stock liquidity is not significantly associated with the deviation of expected investment when firms over-invest. This is consistent with our hypothesis that the effect of stock liquidity on investment efficiency is weaker on over-investing firms.

3.3. Effect of Stock Liquidity on Choice of Investment Level

As described in Section 2.2, we use a categorical variable *INV_CHOICE* that is defined to be increasing with the level of *I_DEV*. Using the middle two quartiles of *I_DEV* as the reference firms (or firms that invest normally), we then estimate choice of investment level as a function of stock liquidity, using a multinomial regression specification (Biddle, Hilary, and Verdi (2009)), and report the results in Table 4. In the first column, we find that the coefficient of stock liquidity is significantly negative when *INV_CHOICE* is one, suggesting that compared to firms that invest normally, firms with higher stock liquidity are less likely to under-invest. This finding is consistent with our hypothesis that stock liquidity is negatively associated with investment efficiency for under-investing firms. Examining the firms' choice to over-invest (i.e., *INV_CHOICE* = 3) in column (2), we find that compared to firms that invest normally, highly liquid firms show a greater likelihood of over-investing. This evidence when viewed with the results in Table 3 suggests that higher stock liquidity does not improve investment efficiency for firms prone to over-invest and at times can even worsen such investment behaviour.

3.4. Endogeneity

As discussed earlier, although the effect of stock liquidity on investment efficiency can be intuitively theorized, the empirical challenge lies in overcoming concerns of endogeneity due to unobservable omitted variables and reverse causality. In this section, we perform additional tests to mitigate these concerns.

3.4.1. Endogeneity: Two Stage Least Squares Regressions

Using the two instrumental variables, *IND_AVG_LIQ* and *POST*, as discussed earlier, we estimate the two-stage least squares regression and report the results in Table 5. The first stage regressions are shown in columns (1) and (2) for *LIQ_A* and $LIQ_A_{i,t}$x$UNDER\ PROP_{i,t}$, respectively. In column (4), the first stage regressions for *LIQ_A* without interaction terms are reported. The estimates for the second stage regressions using the fitted values obtained in the first stage are reported in columns (3) and columns (5)–(7). The second stage results correspond to the results in columns (1) and columns (4)–(6) of Table 3, but these results account for endogeneity. We find that our findings in Table 3 remain qualitatively unchanged. Specifically, we find in the first stages that our instrumental variables are highly correlated with *LIQ_A*. The Cragg-Donald statistic for weak identification is rejected at the 1% level (null hypothesis that the instruments are weak) in all the first stage regressions. In the second stage, modelling for the conditional relationship between stock liquidity and investment, we find that in column (3), the interaction term is positive and significant at the 1% level. The Sargan statistic in column (3) for over-identification is not rejected at the 10% level (the null hypothesis asserting that the specification is over-identified). This suggests that firms with greater propensity to under-invest are likely to invest more when their stock is more liquid, and the finding is robust to endogeneity concerns. Similarly, when using |*I_DEV*| as the dependent variable in the second stage, we find that stock liquidity is related to the level of investment efficiency only within the subsample of under-investing firms (column (6)), consistent with the findings in Table 3. In summary, these results confirm that our findings in Table 3 are robust to endogeneity concerns and support our hypothesis that firms with more liquid stocks have lower levels of under-investment.

3.4.2. Endogeneity: Change Regression

The results of the change regression estimated using Eq. (10) and Eq. (11) are presented in Table 6. In the multinomial specification in the first two columns, we find a negative and significant coefficient on *ΔLIQ_A*. This suggests that the increase in stock liquidity with respect to the split-share structure reform causes an improvement in investment efficiency for both under- and over-investing firms. However, we find that the coefficient in the first column has a higher magnitude, suggesting that the effect of stock liquidity on investment efficiency maybe stronger on mitigating under-investment. In columns (3)–(5), we confirm this observation. We find that *I_DEV* is negatively associated with the change in stock liquidity in the full sample as well as in the subsample of under-investing firms. However, in a subsample of over-investing firms, we do not find any significant coefficient on *ΔLIQ_A*.

3.4.3. Endogeneity: Difference-in-Difference Estimation

To further address endogeneity arising from reverse causality concerns, we perform a set of DiD estimations over the split-share structure reform. This allows a causal inference on the effect of stock liquidity on investment efficiency. Thus, by using this exogenous increase in stock liquidity to identify its effect on investment efficiency, we exploit the reform as a quasi-natural experiment. As discussed earlier in Section 2.3.3, we sort firms into terciles based on the change in average *LIQ_A* in the pre- and post-three years of the split-share structure reform. Firms in the top tercile constitute the treatment, while the remaining firms are included as the control group, implying that the treated firms have the largest increases in stock liquidity with respect to the reform. Next, we match each treatment firm to a control firm, computing the propensity-score using a nearest neighbourhood algorithm without replacement. With the propensity-score matched sample, for the reform adoption year, we compare changes in firm investment efficiency between the treated and control firms.

New variable definitions used in the DiD analysis are presented in Table 7 Panel A. For performing the multivariate analysis using the matched sample, following Fang, Tian, and Tice (2014), we define some additional key explanatory variables. In Panels B to D, we obtain the propensity-score matched sample and perform various diagnostic tests similar to Fang, Tian, and Tice (2014). Panel B of Table 7 presents estimates of a probit model in which the dependent variable is an indicator that takes the value of one for firms in the treatment group and zero otherwise. The *pseudo-*R^2 in column (1) is a high 52.0%, suggesting that significant variation in the treatment assignment is captured by our matching variables. Using these predicted probabilities from the probit model, we perform a nearest-neighbourhood propensity-score matching without replacement. Firms in the top tercile of stock liquidity changes are matched with the remaining control firms with the closest propensity-score. This procedure provides us with 132 firms constituting the treated and control firm pairs. In column (2) of Panel B, we estimate the probit model within the matched sample and find that none of the matching variables are statistically significant in explaining the likelihood of treatment, which reinforces the validity of the DiD estimate. The *pseudo-*R^2 also drops drastically from 52.0% to 6.4%, suggesting that there is no significant difference between treated and control firms in terms of observables and that therefore assignment to treatment can be plausibly thought of as being random within this matched group of firms. Additionally, the distribution of propensity-scores between the treated and control firms reported in Panel C shows a trivial difference between the two groups of firms. In Panel D, we compare the differences in mean and the corresponding *t*-statistics between various observable firm characteristics in our matched sample. All of the differences are insignificant at conventional levels. This helps satisfy the Rosenbaum and Rubin (1983) unconfoundedness assumption, i.e., differences in the pre-treatment firm characteristics in our sample are statistically indistinguishable. In combination, the results in Panels B to D validate the use of the propensity-score matching estimator and alleviates any concern about the validity of our DiD estimator.

Panel E of Table 7 reports the results of the univariate DiD estimator using our propensity-score matched sample. First, unsurprisingly, we find that within our full sample of firms, both *INV* and *I_DEV* do not appear to be statistically affected by the split-share structure reform. However, as we hypothesized, when we divide the sample into under- and over-investing firms, we find acute differences. In dividing the sample, consistent with our baseline specification in Table 3, we split the sample using an ex ante (ex post) measure of investment propensity (investment efficiency) when examining the difference in *INV* (*I_DEV*). Specifically, we find that under-investing firms grouped as defined above invest more and deviate significantly less when the split-share structure reform considerably improves their stock liquidity. On the other hand, the DiD estimates for over-investing firms are opposite in sign, although significant (i.e., invest less but deviate more), suggesting that the increase in stock liquidity brought on by the split-share structure reform does not affect their investment efficiency in a significant manner. These findings show that stock liquidity has a causal effect on under-investment. The average treatment effect of *LIQ_A* on under-investing firms' *INV* (*I_DEV*) is an increase by 0.034 (decrease by 0.025). Given that the average pre-split-share structure reform *INV* (*I_DEV*) in the subsample of under-investing firms is 0.017 (0.069), this effect is economically large.

Panel F of Table 7 reports the results of the multivariate tests using the DiD matched sample. To interpret the time-varying effects of the split-share structure reform, we use new explanatory variables. Specifically, we define *BEFORE* as a new variable that takes the value of one for a firm-year observation one year prior to the split-share reform and zero otherwise. Next, we define an indicator variable, *CURRENT*, that takes the value of one for a firm-year observation in the year of the split-share reform and zero otherwise. Finally, we define an indicator variable, $AFTER^{1}$ ($AFTER^{23}$), that takes the value of one for a firm-year observation one year (two to three years) after the split-share reform and zero otherwise. With *INV* and *I_DEV* measured in the subsequent years following the split-share structure reform as the dependent variable, we perform multivariate regressions. We include all the controls in Table 3 and industry fixed effects. As in panel E, we estimate the regressions using the full sample and the subsamples of under- and over-investing firms formed as discussed earlier. In column (1), we find that *INV* increases in the full sample following the split-share structure reform, which is consistent with Liao, Liu, and Wang (2014), who find that the split-share structure reforms boost immediate output. In column (2) (column (3)), we find that this effect is evident in the first year, i.e., $TREAT\text{x}AFTER^{1}$ (second and third years, i.e., $TREAT\text{x}AFTER^{23}$), with a positive and significant coefficient. This suggests that the reforms improve investment efficiency of under-investing firms, while worsening those of over-investing firms. In columns (4)–(6), examining *I_DEV*, we find similar evidence. *I_DEV* is lower (higher) for under-investing (over-investing) firms in the second and third years following the split-share structure reform, as seen from the negative (positive) and significant coefficient on $TREAT\text{x}AFTER^{23}$. In summary, these results suggest that stock liquidity has a causal effect on improving investment efficiency for under-investing firms.

3.5. How Does Stock Liquidity Improve Under-Investment Problem?

To examine the mechanism through which stock liquidity improves the under-investment problem, we explore various explanations, including the effect on institutional ownership, takeover probability, and financial constraints. As discussed in Section 1, an increase in institutional ownership and takeover probability can increase external monitoring of the firm, leading to an improvement in investment efficiency. On the other hand, a relaxation of financial constraints can help firms overcome capital constraints and subsequently investment policies of the firm.

Therefore, in our full sample and the subsamples of under- and over-investing firms, we examine the effect of the split-share structure reform on institutional ownership, takeover probability, and a measure of financial constraints. We measure institutional ownership as the total proportion of shares outstanding held by discretionary institutional investors as categorized by the Wind database. Using data from the Thomson Reuters SDC database, we measure the takeover probability as an indicator variable that takes the value of one if the firm receives any M&A proposal and zero otherwise. Financial constraints are measured using the Hadlock and Pierce (2010) financial constraints index. In terms of specification, we use the change regressions instead of the DiD framework, as that allows us to maximize our sample.

The results are presented in Table 8. In Panel A, using institutional ownership as the dependent variable, we find that institutional ownership decreases in the full sample with an increase in *LIQ_A* but not in a significant manner. Splitting the sample into under- and over-investing subsamples in columns (2) and (3), respectively, we find that when *LIQ_A* increases, institutional ownership decreases in a significant manner among over-investing firms, whereas it increases insignificantly among under-investing firms. This suggests that the increase in stock liquidity weakens voice strategies and encourages exit among over-investing firms that are more likely to be afflicted by governance problems. On the other hand, the continued presence of institutional ownership in under-investing firms suggests that voice strategies continue to work among them.

In Panel B, examining the change in takeover probability using a logit model, we find that the takeover probability increases insignificantly with stock liquidity in the full sample in column (1). Splitting the sample into subsamples, we find that the increase in takeover probability is significantly (insignificantly) associated with the increase in stock liquidity for under-investing (over-investing) firms. This suggests that managers at under-investing firms face a higher risk of losing their jobs through acquisitions and therefore face more pressure to follow efficient investment policies.

In Panel C, examining the change in HP index, we find that when stock liquidity increases, financial constraints are relaxed (decreasing HP index) for all firms, including the under- and over-investing firms. To the extent that under-investing firms avoid investing in projects due to lack of financing options, this easing in financial constraints will lead to more efficient investment choices in the future. However, the relaxation of financial constraints for over-investing firms can have no positive effect on their investment efficiency, as it does not encourage them to avoid over-investment.

In summary, the results in Table 8 show that when happening as a result of an increase in stock liquidity, the persistence of institutional ownership, an increase in takeover risk, and a relaxation of financial constraints can help improve investment efficiency for firms that are more prone to under-investment.

3.6 Additional Tests

In additional untabulated tests, we replace our key liquidity variable with alternate measures of stock liquidity. The Amihud measure *LIQ_A* might overstate (understate) liquidity for smaller (larger) firms because of not accounting for price levels, which magnifies (reduces) price impact for firms with low (high) absolute stock prices (Brennan and Subrahmanyam (1996), Michaely and Qian (2016)). However, using alternate measures, such as the turnover ratio, which explicitly control for market capitalization, overcomes this concern, and we find that our key findings are unchanged. Specifically, we compute the turnover ratio as the monthly trading volume in stock measured in RMB divided by the shares outstanding, and we use the annual average. We also compute trading volume as the natural logarithm of total trading volume measured in RMB. We repeat the tests in Table 3 and find that our results are qualitatively unchanged, using a conditional relationship model between investment and stock liquidity, i.e., using stock liquidity measured as turnover and trading volume, we find the interaction term between the liquidity variables and the exogenous measure of under-investment propensity to be significant at the 1% level. This suggests that the finding that firms with greater propensity to under-invest are able to improve their investment when their stock is more liquid is robust to using alternative measures of stock liquidity.

Next, in untabulated tests, we also use alternative measures for *INV* and examine the robustness of our findings. Although these alternative definitions as defined below are more inclusive in capturing the different aspects of investment behaviour of the firms, we rely on a much simpler definition of *INV* in our baseline tests because these additional components are not reliably available for all listed Chinese firms (Wu, Gyourko, and Deng (2015)). For alternative measures, first, we compute *INV* as the sum of the change in net fixed assets and net acquisition payments (i.e., payments made to acquire subsidiaries/business units minus payments received from the sale of subsidiaries/business units). Second, we compute *INV* as the sum of the change in net fixed assets, net acquisition payments, the change in investments classified as construction in progress, and investment properties. The latter two components help determine the real estate investments of the firm. Using these two alternative definitions of *INV*, we repeat all our tests in Table 3 and find qualitatively similar results. Thus, our findings about the relationship between stock liquidity and investment efficiency is not a manifestation of a specific definition of *INV*.

4. Conclusion

The ‘feedback effect’, i.e., the effect resulting when managers view the stock market as providing feedback on their decisions, suggests that investment decisions at the firm can be affected by stock market liquidity. Similarly, incentive theories suggest that the effectiveness of incentive compensation offered to managers and the incentives for large shareholders to monitor will increase with greater stock liquidity. In this paper, we empirically examine the relationship between investment efficiency and stock liquidity. We exploit the split-share structure reform in China that provided an exogenous shock to stock liquidity; this allows us to make plausibly causal inferences about the relationship. We find evidence that stock liquidity improves the investment of firms that are more prone to under-investment and thus consequently improves their investment efficiency. A one standard deviation increase in stock liquidity reduces under-investment by 8.6%. From a difference-in-differences estimation with respect to the split-share reform, for under-investing firms, we find the average treatment effect of stock liquidity on investment inefficiency to be a 36% improvement over the pre-split-share reform period. However, for firms that are more prone to over-investment, we do not find such a positive relationship between stock liquidity and investment efficiency.

By investigating the channels through which stock liquidity affects investment efficiency, we find that an increase in stock liquidity is associated with a relaxation of financial constraints, an increase in takeover risk for under-investing firms, and a decrease in institutional ownership of over-investing firms. These findings explain why under-investing firms appear to benefit more from an increase in stock liquidity, as institutional owners persist with these firms, managers face an increasing job threat from acquisitions, and external capital becomes more available. Our findings are robust to the use of different specifications with both the full sample and sub-samples of Chinese firms, as well as with respect to the time periods related to the split-share reform event. Our findings are also unchanged for various alternative definitions of investment efficiency and stock liquidity.

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Table 1: Variable Definitions

Measures of Investment	
INV	Measured as the change in net fixed assets scaled by lagged total assets
|*I_DEV*|	Computed as the absolute value of the residuals from industry-year cross-sectional regressions of *INV* on lagged sales growth
Measures of Liquidity and other control variables	
LIQ_A	-log(1+Amihud measure of illiquidity)
LOGASSET	Logarithm of total assets
TOBIN'S Q	Ratio of market value of total assets to book value of assets
SD_CFO	Standard deviation of the ratio of cash flow from operations to total assets from years t-5 to t-1
SD_SALE	Standard deviation of sales to total assets from years *t*-5 to *t*-1
SD_INV	Standard deviation of *INV* from years t-5 to t-1
Z	Altman Z score computed as ((3.3 x pretax income+sales+1.4 x retained earnings+1.2 x (current assets-current liabilities))/total assets).
TANG	Ratio of property, plant, and equipment to total assets
KSTR	Ratio of long-term debt to the sum of long-term debt and the market value of equity
IND_KSTR	Mean KSTR for firms in the same industry
CFO_Sale	Ratio of cash flow from operations (CFO) to sales
SLACK	Ratio of cash to property, plant, and equipment (PPE)
DIV	An indicator variable that takes the value of one if the firm paid a dividend and zero otherwise
AGE	Number of years the firm has traded in the secondary market
OPERATINGCYCLE	Logarithm of {360 x (receivables/sales + inventories/COGS)}
LOSS	An indicator variable that takes the value of one if net income is negative and zero otherwise
CASH	Ratio of cash and cash equivalents to total assets
ANALYSTS	Number of analysts who have published at least one firm report in the firm-year
SOE	An indicator variable that takes the value of one if the firm is a state-owned enterprise (i.e., the controlling shareholder is the government or its related entities)
CEO_DUAL	An indicator variable that takes the value of one if the CEO of a firm is their chairman as well and zero otherwise

Table 2: Summary Statistics

This table reports summary statistics for variables constructed using a sample of Chinese public firms. The sample consists of non-financial firms with non-missing data in the CSMAR and Wind databases between the years 2002 and 2015. Firms that are relegated to the special treatment (ST) category are excluded. All the variables are defined in Table 1.

Variable	5%	25%	Median	Mean	75%	95%	*SD*	*N*
|I DEV|	0.003	0.015	0.035	0.057	0.065	0.195	0.076	11,305
INV	-0.058	-0.011	0.004	0.031	0.044	0.205	0.098	11,305
LIQ_A	-0.506	-0.123	-0.056	-0.124	-0.028	-0.009	0.192	11,305
LOGASSET	20.070	21.010	21.760	21.880	22.600	24.210	1.252	11,305
TOBIN'S Q	0.346	0.761	1.374	1.976	2.453	5.787	1.859	11,305
SD_CFO	0.014	0.031	0.049	0.060	0.076	0.145	0.043	11,305
SD_SALE	0.026	0.060	0.102	0.140	0.171	0.389	0.129	11,305
SD_INV	0.006	0.025	0.053	0.073	0.099	0.227	0.065	11,305
Z	0.649	1.748	3.041	5.335	5.589	17.890	7.573	11,305
TANG	0.018	0.125	0.231	0.263	0.377	0.607	0.179	11,305
KSTR	0.000	0.059	0.174	0.192	0.294	0.478	0.154	11,305
IND_KSTR	0.098	0.120	0.180	0.182	0.220	0.291	0.066	11,305
CFO_Sale	-0.221	0.008	0.071	0.074	0.159	0.414	0.240	11,305
SLACK	0.073	0.265	0.638	2.494	1.604	9.468	7.137	11,305
DIV	0.000	0.000	1.000	0.621	1.000	1.000	0.485	11,305
AGE	8.000	12.000	15.000	15.470	19.000	24.000	5.177	11,305
OPERATINGCYCLE	3.262	4.354	5.022	5.039	5.667	7.054	1.104	11,305
LOSS	0.000	0.000	0.000	0.119	0.000	1.000	0.323	11,305
CASH	0.028	0.081	0.133	0.162	0.214	0.401	0.115	11,305
ANALYSTS	0.000	0.000	2.000	6.088	9.000	25.000	8.367	11,305
SOE	0.000	0.000	1.000	0.610	1.000	1.000	0.488	11,305
CEO_DUAL	0.000	0.000	0.000	0.191	0.000	1.000	0.393	11,305

Table 3: Effect of Liquidity on Investment Efficiency

This table presents estimates of the pooled OLS regressions of investment efficiency. The sample consists of non-financial firms with non-missing data in the CSMAR and Wind databases between the years 2002 and 2015. Firms that are relegated to the special treatment (ST) category are excluded. Columns (1)-(3) report results of the model $INV_{i,t+1} = a + bLIQ\_A_{i,t} + cUNDER\_PROP_{i,t} + dLIQ\_A_{i,t}xUNDER\_PROP_{i,t} + e'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}$. Columns (4)-(6) report results of the model $|I\_DEV|_{i,t+1} = a + bLIQ\_A_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}$. *UNDER_PROP* is a ranked variable based on the average of a ranked measure of cash and leverage deciles, in which cash is multiplied by minus one to allow both variables to be increasing in the likelihood of under-investment. *UNDER_AGGPROP* is a ranked variable based on the abnormal aggregate investment rate for all listed firms in the economy. It is computed as the negative of the residual from regressing all firm-year *INV* on firm-year lagged sales growth. *UNDER_INDPROP* is a ranked variable based on the abnormal aggregate investment rate for all firms in the same industry-year. It is computed as the negative of the residual from regressing the firm-year *INV* on the firm-year lagged sales growth for each industry-year. The residuals for both *UNDER_AGGPROP* and *UNDER_INDPROP* are multiplied by minus one to allow the measure to be increasing in the likelihood of under-investment. In column (5) (column (6)), the model is estimated on the subsample of under-investing firms (over-investing firms), identified as those firms that have a negative (positive) *I_DEV*. Robust standard errors clustered by firm are displayed in parentheses below the coefficients. All the remaining variables are defined in Table 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var: *INV*			Dep. var: |*I_DEV*|		
	Under-investment propensity measured using			Full sample	Under-investing subsample	Over-investing subsample
	Firm-level cash & leverage	Aggregate I_DEV	Aggregate I_DEV by industry-year			
Variables	(1)	(2)	(3)	(4)	(5)	(6)
LIQ_A: A	0.019*	-0.059***	-0.062***	-0.013	-0.020***	-0.010
	(0.011)	(0.020)	(0.021)	(0.008)	(0.005)	(0.019)
UNDER_PROP: B	0.002					
	(0.002)					
UNDER_AGGPROP: C		-0.025***				
		(0.000)				
UNDER_INDPROP: D			-0.025***			
			(0.000)			
A x *B*	0.011***					
	(0.003)					
A x *C*		0.008***				
		(0.002)				
A x *D*			0.008***			
			(0.002)			
Control Variables						
LOGASSET	-0.000	-0.001	-0.000	-0.002**	-0.001	-0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
TOBIN'S Q	0.005***	0.004***	0.004***	0.005***	0.001**	0.012***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
SD_CFO	0.027	0.058***	0.043**	0.017	0.003	0.016
	(0.028)	(0.020)	(0.020)	(0.022)	(0.011)	(0.053)
SD_SALE	-0.014	-0.017***	-0.016**	-0.007	-0.001	-0.024
	(0.010)	(0.006)	(0.006)	(0.006)	(0.004)	(0.015)
SD_INV	0.069***	0.044***	0.047***	0.058***	0.011	0.113***
	(0.023)	(0.017)	(0.016)	(0.017)	(0.010)	(0.042)

Z	0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
TANG	-0.099***	-0.020***	-0.030***	0.012	0.059***	-0.060***
	(0.012)	(0.007)	(0.008)	(0.008)	(0.005)	(0.021)
KSTR	0.055***	0.020***	0.020***	0.031***	-0.000	0.059***
	(0.020)	(0.007)	(0.007)	(0.007)	(0.004)	(0.019)
IND_KSTR	-0.067	-0.015	0.021	-0.069**	-0.054**	-0.059
	(0.049)	(0.034)	(0.033)	(0.034)	(0.022)	(0.080)
CFO_Sale	0.008	0.007*	0.005	0.002	-0.003	0.009
	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)	(0.009)
SLACK	0.000	0.000**	0.000*	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DIV	0.001	-0.007***	-0.006***	-0.008***	-0.005***	-0.017***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
AGE	-0.001***	0.000	0.000	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OPERATINGCYCLE	-0.011***	-0.008***	-0.007***	-0.006***	-0.000	-0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
LOSS	-0.023***	-0.009***	-0.008***	0.006**	0.013***	-0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.009)
CASH	-0.032	-0.023***	-0.026***	-0.014	0.010**	-0.049**
	(0.023)	(0.008)	(0.008)	(0.009)	(0.005)	(0.023)
ANALYSTS	0.001***	-0.000***	-0.000**	-0.000	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SOE	0.003	0.003	0.002	0.002	-0.002	0.011**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
CEO_DUAL	0.004	0.001	0.000	0.002	0.000	0.005
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
CONSTANT	0.117***	0.216***	0.163***	0.114***	0.038**	0.243***
	(0.038)	(0.028)	(0.028)	(0.030)	(0.018)	(0.069)
Industry fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	9,454	9,454	9,454	9,433	6,193	3,240
R-squared	0.075	0.565	0.566	0.122	0.257	0.161

Table 4: Multinomial Logit Regression of Choice of Investment Level

This table presents estimates of the multinomial regressions of the choice of investment levels. The sample consists of non-financial firms with non-missing data in the CSMAR and Wind databases between the years 2002 and 2015. Firms that are relegated to the special treatment (ST) category are excluded. The table reports multinomial regression results of the model $INV\_CHOICE_{i,t+1} = a + bLIQ\_A_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}$. *INV_CHOICE* is a categorical variable that takes the value of 1 for the bottom quartile of *I_DEV*, the value of 3 for the top quartile of *I_DEV*, and 2 otherwise. The regression jointly estimates the propensity of firms to under-invest (*INV_CHOICE* = 1) or over-invest (*INV_CHOICE* = 3) when compared to remaining firms (*INV_CHOICE* = 2). Robust standard errors clustered by firm are displayed in parentheses below the coefficients. All the variables are defined in Table 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Base case: Optimal investing (*INV_CHOICE* = 2)	
Variables	Case 1: Under-investing (*INV_CHOICE* = 1)	Case 2: Over-investing (*INV_CHOICE* = 3)
LIQ_A	-0.440**	0.457**
	(0.211)	(0.228)
LOGASSET	-0.166***	-0.104**
	(0.044)	(0.041)
TOBIN'S Q	-0.005	0.071**
	(0.031)	(0.028)
SD_CFO	0.745	0.111
	(0.736)	(0.800)
SD_SALE	0.208	0.268
	(0.258)	(0.223)
SD_INV	1.319**	1.509***
	(0.526)	(0.492)
Z	0.008	0.003
	(0.006)	(0.006)
TANG	2.956***	0.621**
	(0.269)	(0.266)
KSTR	0.021	1.575***
	(0.250)	(0.229)
IND_KSTR	-2.463**	-2.473**
	(1.166)	(1.106)
CFO_Sale	0.171	0.408***
	(0.152)	(0.142)
SLACK	-0.040***	-0.004
	(0.013)	(0.005)
DIV	-0.149**	0.034
	(0.071)	(0.073)
AGE	0.022***	-0.025***
	(0.007)	(0.007)
OPERATINGCYCLE	0.048	-0.135***
	(0.043)	(0.041)
LOSS	0.421***	-0.102
	(0.098)	(0.103)
CASH	0.338	-0.401
	(0.350)	(0.317)
ANALYSTS	-0.033***	0.018***
	(0.005)	(0.004)
SOE	-0.012	-0.055
	(0.068)	(0.069)
CEO_DUAL	-0.051	0.123*
	(0.077)	(0.073)
CONSTANT	0.330	1.948*
	(1.089)	(1.003)
Industry fixed effects	Y	
Year fixed effects	Y	
Observations	9,433	
Pseudo R-squared	0.103	

Table 5: Instrumental Variable Regression of the Effect of Liquidity on Investment Efficiency

This table presents estimates of 2SLS regressions of investment efficiency. The sample consists of non-financial firms with non-missing data in the CSMAR and Wind databases between the years 2002 and 2015. Firms that are relegated to the special treatment (ST) category are excluded. We use *IND_AVG_LIQ* and an indicator for *POST* as the instrument variables for *LIQ_A* in 2SLS regressions. The first instrument, *IND_AVG_LIQ*, is the lagged mean liquidity of all firms in the same industry-year as the sample firm. The second instrument, *POST*, is an indicator that takes the value of one for firm-years in which the firm has completed the split-share reform and zero otherwise. The first stage regressions reported in columns (1) and (2) estimate the model $LIQ_{i,t}$ ($LIQ_{i,t}$x$UNDER_PROP_{i,t}$ in column (2)) = $a + bIND\_AVG\_LIQ_{i,t-1} + cPOST_{i,t} + dUNDER\_PROP_{i,t} + eUNDER\_PROP_{i,t}xIND\_AVG\_LIQ\_A_{i,t-1} + fUNDER\_PROP_{i,t}xPOST_{i,t} + g'Controls_{i,t} + IND_i + \varepsilon_{i,t}$. The first stage regression reported in column (4) estimates the model $LIQ_{i,t} = a + bIND\_AVG\_LIQ_{i,t-1} + cPOST_{i,t} + d'Controls_{i,t} + IND_i + \varepsilon_{i,t}$. The second stage regression reported in column (3) estimates the model $INV_{i,t+1} = a + bFIT\_LIQ_{i,t} + cUNDER\_PROP_{i,t} + dLIQ\_A_{i,t}xUNDER\_PROP_{i,t} + e'CONTROLS_{i,t} + IND_i + error_{i,t}$. The second stage regressions reported in columns (5)-(7) estimates the model $|I\_DEV|_{i,t+1} = a + bFIT\_LIQ_{i,t} + c'Controls_{i,t} + YR_t + IND_i + \varepsilon_{i,t}$. *UNDER_PROP* is a ranked variable based on the average of a ranked measure of cash and leverage deciles, in which cash is multiplied by minus one to allow both variables to be increasing in the likelihood of under-investment. *UNDER_PROP (indicator)* is assigned the value of one when *UNDER_PROP* is greater than zero and zero otherwise. In column (6) (column (7)), the model is estimated on the subsample of under-investing firms (over-investing firms), identified as those firms that have a negative (positive) *I_DEV*. Robust standard errors clustered by firm are displayed in parentheses below the coefficients. All the remaining variables are defined in Table 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var.: *LIQ_A*	Dep. var.: *LIQ_A* x *UNDER_PROP*	Dep. var.: *INV*	Dep. var.: *LIQ_A*	Dep. var.: |*I_DEV*|	Dep. var.: |*I_DEV*|	Dep. var.: |*I_DEV*|
	Full sample					Under-investing subsample	Over-investing subsample
	1st Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	2nd Stage	2nd Stage
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LIQ_A: A			-0.058**		-0.029**	-0.021**	-0.024
			(0.027)		(0.013)	(0.009)	(0.037)
UNDER_PROP (indicator): B	-0.033***	-0.179***	0.007				
	(0.012)	(0.012)	(0.004)				
A x *B*			0.063***				
			(0.023)				
Instrumental Variables							
IND_AVG_LIQ: C	0.187***	-0.105***		0.212***			
	(0.024)	(0.011)		(0.019)			
POST (indicator): D	0.091***	-0.002		0.116***			
	(0.008)	(0.003)		(0.007)			
B x *C*	0.037	0.410***					
	(0.029)	(0.025)					
B x *D*	0.050***	0.151***					
	(0.012)	(0.011)					
Control Variables							
LOGASSET	0.058***	0.035***	0.003	0.059***	-0.001	-0.001	-0.006
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)
TOBIN'S Q	0.030***	0.016***	0.005***	0.030***	0.005***	0.001*	0.011***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)
SD_CFO	-0.025	0.004	0.030	-0.021	0.013	-0.013	0.058
	(0.059)	(0.042)	(0.030)	(0.060)	(0.022)	(0.013)	(0.058)

SD_SALE	-0.041**	-0.019	-0.018*	-0.040**	-0.009	-0.001	-0.032*
	(0.017)	(0.012)	(0.010)	(0.017)	(0.007)	(0.004)	(0.017)
SD_INV	-0.002	0.024	0.106***	0.000	0.073***	0.005	0.159***
	(0.036)	(0.029)	(0.025)	(0.036)	(0.018)	(0.011)	(0.046)
Z	-0.000	-0.001***	-0.000	-0.000	-0.000	-0.000	-0.001**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
TANG	0.026	0.014	-0.100***	0.029	0.014	0.061***	-0.068***
	(0.026)	(0.018)	(0.013)	(0.026)	(0.009)	(0.005)	(0.025)
KSTR	-0.037	-0.042*	0.053***	-0.041*	0.029***	-0.001	0.060***
	(0.025)	(0.022)	(0.013)	(0.023)	(0.008)	(0.005)	(0.020)
IND_KSTR	-0.837***	-0.428***	-0.069	-0.825***	-0.048	-0.020	-0.105
	(0.087)	(0.062)	(0.043)	(0.088)	(0.030)	(0.021)	(0.075)
CFO_Sale	0.009	0.009	0.009*	0.009	0.005	-0.001	0.015*
	(0.010)	(0.008)	(0.005)	(0.010)	(0.004)	(0.002)	(0.009)
SLACK	0.000	0.000	0.000	0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DIV	0.027***	0.014***	0.002	0.028***	-0.007***	-0.005***	-0.014***
	(0.005)	(0.004)	(0.003)	(0.005)	(0.002)	(0.001)	(0.005)
AGE	0.001	0.000	-0.000*	0.000	0.000	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
OPERATINGCYCLE	0.004	-0.001	-0.009***	0.004	-0.005***	0.000	-0.011***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)
LOSS	-0.027***	-0.031***	-0.024***	-0.029***	0.004	0.012***	-0.007
	(0.008)	(0.007)	(0.004)	(0.008)	(0.003)	(0.002)	(0.009)
CASH	0.064**	0.029**	-0.041***	0.065***	-0.016*	0.009*	-0.059**
	(0.028)	(0.014)	(0.014)	(0.025)	(0.009)	(0.005)	(0.027)
ANALYSTS	-0.001***	-0.001***	0.001***	-0.001***	-0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SOE	-0.028***	-0.012***	0.004	-0.029***	0.002	-0.002*	0.009*
	(0.005)	(0.004)	(0.003)	(0.005)	(0.002)	(0.001)	(0.005)
CEO_DUAL	0.007	0.002	0.004	0.009	0.004*	0.001	0.009*
	(0.006)	(0.004)	(0.003)	(0.006)	(0.002)	(0.001)	(0.006)
CONSTANT	-1.364***	-0.731***	0.007	-1.398***	0.072**	0.026	0.222**
	(0.086)	(0.062)	(0.049)	(0.085)	(0.035)	(0.022)	(0.097)
Industry fixed effects	Y	Y	Y	Y	Y	Y	Y
First-stage Cragg-Donald statistic (Weak identification test)	*F*-stat: 101.86 (0.00)	*F*-stat: 105.60 (0.00)		*F*-stat: 199.22 (0.00)			
Second-stage Sargan statistic (Over identification test)			*Chi*^{2} stat: 4.78 (0.10)		*Chi*^{2} stat: 4.42 (0.04)	*Chi*^{2} stat: 10.21 (0.00)	*Chi*^{2} stat: 0.81 (0.37)
Observations	7,728	7,728	7,728	7,728	7,728	5,184	2,544
R-squared	0.495	0.565	0.069	0.491	0.122	0.255	0.172

Table 6: Effect of Liquidity Changes Around Split-Share Reform on Investment Efficiency

This table presents estimates of the multinomial regressions of the choice of investment levels and the OLS regressions of investment efficiency. The sample consists of non-financial firms that have non-missing data in the CSMAR and Wind databases between the years 2002 and 2015 and that experienced the split-share reform during this period. Firms that are relegated to the special treatment (ST) category are excluded. Columns (1) and (2) report multinomial regression results of the model $INV\_CHOICE_{i,t+2} = a + b\Delta LIQ\_A_{i,t\text{-}1\ to\ t+1} + c'\Delta Controls_{i,t\text{-}1\ to\ t+1} + \varepsilon_{i,t\text{-}1\ to\ t+1}$. *INV_CHOICE* is a categorical variable that takes the value of 1 for the bottom quartile of *I_DEV*, the value of 3 for the top quartile of *I_DEV*, and 2 otherwise. Model (1) jointly estimates the propensity of a firm to under-invest *(INV_CHOICE* = 1) or over-invest (*INV_CHOICE* = 3) when compared to remaining firms (*INV_CHOICE* = 2). Columns (2)-(4) report the OLS regression results of the model $|I\_DEV|_{i,t+2} = a + b\Delta LIQ\_A_{i,t\text{-}1\ to\ t+1} + c'\Delta Controls_{i,t\text{-}1\ to\ t+1} + \varepsilon_{i,t\text{-}1\ to\ t+1}$. In column (3) (column (4)), the model is estimated on the subsample of under-investing firms (over-investing firms), identified as those firms that have a negative (positive) *I_DEV*. Δ denotes the change in each variable from the fiscal year before the split-share reform (year *t-1*) to the fiscal year after the split-share reform (year *t+1*), with *t* indicating the year during which the firm underwent the split-share reform. Robust standard errors are displayed in parentheses below the coefficients. All the remaining variables are defined in Table 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Multinomial logit regression		Pooled OLS regression		
	Base case: Optimal investing (*INV_CHOICE* = 2)		Dep. var.: *I_DEV*		
	Case 1: Under-investing (*INV_CHOICE* = 1)	Case 2: Over-investing (*INV_CHOICE* = 3)	Full sample	Under-investing subsample	Over-investing subsample
Variables	(1)		(2)	(3)	(4)
ΔLIQ_A	-0.832***	-0.591**	-0.032***	-0.016**	-0.038
	(0.292)	(0.285)	(0.011)	(0.007)	(0.026)
ΔLOGASSET	-0.745***	0.102	0.010	-0.008**	0.028
	(0.254)	(0.186)	(0.009)	(0.004)	(0.021)
ΔTOBIN'S Q	-0.002	0.121**	0.003	0.000	0.003
	(0.066)	(0.057)	(0.002)	(0.001)	(0.007)
ΔZ	-0.026	-0.023	-0.001	-0.000	-0.001
	(0.023)	(0.017)	(0.001)	(0.000)	(0.003)
ΔTANG	0.100	-0.285	-0.026	0.052**	-0.117
	(0.875)	(0.751)	(0.036)	(0.020)	(0.072)
ΔKSTR	-0.040	1.196	0.056**	-0.025	0.134**
	(0.791)	(0.851)	(0.028)	(0.019)	(0.059)
ΔCFO_Sale	0.725**	-0.289	-0.008	0.008	-0.014
	(0.349)	(0.303)	(0.009)	(0.009)	(0.020)
ΔSLACK	-0.021	0.014	0.000	0.001	-0.000
	(0.015)	(0.014)	(0.001)	(0.000)	(0.001)
ΔDIV	0.284	-0.210	-0.011**	0.000	-0.027**
	(0.177)	(0.173)	(0.006)	(0.003)	(0.012)
ΔOPERATINGCYCLE	-0.180	-0.070	-0.019**	-0.004	-0.039**
	(0.182)	(0.139)	(0.008)	(0.004)	(0.017)
ΔLOSS	0.386*	0.143	0.004	0.016***	-0.023*
	(0.219)	(0.202)	(0.005)	(0.005)	(0.013)
ΔCASH	-2.027**	0.501	-0.015	-0.032*	-0.049
	(1.012)	(0.885)	(0.029)	(0.019)	(0.070)
ΔANALYSTS	-0.021	0.035	-0.001	-0.001*	-0.001
	(0.023)	(0.022)	(0.001)	(0.000)	(0.001)
CONSTANT	-0.208	-0.656***	0.065***	0.057***	0.078***
	(0.162)	(0.158)	(0.006)	(0.004)	(0.016)
Observations	922		922	563	359
R-squared/Pseudo R-squared	0.035		0.042	0.084	0.097

Table 7: Difference-in-Differences Analysis Around Split-Share Reform

This table presents estimates of DiD tests that examine how an exogenous shock to stock liquidity due to the split-share reform affects firm investment. Panel A provides variable definitions for new variables used in the DiD analysis. All remaining variables are defined in Table I. Firms are sorted into terciles based on their change in *LIQ_A* from the pre-split-share reform period to the post-split-share reform period. Firms in the top tercile (middle and bottom terciles) constitute the treatment (control) group. Each treatment firm is matched to a control firm by propensity score matching with the nearest neighbourhood algorithm, without replacement. Panel B presents estimates from the probit model for the pre-matched sample (column (1)) and post-matched sample (column (2)). The dependent variable is an indicator variable that takes the value of one (zero) if the firm belongs to the treatment group (control group). Industry and year fixed effects are included in both columns. Panel C reports the distribution of estimated propensity scores for the treatment firms, control firms, and the difference in estimated propensity scores for the matched sample. Panel D reports the mean measures of firm characteristics of the treatment and control firms, the univariate difference between them and the corresponding *t*-statistics. Panel E presents the DiD test results. *D_I_DEV* (*D_INV*) is the difference in the three-year average |*I_DEV*| (*INV*) between the post- and pre-split-share reform periods. Standard errors are reported in parentheses below the mean differences in investment measures. Panel F reports regressions estimates of investment measures surrounding the split-share reform. The dependent variable is INV_{t+1} ($|I\_DEV|_{t+1}$) in columns (1)-(3) (columns (4)-(6)). Robust standard errors clustered by year are reported in parentheses below the coefficient estimates. In panels E and F, the under-investing (over-investing) subsample of firms are identified as those firms that have a positive (negative) *UNDER_PROP* when examining *D_INV* or *INV* and a negative (positive) *I_DEV* when examining *D_I_DEV* or *I_DEV*, respectively. In all panels, ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: New variable definitions

TREAT	An indicator variable that takes the value of one for treatment firms and zero for control firms
BEFORE^{-1}	An indicator variable that takes the value of one for a firm-year observation one year before the split-share reform and zero otherwise.
CURRENT	An indicator variable that takes the value of one for a firm-year observation in the year of the split-share reform and zero otherwise.
AFTER^{1}	An indicator variable that takes the value of one for a firm-year observation one year after the split-share reform and zero otherwise.
AFTER^{23}	An indicator variable that takes the value of one for a firm-year observation 2 or 3 years after the split-share reform and zero otherwise.
BEFORE_I_DEV	Mean *I_DEV* in the pre-split-share reform period (year -3 to year -1), in which year 0 indicates the year during which the firm underwent the split-share reform.
BEFORE_INV	Mean *INV* in the pre-split-share reform period (year -3 to year -1), in which year 0 indicates the year during which the firm underwent the split-share reform.

Panel B: Pre-match propensity score regression and post-match diagnostic regression

	Dummy=1 if in Treatment group and 0 if in Control group	
Variables	Before matching	After matching
LIQ_A	-4.650***	0.358
	(0.394)	(0.762)
LOGASSET	-0.202	0.078
	(0.143)	(0.268)
TOBIN'S Q	0.423***	-0.010
	(0.140)	(0.230)
SD_CFO	2.108	1.153
	(1.964)	(3.531)
SD_SALE	-0.439	-1.597
	(0.668)	(1.443)
SD_INV	-1.618	3.677
	(1.558)	(3.814)
Z	0.001	0.028
	(0.022)	(0.040)
TANG	-0.363	0.818
	(0.642)	(1.133)
KSTR	-0.138	-0.262
	(0.568)	(0.972)
IND_KSTR	-5.432	3.012
	(7.013)	(31.243)
SLACK	-0.012	0.073
	(0.018)	(0.074)
OPERATINGCYCLE	0.026	-0.046

	(0.104)	(0.186)
CASH	0.678	0.764
	(0.915)	(1.932)
DIV	0.077	0.132
	(0.170)	(0.293)
LOSS	-0.394*	-0.143
	(0.217)	(0.423)
BEFORE_I_DEV	-8.710	42.446
	(8.473)	(28.282)
BEFORE_INV	11.320	-44.892
	(8.258)	(27.656)
CONSTANT	-0.535	-2.892
	(3.926)	(10.604)
Industry fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	711	132
p-value of Chi^2	0.000	0.996
Pseudo R-squared	0.520	0.064

Panel C: Estimated propensity score distributions

Propensity scores	N	Min	P5	P50	Mean	SD	P95	Max
Treatment	66	0.046	0.135	0.422	0.473	0.252	0.953	0.993
Control	66	0.047	0.134	0.424	0.475	0.255	0.971	0.999
Difference	66	0.000	0.000	0.002	0.003	0.004	0.015	0.019

Panel D: Differences in pre-split-share reform characteristics

Variables	Treatment	Control	Difference	*t*-statistic
LIQ_A	-0.589	-0.592	0.003	0.120
LOGASSET	20.960	20.963	-0.003	-0.031
TOBIN'S Q	1.137	1.027	0.111	0.545
SD_CFO	0.065	0.063	0.002	0.278
SD_SALE	0.131	0.132	-0.001	-0.041
SD_INV	0.066	0.062	0.004	0.506
Z	3.018	2.516	0.502	0.498
TANG	0.293	0.304	-0.011	-0.356
KSTR	0.237	0.249	-0.012	-0.381
IND_KSTR	0.244	0.245	-0.001	-0.174
SLACK	1.575	0.904	0.670	1.293
OPERATINGCYCLE	5.153	5.241	-0.089	-0.509
CASH	0.134	0.111	0.023	1.268
DIV	0.394	0.348	0.045	0.597
LOSS	0.121	0.152	-0.030	-0.469
BEFORE_I_DEV	-0.018	-0.012	-0.006	-0.757
BEFORE_INV	0.012	0.019	-0.007	-0.829

Panel E: Univariate difference-in-differences test

Subsample	Variable	Mean treatment difference (after - before)	Mean control difference (after - before)	Mean DiD estimator (treatment - control)	*t*-statistic for DiD estimator
FULL SAMPLE	*D_INV*	0.001	-0.011	0.012	0.853
		(0.009)	(0.011)	(0.014)	
	D_I_DEV	0.003	0.006	-0.003	-0.347
		(0.005)	(0.006)	(0.009)	
UNDER INVESTING	*D_INV*	0.004	-0.030**	0.034**	2.246
		(0.012)	(0.011)	(0.015)	
	D_I_DEV	-0.007	0.017	-0.025*	-1.747
		(0.009)	(0.011)	(0.014)	
OVER INVESTING	*D_INV*	-0.005	0.017	-0.022	-0.843

	(0.012)	(0.021)	(0.026)	
D_I_DEV	-0.003	-0.006	0.003	0.199
	(0.010)	(0.011)	(0.016)	

Panel F: Multivariate difference-in-differences test

	Dep. var.: INV_{t+1}			Dep. var.: I_DEV_{t+1}		
	Full sample	Under-investing subsample	Over-investing subsample	Full sample	Under-investing subsample	Over-investing subsample
Variables	(1)	(2)	(3)	(4)	(5)	(6)
*TREAT*x*BEFORE*$^{-1}$	0.018	0.001	0.052***	-0.006	-0.010	0.005
	(0.017)	(0.018)	(0.013)	(0.019)	(0.007)	(0.034)
*TREAT*x*CURRENT*	0.010	0.009	0.017*	0.028***	0.019**	0.045***
	(0.007)	(0.007)	(0.010)	(0.006)	(0.008)	(0.012)
*TREAT*x*AFTER*^{1}	0.031*	0.041**	0.016	0.023**	0.022	0.018
	(0.017)	(0.017)	(0.027)	(0.010)	(0.016)	(0.013)
*TREAT*x*AFTER*^{23}	0.031***	0.006	0.063***	-0.000	-0.017*	0.030**
	(0.011)	(0.007)	(0.021)	(0.009)	(0.010)	(0.013)
BEFORE^{-1}	-0.006	-0.001	-0.022***	0.013	0.005	0.026
	(0.014)	(0.020)	(0.008)	(0.015)	(0.006)	(0.028)
CURRENT	-0.022***	-0.018**	-0.034***	-0.000	-0.000	0.001
	(0.006)	(0.008)	(0.010)	(0.005)	(0.004)	(0.014)
AFTER^{1}	-0.015	-0.016	-0.018	-0.013	-0.003	-0.028**
	(0.011)	(0.013)	(0.026)	(0.010)	(0.013)	(0.012)
AFTER^{23}	-0.015**	-0.012**	-0.023	0.002	0.011*	-0.014
	(0.008)	(0.006)	(0.018)	(0.005)	(0.006)	(0.012)
TREAT	-0.020***	-0.014**	-0.033***	-0.013***	-0.006	-0.036**
	(0.006)	(0.006)	(0.009)	(0.004)	(0.004)	(0.014)
CONSTANT	-0.002	-0.007	0.010	0.026***	0.036***	0.027***
	(0.004)	(0.005)	(0.008)	(0.005)	(0.010)	(0.009)
Controls in Table 2	Y	Y	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y	Y	Y
Observations	791	490	301	790	514	276
R-squared	0.054	0.064	0.084	0.140	0.156	0.224

Table 8: Effect of Liquidity Changes Related to Split-Share Reform on Institutional Ownership, Takeover Probability, and Financial Constraints

This table presents estimates of the OLS regressions of institutional ownership, takeover probability, and financial constraints. The sample consists of non-financial firms that have non-missing data in the CSMAR and Wind databases between the years 2002 and 2015 and that experienced the split-share reform during this period. Firms that are relegated to the special treatment (ST) category are excluded. The table reports OLS (logit) regressions results in panels A and C (panel B) of the model $a + b\Delta LIQ\_A_{i,t\text{-}1\ to\ t+1} + c'\Delta Controls_{i,t\text{-}1\ to\ t+1} + \varepsilon_{i,t\text{-}1\ to\ t+1}$. The dependent variable in panel A is $INS\_OWN_{i,t+2}$, measured as the total proportion of shares outstanding held by investors aggregated by the Wind database into categories that include qualified foreign institutional investors, insurers, banks, and pension funds. The dependent variable in panel B is $Target_{i,t+2}$, an indicator variable that takes the value of one if the firm is a target in an M&A proposal and zero otherwise. The dependent variable in Panel C is the $HP\ index_{i,t+2}$, and the Hadlock and Pierce (2010) financial constraints index is measured as $-0.737log(assets) + 0.043log\ (assets)^2 + 0.04firm\ age$. In all the panels in column (2) (column (3)), the model is estimated on the subsample of under-investing firms (over-investing firms) identified as those firms that have a negative (positive) *I_DEV* in year *t+2*. Δ denotes the change in each variable from the fiscal year before the split-share reform (year *t-1*) to the fiscal year after the split-share reform (year *t+1*), with *t* indicating the year during which the firm underwent the split-share reform. Robust standard errors are displayed in parentheses below the coefficients. All the remaining variables are defined in Table 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of Liquidity Changes on Institutional Ownership

	Dep. var.: *INS_OWN*		
	Full Sample	Under-investing subsample	Over-investing subsample
Variables	(1)	(2)	(3)
ΔLIQ_A	-0.157	0.272	-0.839**
	(0.356)	(0.453)	(0.404)
Controls in Table 6	Y	Y	Y
Observations	922	563	359
R-squared	0.035	0.048	0.053

Panel B: Effect of Liquidity Changes on Takeover Probability

	Dep. var.: *Target (indicator)*		
	Full Sample	Under-investing subsample	Over-investing subsample
Variables	(1)	(2)	(3)
ΔLIQ_A	1.026	1.422*	-0.566
	(0.638)	(0.778)	(1.219)
Controls in Table 6	Y	Y	Y
Observations	922	563	359
Pseudo R-squared	0.0850	0.0981	0.172

Panel C: Effect of Liquidity Changes on Financial Constraints

	Dep. var.: *HP Index*		
	Full Sample	Under-investing subsample	Over-investing subsample
Variables	(1)	(2)	(3)
ΔLIQ_A	-1.559***	-1.303***	-1.978***
	(0.156)	(0.191)	(0.247)
Controls in Table 6	Y	Y	Y
Observations	922	563	359
R-squared	0.371	0.384	0.380