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北京大學
汇丰商学院
Peking University HSBC Business School
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Does Share Liquidity Increase the Propensity to Raise Debt Finance?

Hyun Joong Im

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Abstract

This study investigates the relation between market liquidity of firms' shares and their propensity to raise debt in funding large investment requirements. I find that firms with more liquid shares tend to rely more on net debt issuances and less on net equity issuances at the time of "investment spikes" and have higher target leverage ratios in normal periods. This happens because more information on firms with more liquid shares is produced in the stock market and that information may be of benefit to banks and credit rating agencies in pricing debt finance and therefore reducing the cost of credit.

Keywords: Share Liquidity, Debt Finance, Investment Spikes, Information Spillover

*Address: HSBC Business School, Peking University, University Town, Nanshan District, Shenzhen, 518055, CHINA, Tel: +86 (0)755 2603 3627, Email: hyun.im@phbs.pku.edu.cn

1 Introduction

This paper focuses on share liquidity as a determinant of the sources used to meet firms' large financing requirements. Theoretical research, such as that of Boot and Thakor (1993), and empirical research, such as that of Fang, Noe and Tice (2009), has begun to document the effect of share liquidity on corporate performance and financing behavior. In this paper, share liquidity as measured by Hasbrouck's (2009) Gibbs spread measure and Amihud's (2002) price impact measure is treated as a slowly changing firm characteristic[1]. This paper investigates whether firms with a more liquid market for their shares would prefer debt to equity more than firms with a less liquid market for their shares, when all else is equal. An investigation of the related literature reveals that there are conflicting views about the effect of share liquidity on how firms finance investment activities. Nevertheless, this issue has not received sufficient attention in empirical studies of corporate finance. This paper is the first work to my knowledge to study the effect of share liquidity on how firms meet their large financing requirements. The main finding of this paper is that firms with a more liquid market for their shares rely more on net debt issuances and less on net equity issuances compared with firms with a less liquid market for their shares.

It has been believed that share liquidity has a *negative* effect on the propensity to raise debt finance since firms with more liquid shares will find equity finance more attractive. For example, Lipson and Mortal (2009) and Frieder and Martell (2006) argue that firms with more liquid shares are likely to raise more equity finance because those firms have lower costs for rasing equity capital (Butler *et al.*, 2005). However, there are some reasons to believe that share liquidity has a *positive* effect on the propensity to raise debt finance. Although it seems obvious that firms with more liquid shares incur lower costs when

[1] I have investigated whether firms' classifications as high-liquidity firms and low-liquidity firms are stable over the period of this study using the Markov-switching mean model applied to demeaned liquidity measures. I conclude that the classifications are very stable because probabilities of sticking to the low-liquidity state and high-liquidity state are sufficiently high (both 0.86).

raising equity capital, there are good reasons to believe that firms with more liquid shares have lower costs for raising debt capital as well (Butler and Wan, 2010). One of the most promising rationales as to why firms with more liquid shares have lower borrowing costs is based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2011). Despite the existence of conflicting arguments on the effect of liquidity on the propensity to raise debt finance, this issue has not received sufficient attention in empirical research on corporate finance.

To precisely study the effect of share liquidity on the way firms meet their financing requirements, I utilize a novel approach which focuses on firm-years with unusually large investment activities or "*investment spikes*[2]". Using the US data, Mayer and Sussman (2005) find that financing patterns in the years categorized as investment spikes are very different from financing patterns in non-spike years and very different from overall financing patterns. Thus, pooling data from two regimes of routine investment (i.e spike years) and non-routine investment (i.e. non-spike years) dilutes the sample and obscures the results, without increasing the efficiency of the estimation (Mayer and Sussman, 2005). Therefore, by focusing on the firm-years categorized as investment spikes, one can investigate the effects of share liquidity on financing patterns more precisely. Using a structural estimation method, DeAngelo, DeAngelo, and Whited (2011) analyze the financing decisions associated with investment spikes and find that, even when leverage is currently above average, large investment outlays are typically accompanied

[2]The lumpiness of investment has been very well known to economists since Doms and Dunne's (1998) influential work suggesting that plant-level investment is lumpy using the plant-level investment data from US Census Bureau micro data files (Caballero, Engel, and Haltiwanger, 1995; Power, 1994; Cooper, Haltiwanger and Power, 1999). Firm-level investment is found to be less lumpy than plant-level investment because of the aggregation effect, but there is still a large body of literature suggesting that aggregation does not substantially eliminate the lumpiness of firm-level investment (Caballero and Engel, 1999; Doyle and Whited, 2001). In addition, there are several promising theoretical explanations for the lumpiness of investment. Scholars have attempted to explain lumpy investment patterns through the ideas of non-convex capital adjustment costs (Rothchild, 1971), irreversibility of investment (Pindyck, 1991; Dixit, 1995; Dixit and Pindyck, 1994), and external financing costs arising from the presence of financing constraints (Whited, 2006). Mayer and Sussman (2005) were the first to notice that the summary statistics for typical financing patterns would overstate the importance of internal finance in funding firms' large investment activities. They proposed using the flow-of-funds approach combined with a filtering device designed to identify "unusually large investment events". Im (2012) also proposes and compares various algorithms in order to identify "investment spikes".

by substantial debt issuances that increase leverage, confirming Mayer and Sussman's (2005) major findings. In this study, I aim to examine whether share liquidity increases the propensity to raise debt finance after controlling for the size of investment spikes and various firm characteristics, and determine the mechanisms through which this works.

First of all, I investigate whether share liquidity has a positive effect on abnormal borrowing at the time of an investment spike. To answer the question, I use a dynamic leverage change model in which the dependent variable is the increase in leverage during an investment spike and the right-hand side variables include a lagged leverage, various firm characteristics, share liquidity, industry dummies, and year dummies[3]. This model is equivalent to the reduced-form partial adjustment model which is often used to estimate the speed of adjustment of actual leverage to target leverage (Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007; Leary and Roberts, 2005; Lemmon *et al.*, 2008; Huang and Ritter, 2009). To make a clear distinction between share liquidity as a determinant of target leverage and share liquidity as a determinant of abnormal borrowing at the time of an investment spike, I use an empirical specification with the following three key variables: 1) the basic liquidity terms in the dynamic leverage models, telling us about the effect of share liquidity on target leverage ratios; 2) a measure of spike size, telling us about abnormal borrowing when faced with an investment spike; and 3) an interaction term between spike size and share liquidity, telling us about the effect of share liquidity on this abnormal borrowing. Using this framework, I show that share liquidity has a positive effect on abnormal borrowing when faced with an investment spike, meaning that high-liquidity firms have a higher propensity to raise debt finance in order to fund unusually large investment outlays.

[3] *"A change in leverage during an investment spike"* is an excellent proxy for the propensity to raise debt finance because it reflects the significance of debt finance in funding a large investment requirement. A change in leverage during a routine investment period would reflect the rate of leverage adjustment rather than the propensity to raise debt finance. By restricting attention to a leverage change during an investment spike, one can investigate the factors affecting the propensity to raise debt finance more precisely and implement more reasonable dynamic models with intuitive interpretations.

Some additional analyses are then executed. First, I investigate whether the positive effect of share liquidity on the propensity to raise debt finance or engage in abnormal borrowing during an investment spike remains, after controlling for the effects of various firm characteristics such as firm size, initial leverage, and profitability. This study also finds that firms with higher initial leverage have a lower propensity to raise debt finance, while firms with higher profitability, higher market-to-book ratios, and higher research and development (R&D) intensity have a higher level of abnormal borrowing during an investment spike. Strikingly, both firm size and tangibility of assets do not have a significant effect on abnormal borrowing during an investment spike, although they have a significant effect on target leverage. Even after controlling for the effects of various firm characteristics, share liquidity has a significant positive effect on the propensity to raise debt finance. Second, I show that the positive effect of share liquidity on the propensity to raise debt finance is robust to the use of various leverage measures, including a book leverage measure. Third, one could argue that the positive effect of share liquidity on the propensity to raise debt finance is driven by the use of the investment spikes sample instead of the whole sample. To test this possibility, I implement a dynamic leverage change model for the whole sample and the non-spike sample (i.e. the sample consisting of firm-years not categorized as investment spikes) as well, finding that a positive effect of share liquidity is found in the whole sample while the effect is less stable in the non-spike sample. I therefore conclude that the main results are not just driven by the use of the investment spikes sample, although the firm-years categorized as investment spikes have distinct features and the effect of share liquidity is more pronounced when the spikes sample is used. Based on various robustness tests, I conclude that firms with more liquid shares do indeed rely more on net debt issuances compared with firms with less liquid shares during investment spikes.

Having found the positive effect of share liquidity on the propensity to raise debt finance during investment spikes, I turn to the assessment of the mechanisms through which share liquidity increases this propensity. To assess whether information spillover mechanism and credit ratings mechanism work, I first compare the observed correlation coefficients between share liquidity and key variables in each mechanism with the correlation coefficients predicted in different mechanisms. Then, I check whether the coefficient of an interaction term between a spike size measure and a dummy variable for high-liquidity firms vanishes when a key variable and an interaction term between the spike size measure and a dummy variable based on the key variable are included as explanatory variables in the regression. This study shows that the information spillover and credit ratings arguments are well supported. Those two arguments provide interesting explanations as to why firms with a more liquid market for their shares have a higher propensity to raise debt finance. Firms with more liquid shares are less likely to have severe asymmetric information problems between informed investors, including managers, and uninformed investors. Thus, high-liquidity firms are likely to have more informative share prices. In addition, there is a higher level of information production for high-liquidity firms because those firms are followed by a larger number of financial analysts and the shares of those firms are owned by more financial institutions. Hence, banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices and propose lower loan spreads to high-liquidity firms. Moreover, firms with more liquid shares tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, firms with a more liquid market for their shares have lower costs of raising debt finance in subsequent periods and are likely to raise more debt finance to meet large investment requirements.

Finally, using the whole sample which allows us to exploit both within-firm variations as well as cross-sectional variations, I find that the effect of share liquidity on target leverage is positive and significant at the 1% level, regardless of model specifications and estimation methods. One interpretation of these results is that the information spillovers from the presence of more informative share prices as well as more active information production in the stock market allow firms with more liquid shares to borrow on more favourable terms in normal times, as well as to obtain additional debt finance at lower costs when taking advantage of unusually large investment opportunities.

The structure of the remainder of this paper is as follows. In Section 2, I discuss various arguments as to how share liquidity affects the propensity to raise debt finance. Section 3 describes the sample selection procedures, the algorithm to identify investment spikes, and the variables used in this study. The descriptive statistics are also presented. Section 4 presents the issues in research design and the main empirical results. Finally, Section 7 provides conclusions.

2 Share liquidity and the propensity to raise debt finance

The stock market is often characterized by the liquidity of shares. Share liquidity is crucial to market participants because it entails transaction costs to them. In addition, share liquidity has been viewed not only as a reflection of the direct trading costs such as fees or taxes and the costs associated with inventory (Garman, 1976; Ho and Stoll, 1981), but also as a reflection of adverse selection due to the presence of better-informed traders in a stock market (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). Recently, the effects of share liquidity on various corporate finance issues (e.g. firm value, innovation, corporate governance, credit ratings) have been actively studied. More broadly, the interaction of market microstructure and corporate finance is a hot area of research. It is highly likely that share liquidity affected by transaction costs or the extent of information asymmetry has an impact on the way firms finance their investment activities. In addition, there are conflicting views about the effect of share liquidity on how firms meet their investment requirements. Nevertheless, this issue has not received sufficient attention in empirical studies of corporate finance.

Unlike this study, which finds a positive effect of share liquidity on the propensity to raise debt finance, some existing empirical studies argue that they found a negative effect of share liquidity on the propensity to raise debt finance. For example, Lipson and Mortal (2009) examine the cross-sectional relation between leverage and share liquidity and argue that they found that firms with higher share liquidity tend to use more equity finance. Similarly, Frieder and Martell (2006) argue that share liquidity has a significant negative effect on leverage, even after taking the endogeneity of share liquidity into account. Some of the asset-pricing literature, including the studies by Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005), show that investors are willing to pay more for high-liquidity shares and require a premium for bearing the costs of illiquidity. Although the secondary-market returns might be closely linked with the primary-market costs of equity finance in equilibrium, it is not clear whether secondary-market liquidity would have parallel effects on secondary-market returns and the primary-market costs of equity capital. However, Butler *et al.* (2005) show that the costs of issuing equity, measured by gross fees paid to investment banks, are significantly lower for high-liquidity firms when other factors are controlled for. Based on these premises, Lipson and Mortal (2009) and Frieder and Martell (2006) derive the hypothesis that firms with more liquid shares would use less debt finance because those firms would find it more attractive to issue equity than to use other financing options.

In addition, Bharath *et al.* (2009) argue that they found that firms with greater adverse selection costs (i.e. lower share liquidity) tend to fund a greater portion of their financing deficit through debt in the current fiscal year. They argue that their finding is highly consistent with the pecking order theory. Myers (1984) argues that if managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Therefore, his theory predicts that firms will use equity issuances to meet large exceptional financing needs only as a last resort, after less information-sensitive financing sources such as internal cash and debt have been exhausted (Myers, 1984; Myers and Majluf, 1984). Extending this idea, Bharath *et al.* (2009) argue that firms with less liquid shares or more severe severe asymmetric information problems are likely to have a stronger preference for debt than for equity.

However, there are some reasons to believe that share liquidity has a *positive* effect on the propensity to raise debt finance. Although it seems obvious that firms with more liquid shares incur lower costs when raising equity capital (Butler *et al.*, 2005), there are good reasons to believe that firms with more liquid shares have lower costs for raising debt capital as well (Butler and Wan, 2010)[4]. According to Butler and Wan (2010), an increase in liquidity from the bottom quintile to the top quintile would predict a decrease in investment bank gross spreads in seasoned equity offerings of 21% of the mean spread, whereas the same liquidity change would predict a decrease in bond underwriting fees of 36% of the mean spread. This means that the liquidity-sensitivity of costs of rasing debt capital is greater than that for costs of raising equity capital. There are several rationales as to why firms with higher share liquidity might have lower costs of raising debt capital (see Butler and Wan (2010) for a comprehensive survey).

The most promising one is based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2011). Firms with more liquid shares are less likely to have problems arising from asymmetric information between informed investors, including firm managers, and uninformed investors. Therefore, firms with more liquid shares are likely to have more informative share prices. In addition, it is likely that more information on firms with a more liquid market for their shares will be produced because those firms are followed by a relatively large number of financial analysts and the shares of those firms are owned by a relatively large number of financial institutions.

[4]Butler and Wan (2010) investigate whether there are liquidity differences between debt issuers and matched firms, finding that debt issuers have significantly higher share liquidity. They also study the long-run stock performance of debt issuers, finding that the under-performance of debt issuers disappears when a liquidity factor is included in the model for expected returns.

Therefore, banks can monitor those firms more efficiently by supplementing their own information with more informative share prices. Due to the lower monitoring costs, banks would thus propose lower loan spreads to firms with more liquid shares. Sunder (2004) also shows that firms' borrowing costs decrease with measures of information production in the stock market. Furthermore, firms with more liquid shares have stronger bargaining power on the conditions of loan contracts as they have equity financing as quite an attractive outside option. Therefore, it is expected that share liquidity will have a positive effect on the propensity to raise debt finance. Sunder (2004) and Saunders and Steffen (2011) provide some empirical evidence. Sunder (2004) reports that one standard deviation decrease in relative bid-ask spread reduces the borrowing costs by over 18 basis points on average. Saunders and Steffen (2011), using UK data, show that private firms have substantially higher borrowing costs than public firms. Going public increases the availability of equity market information that banks use to determine loan rates. Other arguments related to the loan costs disadvantage of private firms are quite similar to those on the loan costs disadvantage of firms with less liquid shares (see Saunders and Steffen (2011) for details).

Another argument explaining why firms with more liquid shares have lower costs of debt capital is based on the shared information content in credit ratings and liquidity measures or the risk of private shocks to future firm value. Odders-White and Ready (2006) assume that uncertainty about future firm value has two components: a public information component and a private information component. Both components affect credit ratings while only the private information component affects share liquidity and adverse selection. Due to the private information content, share liquidity is positively correlated with a firm's credit rating. On the other hand, firms with better credit ratings tend to have a lower cost of raising debt capital. Thus, firms with more liquid shares are likely to use more debt to meet investment requirements. Odders-White and Ready also empirically show that credit ratings are poorer when adverse selection risk as measured by various share illiquidity measures is higher and that adverse selection measures can be used to predict future credit ratings changes. Furthermore, as credit ratings information is available to banks, firms with low share liquidity are more likely to be credit rationed in the sense that they cannot obtain the loan that they want even though they are willing to pay the interest that the banks require, or perhaps even higher interest[5]. In this case, firms with less liquid shares are more likely to use new equity finance, as this might be the only viable option to meet external financing needs.

The various arguments stated above give rise to the following hypotheses:

H1. Firms with more liquid shares have a higher propensity to raise debt finance than firms with less liquid shares.

H1A. ***(Information spillover)*** Firms with more liquid shares are less likely to have severe asymmetric information problems between informed investors, including managers, and uninformed investors. Thus, high-liquidity firms are likely to have more informative share prices. In addition, more information on high-liquidity firms is produced because those firms are followed by a large number of financial analysts and the shares of those firms are owned by many financial institutions. Banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices and propose lower loan spreads to high-liquidity firms (Sunder, 2004; Saunders and Steffen, 2011; Butler and Wan, 2010).

H1B. ***(Credit ratings)*** Firms with less liquid shares have poorer credit ratings due to the shared information content in credit ratings and liquidity measures or the risk of private shocks to future firm value. Thus, firms with less liquid shares incur higher costs when raising debt finance in subsequent periods (Odders-White and Ready, 2006; Butler and Wan, 2010). In addition, as credit ratings information is

[5]There are, broadly speaking, two explanations for credit rationing: the adverse selection explanation and the moral-hazard explanation. See Tirole (2006) for details.

available to debt market participants, low-liquidity firms have a higher cost of debt or are more likely to be credit rationed.

H2. Firms with more liquid shares have a lower propensity to raise debt finance than firms with less liquid shares.

H2A. ***(Asymmetric information)*** If managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Thus, firms will use equity issuances only as a last resort, after less information-sensitive sources such as internal cash and debt have been exhausted. Thus, firms with less liquid shares or more severe asymmetric information problems have stronger preference for debt finance over equity finance (Bharath *et al.*, 2009).

H2B. ***(Liquidity premium)*** Investors are willing to pay more for highly liquid shares and require a liquidity premium for bearing the costs of illiquidity (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). There is empirical evidence that high-liquidity firms have lower costs for rasing equity capital (Butler *et al.*, 2005). Based on these premises, Lipson and Mortal (2009) and Frieder and Martell (2006) argue that firms with more liquid shares are likely to raise more equity finance.

In the next section, I describe the sample selection procedures, the variables used in this study, and the descriptive statistics.

3 Data and methodology

3.1 Sample selection

I use data from annual consolidated financial statements[6] of publicly traded US companies reported in Standard and Poor's Compustat North America Fundamental Annual Dataset for the years 1988 to 2007. The data starts from 1988 because I investigate the financing patterns during investment spikes and this requires the use of firm-level flow-of-funds data, i.e. the data from the cash-flow statements[7]. I also use the stock market data from the Center for Research in Security Prices (CRSP) to construct two liquidity measures such as Amihud's (2002) price impact measure and Hasbrouck's (2009) Gibbs spread measure. Access to the S&P Long-Term Issuer Credit Ratings Database and Thomson-Reuters Institutional Holdings (13F) Database[8] is also obtained through Wharton Research Data Services (WRDS). I exclude firms with a Standard Industrial Classification (SIC) code between 6000 and 6999 or between 4900 and 4999, meaning firms whose main activity is financial services or regulated utilities are dropped to construct the final sample.

All nominal items from the statement of cash flows, income statement and balance sheet are deflated or inflated to year 2000 US dollars using the Gross Domestic Product (GDP) deflator obtained from the International Monetary Fund database of country GDP deflators. An interpolated GDP deflator is used if the fiscal year ends in other months than December. I also perform a minimum level of data cleaning. First, I drop observations if the firms are observed for less than five years. Second, I drop observations

[6]The majority of US companies report the consolidated financial statements, which include the accounts of both parents and subsidiaries.

[7]Mayer and Sussman (2005), in their seminal paper on the use of a filtering technique and flow-of-funds approach in studies of financing patterns, report that they could not use the data prior to 1988 because FASB (Financial Accounting Standards Board) #5 replaced "cash statements by sources and uses of funds" with the "statement of cash flows" from 1988.

[8]This database is also known as the CDA/Spectrum 3 4 database, and contains ownership information by institutional managers with USD 100 million or more in assets under management.

if any variable which constitutes the cash-flow identity is missing. However, I replace the missing item with zero if at least one component of each financing source is reported because ”missing” does not mean ”unaccounted for”. For example, note that that $LTDEBT$, the amount of long-term debt financing, can be calculated as ”issuance of long-term debt ($dltis$)” less ”reduction of long-term debt ($dltr$)”. It is clear that the firm-year observation should be deleted if both $dltis$ and $dltr$ are missing. However, if only one of the two components is missing, then it is likely that that only ”net issuance of long-term debt” is reported. In this case, it makes more sense to replace the missing item with zero rather than remove the firm-year observation. Finally, to reduce the effects of outliers and eradicate errors in the data, all variables in ratios used in the baseline regression specification are winsorized at the 1st and 99th percentiles, as in Flannery and Rangan (2006).

3.2 Algorithm to identify investment spikes

This paper uses a novel approach[9] suggested by Mayer and Sussman (2005). They suggest that the question of how investment is financed can be precisely answered by using the firm-level flow-of-funds data combined with a filtering device to identify investment spikes. This new approach eliminates a potential bias caused by the merging of routine and non-routine investment periods. The bias arises if investment is lumpy (i.e. firms change between high investment regimes and low investment regimes), if financing patterns are markedly different across regimes, and if the data from two regimes are merged to make inferences on financing patterns. They argue that pooling data from two regimes dilutes the sample and obscures results, without increasing the efficiency of the estimation.

Mayer and Sussman (2005) also propose a simple and intuitive algorithm to identify investment spikes. However, the algorithm has one important disadvantage in that the threshold is arbitrary and not

[9] Bond *et al.* (2006) and Huang *et al.* (2007) use a similar approach to study financing patterns.

statistically interpretable. To overcome the problem, I utilize an algorithm used by Bond *et al.* (2006)[10]. The advantages of the new algorithm are that the threshold is statistically interpretable and that it works well when there is a trend in the investment sequence. Let the investment data, $I_{i,t}$, for $i = 1, 2, \cdots, N$ and $t = 1, \cdots, T_i$, be defined as investment outlays on net capital expenditures ($capx - sppe$) and acquisitions (aqc). See below for more details on the algorithm.

The first step is to regress each five-year investment sequence, $y = (I_{i,t-2}, I_{i,t-1}, I_{i,t}, I_{i,t+1}, I_{i,t+2})'$, for $i = 1, 2, \cdots, N$ and $t = 3, \cdots, (T_i - 2)$, on a constant, a linear trend, and a dummy variable for the middle-year t, where N is the number of firms and T_i is the length of firm i's investment series[11]. The regression for identifying an investment spike can be expressed compactly as

$$y = \mathbf{X}b + \varepsilon, \text{ where } \varepsilon \sim N(0, \sigma^2), \tag{1}$$

with the matrix $\mathbf{X}$ and the vectors b and ε specified as follows:

$$\mathbf{X} = [\mathbf{1} \quad \tau \quad \mathbf{D}_{\tau=\mathbf{0}}] = \begin{pmatrix} 1 & -2 & 0 \\ 1 & -1 & 0 \\ 1 & 0 & 1 \\ 1 & +1 & 0 \\ 1 & +2 & 0 \end{pmatrix}, \tag{2}$$

$b = (\alpha_{it}, \beta_{it}, \delta_{it})'$, and $\varepsilon = (\varepsilon_{i,t-2}, \varepsilon_{i,t-1}, \varepsilon_{i,t}, \varepsilon_{i,t+1}, \varepsilon_{i,t+2})'$. Note that $n = 5$ and $k = 3$, where n is the sample size and k is the number of regressors including a constant.

[10] They use the algorithm suggested by Mayer and Sussman (2005) but propose two new algorithms as a robustness test.

[11] If $T_i = 20$, $16 (= T_i - 4)$ regressions should be implemented for firm i. Therefore, a total of $N(T_i - 4)$ regressions should be implemented. However, the following anatomy of a regression makes the algorithm simpler in the sense that the algorithm does not require the running of a large number of full regressions. In addition, the anatomy provides interesting measures, such as $\widehat{\alpha}_{it}$, $\widehat{\delta}_{it}$, and $\widehat{\gamma}_{it}$.

Using $\widehat{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'y$, it can be easily shown that

$$\widehat{\alpha}_{it} = \frac{I_{i,t-2} + I_{i,t-1} + I_{i,t+1} + I_{i,t+2}}{4}, \tag{3}$$

$$\widehat{\beta}_{it} = \frac{-2I_{i,t-2} - I_{i,t-1} + I_{i,t+1} + 2I_{i,t+2}}{10}, \tag{4}$$

and

$$\widehat{\delta}_{it} = I_{i,t} - \widehat{\alpha}_{it}. \tag{5}$$

In addition, the standard error of $\widehat{\delta}_{it}$ can also be shown to be

$$se(\widehat{\delta}_{it}) = \sqrt{\frac{5}{4}s^2}, \tag{6}$$

using $\widehat{V}(\widehat{b}|\mathbf{X}) = s^2(\mathbf{X}'\mathbf{X})^{-1}$, where $s^2 = \widehat{\varepsilon}'\widehat{\varepsilon}/(n-k)$ and $\widehat{\varepsilon} = (\widehat{\varepsilon}_{i,t-2}, \widehat{\varepsilon}_{i,t-1}, \widehat{\varepsilon}_{i,t}, \widehat{\varepsilon}_{i,t+1}, \widehat{\varepsilon}_{i,t+2})'$ and $\widehat{\varepsilon}_{i,t} = 0$.

The second step is to execute a one-sided t-test for δ_{it} or the coefficient for the dummy variable $\mathbf{D}_{\tau=\mathbf{0}}$. The null and alternative hypotheses are $H_0 : \delta_{it} = 0$ and $H_1 : \delta_{it} > 0$, respectively. Under the null hypothesis, the statistic

$$t_{\widehat{\delta}_{it}} = \frac{\widehat{\delta}_{it}}{se(\widehat{\delta}_{it})} \tag{7}$$

follows a Student's t-distribution with $2(= n-k)$ degrees of freedom. The final decision is made based upon the result from the one-sided t-test at a conventional significance level of 5%. That is, $I_{i,t}$ is classified as an investment spike if $\widehat{\delta}_{it}$ is positive and statistically significant at the 5% significance level, regardless of the magnitude of the coefficient[12]. Alternatively, a 1% or 10% significance level can be used.

Note also that $\tau \in \{-2, -1, 0, +1, +2\}$ denotes the time index in relation to an investment spike,

[12] In other words, firm i has an investment spike in year t if $t_{\widehat{\delta}_{it}} > t(0.95, df = 2)$.

and $\widehat{\alpha}_{it}$ is equal to the base-level investment defined in Mayer and Sussman (2005). In addition, the magnitude of an investment spike as a factor of the base-level investment is measured as

$$\widehat{\gamma}_{it} = \frac{\widehat{\delta}_{it}}{\widehat{\alpha}_{it}}. \tag{8}$$

Repeating the procedures as many times as $N(T_i - 4)$ will identify a total of J firm-years as those with an investment spike. For simplicity, the base-level investment and the relative magnitude of the j-th investment spike are denoted as $BASE_j$ and $GAMMA_j$, for $j \in \{1, 2, \cdots, J\}$, respectively. The procedures give a sample of 6,457 investment spikes, 9.56% of the 67,544 firm-year observations for which five consecutive years of investment data are observed. I restrict my attention to $(Low, Low, High, Low, Low)$-type investment spikes only, obtaining 6,424 investment spikes after dropping 33 investment spikes that do not conform to this pattern. The median $GAMMA$ of 6,424 investment spikes is 3.42.

Notation

The identifier $i \in \{1, 2, \cdots, N\}$ represents the firm code, whereas the identifier $j \in \{1, 2, \cdots, J\}$ represents the investment spike code. The time index $t \in \{2, \cdots, T\}$ represents the fiscal year reported in Compustat, whereas the time index $\tau \in \{-2, -1, 0, +1, +2\}$ represents the time in relation to an investment spike. For example, $\tau = 0$ indicates the year categorized as an investment spike, whereas $\tau = -1$ indicates the year before an investment spike. The subscripts (i, t) are used when investment spikes are not treated specially (i.e. in the whole sample), whereas the subscripts (j, τ) are used when investment spikes are treated specially (i.e. in the investment spikes sample). For instance, $LEV_{i,t-1}$ represents the leverage of a given firm i measured in year $t-1$, while $LEV_{j,\tau=-1}$ represents the leverage measured in the year before the spike (i.e. $\tau = -1$) for the $j-$th investment spike.

3.3 Construction of variables

3.3.1 Variables used in regression analysis

The dependent variable in the baseline specification (Table 5) is defined as the change in a leverage ratio during an investment spike[13] ($\Delta LEV_{j,\tau=0} = LEV_{j,\tau=0} - LEV_{j,\tau=-1}$), where the leverage ratio is measured as:

$$LEV = \frac{\text{Total liabilities}}{\text{Total liabilities + Market value of equity}}. \tag{9}$$

As a robustness test, the following two alternative leverage measures[14] are used in this paper:

$$BLEV = \frac{\text{Total long-term debt + Total short-term debt}}{\text{Total assets}}, \tag{10}$$

and

$$MLEV = \frac{\text{Total long-term debt + Total short-term debt}}{\text{Total long-term debt + Total short-term debt + Market value of equity}}. \tag{11}$$

The liquidity of shares is measured by multiplying either Hasbrouck's Gibbs spread or Amihud's price impact by (-1)[15]. The liquidity measure based on Hasbrouck's Gibbs spread and the liquidity mea-

[13]The change in leverage during an investment spike is an excellent proxy for the propensity to raise debt finance because it reflects the significance of debt finance in funding the large investment event. The change in leverage during the routine investment period would reflect the rate of leverage adjustment rather than the propensity to raise debt finance. By restricting attention to a leverage change during an investment spike, one can investigate the factors involved in the propensity to raise debt finance more precisely and implement more reasonable dynamic models with intuitive interpretations. Welch (2011) argues that the correlation between issuing activities and capital structure changes is "either insignificant or outright perverse". Welch's argument may be correct when it comes to routine investment periods. However, when it comes to non-routine investment periods, issuing activities and capital structure changes are highly significantly correlated. In the spikes sample, the correlation coefficient between $[Net\ debt\ issuance]_{j,\tau=0}$ / $[Total\ liabilities + Market\ value\ of\ equity]_{j,\tau=-1}$ and $\Delta LEV_{j,\tau=0}$ is 0.4015 and significant at the 1% level of significance (p-value=0.0000).

[14]*MLEV* is an alternative market leverage measure, while *BLEV* is a book leverage measure. The three measures are defined as in Flannery and Rangan (2006). However, Welch (2011) argues that future research should avoid any "financial debt to total assets ratio" such as *BLEV*. He argues that the measure would be problematic in the sense that non-financial liabilities are considered as equity rather than debt. The main leverage measure in this paper, *LEV*, is free from this criticism.

[15]Recently, there has been some research on testing whether available liquidity proxies can capture the actual transaction costs of market participants. For example, Hasbrouck (2009) compares several indirect measures of liquidity to measures of spreads and price impact constructed with the Trades and Quotes (TAQ) database, and finds that the Gibbs sampler estimate of the Roll (1984) model suggested by Hasbrouck (2009) is the best measure of effective trading costs and the Amihud (2002)

sure based on Amihud's price impact are denoted as $LIQ^{G}_{j,\tau=-1}$ and $LIQ^{A}_{j,\tau=-1}$, respectively. The higher $LIQ^{G}_{j,\tau=-1}$ or $LIQ^{A}_{j,\tau=-1}$, the higher the share liquidity. To investigate whether high-liquidity firms use more abnormal borrowing during an investment spike, I include a spike size measure ($SPIKESIZE_{j,\tau=0}$) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ or $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$) in the regression equation. The spike size measure ($SPIKESIZE_{j,\tau=0}$) measures abnormal investment[16] as a proportion of market value of total assets at the beginning of the year, where abnormal investment is calculated as spike investment less base-level investment[17]. $D\_HLIQ^{G}_{j,\tau=-1}$ and $D\_HLIQ^{A}_{j,\tau=-1}$ represent the dummy variable for high-liquidity firms based on Hasbrouck's Gibbs spread and that based on Amihud's price impact, respectively. To investigate whether acquisitions tend to be funded differently from capital expenditures, the dummy variable for acquisitions ($D\_AQC_{j,\tau=0}$) is also included in the regression equation.

The control variables used in this study are very similar to those used in Flannery and Rangan (2006), Lemmon *et al.* (2008), and Rajan and Zingales (1995). These controls include the one-lagged leverage ($LEV_{j,\tau=-1}$), natural logarithm of total assets ($LnTA_{j,\tau=-1}$), ratio of earnings before interests and taxes to total assets ($EBIT\_TA_{j,\tau=-1}$), market-to-book ratio ($MV\_BV_{j,\tau=-1}$), tangibility of assets ($FA\_TA_{j,\tau=-1}$), and R&D expenses as a proportion of total assets ($RD\_TA_{j,\tau=-1}$). In addition, both industry and year dummies are included. The companies in the sample are allocated to 43 industries based on SIC codes following Fama and French (1997). They classify all firms into 48 industries; four of them belong to financial services and one of them belongs to regulated utilities. Panel A and Panel B of Table 1 present detailed formulas with Compustat item codes required to construct the variables mentioned in

measure is the best measure of price impact. In this paper, Hasbrouck's (2009) Gibbs spread measure and Amihud's (2002) price impact measure are the two liquidity measures used. One major advantage that those two measures have over some other liquidity measures is that they can be computed over more extensive sample periods than liquidity measures that require the TAQ data, because they are calculated using CRSP data (Butler and Wan, 2010). The TAQ data are only available dating back to 1993, whereas this study needs data for the period 1988 to 2007.

[16] Note that the abnormal investment is the same as $\widehat{\delta}_{it}$ in Equation (5).

[17] See Table 1 Panel B for details

this section.

[Insert Table 1 Here.]

3.3.2 Additional variables

Some additional variables are used to investigate how share liquidity increases the propensity to raise debt finance. The correlations between the two liquidity measures ($LIQ^{G}_{j,\tau=-1}$ and $LIQ^{A}_{j,\tau=-1}$) and the key variables in the information spillover and credit ratings mechanisms such as the number of institutional managers for each firm-year (*NUMMGRS*) and a modified Altman's Z-score (*MALTMANZ*) are reported in Table 3 Panel C. Furthermore, the results of the regressions used to evaluate the information spillover and the credit ratings mechanisms are reported in Table 9 and Table 10, respectively.

To test the information spillover mechanism, the number of institutional fund managers that own shares in a particular company for each firm-year (*NUMMGRS*) is constructed. *NUMMGRS* is used as a proxy for the amount of information produced in the share market. The data obtained from WRDS are based on the reports filed by institutional investment managers (Form 13F)[18]. *NUMMGRS* is calculated as the number of institutional investors who filed Form 13F for each firm-year.

Altman's Z-score is often used to measure a firm's probability of survival (i.e. 1 - probability of default) and this is highly positively correlated with credit ratings. Focusing on firms with credit ratings reduces sample size, and I use a modified Altman's Z-score as a proxy for credit rating. Since Altman's Z-score already contains a measure of leverage, I construct a modified version of Altman's Z-score without leverage following Graham *et al.* (1998) and Chava *et al.* (2009).

[18]See http://www.sec.gov/answers/form13f.htm for more details on the reporting requirements and the definition of institutional managers.

3.4 Descriptive statistics

Table 2 shows the summary statistics of the major variables based on the whole sample and the investment spikes sample. Panel A reports summary statistics for the whole sample, whereas Panel B reports summary statistics for the investment spikes sample. The whole sample denotes the sample after data-cleaning procedures. The investment spikes sample is constructed following the procedures described in Section 3.2. The firm characteristics variables measured in the year before investment spikes have similar means and medians to those in the whole sample. This suggests that the firms in the subsample are not significantly different from the firms in the whole sample.

[Insert Table 2 Here.]

However, the following differences should be noted. First, the mean and median of leverage changes during investment spikes are 7.3% and 5.0%, whereas the mean and median of leverage changes in the whole sample are as low as 1.4% and 0.6%, respectively. Second, the means LIQ^G and LIQ^A are slightly higher for the investment spikes sample than for the whole sample, whereas their medians are almost the same in the two samples. However, a Logit regression analysis shows that share liquidity does not have a statistically and economically significant effect on the incidence of investment spikes.

[Insert Table 3 Here.]

Table 3 presents Pearson correlation coefficients between change in leverage ratio, lagged leverage ratio, two liquidity measures, and the major control variables used in the baseline specification. Panel A shows those for the whole sample, while Panel B shows those for the investment spikes sample. Panel C reports the correlations between the two share liquidity measures ($LIQ^G_{j,\tau=-1}$ and $LIQ^A_{j,\tau=-1}$) and the key variables in the mechanisms through which share liquidity increases the propensity to raise debt finance. The results in Panel C are discussed in relation to the correlations predicted by those mechanisms in Section 6.

It should be noted that, in the whole sample, the two liquidity measures ($LIQ^G_{i,t-1}$ and $LIQ^A_{i,t-1}$) have significantly positive correlations with the change in leverage (ΔLEV_{it}), while they have significantly negative correlations with lagged leverage ($LEV_{i,t-1}$). Also in the investment spikes sample, the two liquidity measures ($LIQ^G_{j,\tau=-1}$ and $LIQ^G_{j,\tau=-1}$) are significantly positively correlated with the change in leverage during an investment spike ($\Delta LEV_{j,\tau=0}$), while they are significantly negatively correlated with lagged leverage ($LEV_{j,\tau=-1}$). Although they do not reflect partial correlations, these results are quite puzzling. This result appears to suggest that the level of leverage prior to an investment spike ($LEV_{j,\tau=-1}$) has a negative effect on the liquidity of shares ($LIQ^G_{j,\tau=-1}$ or $LIQ^G_{j,\tau=-1}$), which might have a positive effect on the leverage change during an investment spike ($\Delta LEV_{j,\tau=0}$), although this causal link needs to be investigated more carefully.

In addition, it is also noteworthy that, in the case of the investment spikes sample, only initial leverage ($LEV_{j,\tau=-1}$) and two liquidity measures ($LIQ^G_{j,\tau=-1}$ and $LIQ^A_{j,\tau=-1}$) are significantly correlated with the change in leverage during an investment spike ($\Delta LEV_{j,\tau=0}$). This implies that both initial leverage and share liquidity might have much more significant effects on the funding pattern during an investment spike than any other firm characteristics. It seems that *high-leverage firms* have a lower propensity towards raising debt finance as predicted by the trade-off argument, while *high-liquidity firms* have a higher propensity to raise debt finance. This study investigates whether those relationships hold even after controlling for various firm characteristics, investment characteristics, industry effects, and year effects.

3.5 Share liquidity and debt/equity issuances

Table 4 shows summary statistics for debt finance dependence and equity finance dependence in the years categorized as investment spikes. The debt finance dependence and equity finance dependence measures are constructed as follows:

$$\begin{aligned} DFD_{j,\tau=0} &= \frac{LTDEBT_{j,\tau=0}}{(I_{j,\tau=0} - OPR_{j,\tau=0})} \\ EFD_{j,\tau=0} &= \frac{EQUITY_{j,\tau=0}}{(I_{j,\tau=0} - OPR_{j,\tau=0})}. \end{aligned}$$

where I measures investment outlays on tangible assets, intangible assets and acquisitions [*capx-sppe+aqc*], *OPR* measures after-tax cash flow from operating activities [*ibc+dpc-dv*], *LTDEBT* measures funds from issuances of long-term debt capital net of retirements [*dltis-dltr*], and *EQUITY* measures funds from issuances of ordinary and preferred shares net of retirements [*sstk-prstkc*][19].

[Insert Table 4 Here.]

Panel A clearly shows that firms with high share liquidity have substantially higher debt dependence and lower equity dependence than firms with low share liquidity. For example, firms with above-median liquidity as measured by $LIQ^G_{j,\tau=-1}$ have mean debt finance (equity finance) dependence of 49.6% (11.3%), while firms with below-median liquidity as measured by $LIQ^G_{j,\tau=-1}$ have mean debt finance dependence of 33.6% (17.6%). Panel B shows whether various firm characteristics make differences in debt/equity issuances at the time of investment spikes. Overall, the results are highly consistent with predictions of standard corporate finance theories and existing empirical studies. To summarize, firms with larger size, higher profitability, lower market to book ratios, more tangible assets, and lower R&D

[19] The italicized codes in the brackets ([ ]) represent item codes in Compustat North America

intensity have substantially higher debt finance dependence and lower equity finance dependence when financing investment spikes. Panel C shows how variables related to information spillover and credit ratings affect debt/equity issuances at the time of investment spikes. Consistent with the information spillover argument, firms with 13f filing and high institutional holdings have substantially higher debt finance dependence and lower equity finance dependence. Also consistent with the credit ratings argument, firms with high modified Altman's Z and investment-grade credit ratings have substantially higher debt finance dependence and lower equity finance dependence. This exploratory analysis suggests that share liquidity increases the propensity to raise debt finance and this works through both information spillover and credit ratings channels.

4 Empirical models and results

In this section, the effect of share liquidity on the propensity to raise debt finance to fund investment spikes and the mechanisms through which share liquidity affects the propensity to raise debt finance during investment spikes are investigated in a regression framework in which firms' financial status and investment size are controlled for.

4.1 Baseline regression: specifications and results

To investigate whether share liquidity has a positive or negative effect on abnormal borrowing at the time of an investment spike, the change in leverage during an investment spike is regressed on a lagged leverage, a liquidity measure, a spike size measure, and several other variables including firm size, profitability, and market-to-book ratio.

4.1.1 Issues in empirical research design

In this section, I consider two dynamic leverage change models: one with a measure of spike size and an interaction term between spike size and share liquidity and the other without those variables. First, consider a specification without spike size-related variables defined as follows:

$$\Delta LEV_{j,\tau=0} = \alpha + \beta LEV_{j,\tau=-1} + X'_{j,\tau=-1}\gamma + \delta LIQ_{j,\tau=-1} + IND_k + YR_t + \varepsilon_j, \tag{12}$$

where the dependent variable measures the increase in leverage during an investment spike ($\Delta LEV_{j,\tau=0} = LEV_{j,\tau=0} - LEV_{j,\tau=-1}$). $LEV_{j,\tau=-1}$ represents the lagged leverage or the leverage level at the beginning of the year with an investment spike. $X_{j,\tau=-1}$ represents a 5×1 column vector filled with the values of the control variables measured for the j-th spike during the year before an investment spike ($\tau = -1$). The control variables are firm size (*LnTA*), profitability (*EBIT_TA*), market-to-book ratio (*MV_BV*), tangibility of assets (*FA_TA*), and R&D intensity (*RD_TA*). $LIQ_{j,\tau=-1}$ represents either the liquidity measure based on Hasbrouck's (2009) Gibbs spread ($LIQ^G_{j,\tau=-1}$) or the liquidity measure based on Amihud's (2002) price impact ($LIQ^A_{j,\tau=-1}$). An industry fixed effect for industry k (IND_k) and a year fixed effect for year t (YR_t) are also included. For simplicity, industry dummies and year dummies are used to capture these effects. See Table 1 Panel A for detailed formulas with the Compustat item codes required to construct the variables used in the regressions.

Note that Equation (12) is equivalent to the reduced-form partial adjustment model, which is often used to estimate the speed of adjustment (*SOA*) of actual leverage to target leverage (Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007; Leary and Roberts, 2005; Lemmon *et al.*, 2008; Huang and Ritter, 2009). Note also that δ should be interpreted as "*SOA* $\times$ *Sensitivity of Target Leverage to Share Liquidity*". However, as long as *SOA* is positive, δ could be roughly interpreted as the effect of share liquidity on target leverage. Although δ captures the effect of share liquidity on target or normal leverage ratios, δ does not capture whether share liquidity increases abnormal borrowing at the time of an investment spike.

In designing an empirical specification, I make a clear distinction between share liquidity as a determinant of target leverage and share liquidity as a determinant of abnormal borrowing at the time of an investment spike. In the empirical specification, the basic liquidity terms in the dynamic leverage models tell us about the effect of share liquidity on target leverage ratios, a measure of spike size tells us about abnormal borrowing when faced with an investment spike, and an interaction term between spike size and share liquidity tells us about the effect of share liquidity on this abnormal borrowing.

Formally, the baseline specification with a measure of spike size and an interaction term between spike size and share liquidity is defined as follows:

$$\begin{aligned}\Delta LEV_{j,\tau=0} \quad = \quad & \alpha + \beta LEV_{j,\tau=-1} + X'_{j,\tau=-1}\gamma + \delta LIQ_{j,\tau=-1} + \pi D\_AQC_{j,\tau=0} \\ & + \theta_L SPIKESIZE_{j,\tau=0} + \theta_D SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1} \\ & + IND_k + YR_t + \varepsilon_j,\end{aligned} \tag{13}$$

where $\Delta LEV_{j,\tau=0}$, $LEV_{j,\tau=-1}$, $X_{j,\tau=-1}$, and $LIQ_{j,\tau=-1}$ are defined as in Equation (12). To investigate whether acquisitions tend to be funded differently to capital expenditures, a dummy variable for acquisitions ($D\_AQC_{j,\tau=0}$) is also included in the regression equation. $D\_AQC_{j,\tau=0}$ is 1 if a firm reports positive acquisitions during the year categorized as an investment spike and 0 otherwise. To investigate whether high-liquidity firms use more abnormal borrowing during an investment spike, a spike size measure ($SPIKESIZE_{j,\tau=0}$) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$ or $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^A_{j,\tau=-1}$) are included in the regression equation. Section 3.3.1 and Table 1 Panel B provides details on how to construct those variables. θ_L represents the propensity to raise debt finance of low-liquidity firms, whereas θ_H $(= \theta_L + \theta_D)$ represents the propensity to raise debt finance of high-liquidity firms. Hypothesis **H1** is supported if $\theta_D > 0$, whereas Hypothesis **H2** is supported if $\theta_D < 0$.

[Insert Table 5 Here.]

4.1.2 Results from baseline regression specifications

Table 5 reports the results of the regressions designed to investigate whether high liquidity firms have higher abnormal borrowing during investment spikes, as well as whether high-liquidity firms have higher target leverage ratios. First of all, the coefficient of an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$ or $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^A_{j,\tau=-1}$), or θ_D in Equation (13), is positive and significant at the 1% level of significance (see columns (2) and (4) in Table 5.). Note that $\theta_D = 0.080$ in the case of the liquidity measure based on the Gibbs spread, while $\theta_D = 0.085$ in the case of the liquidity measure based on the Amihud measure. These results support Hypothesis **H1**, since share liquidity has a positive effect on abnormal borrowing during an investment spike. The results appear economically significant as well. Note that $\theta_L = 0.162$ and $\theta_H = 0.162 + 0.080 = 0.242$ in the case of the liquidity measure based on the Gibbs spread, while $\theta_L = 0.164$ and $\theta_H = 0.164 + 0.085 = 0.249$ in the case of the liquidity measure based on the Amihud measure. This suggests that firms with higher share liquidity tend to use substantially more debt finance when they are faced with unusually large investment requirements.

However, it appears that share liquidity has a weakly positive effect on target or normal leverage ratio, but the effects are not always significant in the spikes sample[20]. In column (1), the coefficient of the liquidity measure based on Hasbrouck's Gibbs spread ($LIQ^G_{j,\tau=-1}$) is positive and significant at the 1% level, but its significance vanishes in column (2), in which investment spike characteristics are included. In columns (3) and (4), the coefficient of the liquidity measure based on Amihud's price impact ($LIQ^A_{j,\tau=-1}$) is positive but insignificant. Therefore, there are minimal differences between high-liquidity firms and low-liquidity firms, all else being equal.

Some of the explanatory variables contained in the vector $X_{j,\tau=-1}$ are significant. It should be noted that in a partial adjustment model they are interpreted as determinants of target leverage ratio[21]. The following analysis is based on columns (2) and (4). First, the coefficient of firm size ($LnTA_{\tau=-1}$) is negative and significant at the 1% level in both columns. This suggests that, after controlling for other factors, large firms tend to have lower target leverage ratios on average. Second, the coefficient of $EBIT\_TA_{j,\tau=-1}$ is negative and significant at the 5% level in both columns. This suggests that more profitable firms tend to have somewhat lower target leverage ratios on average. Third, the coefficient on market-to-book ratio ($MV\_BV_{\tau=-1}$) is negative and significant at the 5% level in both columns. This suggests that firms with more future growth opportunities tend to have somewhat lower target leverage ratios on average. Fourthly, the coefficient of tangibility of assets ($FA\_TA_{\tau=-1}$) is positive and significant at the 1% level in both columns. Firms with higher tangibility of assets or a higher proportion of fixed assets tend to have higher target leverage ratios on average. This might happen because they have more collateral to pledge against and therefore have better access to bank loans. Finally, It is very interesting that the

[20]In Table 8, I run similar regressions in the whole sample. In this case, within-firm variation as well as cross-sectional variation are exploited. Therefore, using the whole sample, I can better evaluate whether the increase in share liquidity induces the increase in target leverage ratio. However, it should be noted at this point that the models based on the investment spikes sample provide a sharper inference of the effect of share liquidity on the propensity to raise debt finance as measured by abnormal borrowing at the time of an investment spike.

[21]The coefficient of lagged leverage is negative and significant at the 1% level in the dynamic leverage change models reported in columns (1)-(4). The speed of adjustment is estimated to be 0.173 in the case of column (1). This suggests that firms also show mean reverting behaviors or target adjusting behaviors during investment spikes.

coefficients of *D_AQC* have positive signs in all regressions, meaning that investment spikes involving acquisitions tend to be more debt-financed compared with investment spikes with capital expenditures only.

I conclude that high-liquidity firms tend to have a higher propensity to raise debt finance or higher abnormal borrowing during an investment spike. Under the Conditional Independence Assumption (CIA), this finding has a causal interpretation that a given firm would have a higher propensity to raise debt finance to fund investment spikes if the firm had a higher level of share liquidity.

4.2 Robustness tests

4.2.1 Controlling for the effects of firm characteristics on abnormal borrowing during an investment spike

In this section, I investigate whether the positive and significant coefficients on the interaction terms between a spike size measure and a dummy variable for high share liquidity firms are robust to the inclusion of additional interaction terms between a spike size measure and dummy variables for large firm size, high initial leverage, high profitability, etc. Table 6 shows the results. As the results reported in Panel A and Panel B are very similar, the following analysis is based on Table 6 Panel A, which uses the liquidity measure based on the Gibbs spread ($LIQ^G_{j,\tau=-1}$) as the measure of share liquidity.

First of all, column (1) shows that the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$) is not affected at all, after inclusion of an interaction term between the spike size measure and a dummy variable for large firms ($SPIKESIZE_{j,\tau=0} \times D\_LARGE_{j,\tau=-1}$)[22] Im (2012) shows that there are substantial differences in funding

[22]$D\_LARGE_{j,\tau=-1}$ has 1 if $LnTA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise. The other dummy variables used in this paper are also defined analogously. See Table 1 Panel C for details.

patterns between large firms and small firms. In addition, he shows that the financing patterns of large firms are similar to those of high-liquidity firms, whereas the financing patterns of small firms are similar to those of low-liquidity firms. For those reasons, one might surmise that the effects attributed to share liquidity could be driven by firm size. However, this result shows that this is not the case. Furthermore, the effect of share liquidity ($\theta_D = 0.101$) is larger than that in column (2) of Table 5 ($\theta_D = 0.080$). This means that the effect of share liquidity on the propensity to raise debt finance is stronger when firm size is controlled for.

Second, columns (2)-(4) show that the effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$) is reduced to some extent, but still positive and significant, when an interaction term between the spike size measure and a dummy variable for high-leverage firms ($SPIKESIZE_{j,\tau=0} \times D\_HLEV_{j,\tau=-1}$), an interaction term between the spike size measure and a dummy variable for high-profitability firms ($SPIKESIZE_{j,\tau=0} \times D\_HPRF_{j,\tau=-1}$), or an interaction term between the spike size measure and a dummy variable for firms with high market-to-book ratios ($SPIKESIZE_{j,\tau=0} \times D\_HMB_{j,\tau=-1}$) is included in the regression equation. Column (2) shows that highly leveraged firms have a lower propensity to raise debt finance, while columns (3)-(4) show that firms with high profitability and higher growth opportunities tend to use more abnormal borrowing during investment spikes.

Third, columns (5)-(6) show that the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$) is not reduced almost at all, when an interaction term between the spike size measure and a dummy variable for firms with high assets tangibility ($SPIKESIZE_{j,\tau=0} \times D\_HTAN_{j,\tau=-1}$) or an interaction term between the spike size measure and a dummy variable for firms with high R&D intensity ($SPIKESIZE_{j,\tau=0} \times D\_HRD_{j,\tau=-1}$) is included in the regression. Note that asset tangibility does not have a significant effect on abnormal borrowing during a spike, while R&D intensity has a weakly significant positive effect on the propensity to raise debt finance. It is also noteworthy that firms with higher tangibility of assets tend to have higher target leverage ratios. This suggests that tangibility of assets does not have a significant effect on the propensity to raise debt finance, although firms with higher tangibility of assets tend to have higher target leverage ratios.

Finally, the regression result reported in column (7) is based on the specification with all the interaction terms used in columns (1)-(6) included at once. This specification does not change the findings explained above. Firms with higher initial leverage have a lower propensity to raise debt finance, while firms with higher profitability, higher market-to-book ratios, and higher R&D intensity have a higher propensity to raise debt finance.

In summary, the positive and significant coefficients on the spike size-share liquidity interaction terms are robust to the inclusion of additional spike size interaction terms. Therefore, I conclude that **H1** is well supported after controlling for the effects of various firm characteristics. Table 6 Panel B, which uses the liquidity measure based on the Amihud measure ($LIQ^{A}_{j,\tau=-1}$) as a measure of share liquidity, shows almost identical results.

[Insert Table 6 Here.]

4.2.2 Using various definitions of leverage ratios

In this section, I investigate whether the positive effect of share liquidity on the propensity to raise debt finance during investment spikes is robust to the use of various leverage measures. Two alternative leverage measures, *BLEV* and *MLEV* (as defined in Section 3.3.1), are used for this purpose. Table 7 reports the regression results. The dependent variable in columns (1)-(2) is the increase in a book leverage ratio during an investment spike ($\Delta BLEV_{j,\tau=0}$), whereas the dependent variable in columns (3)-(4) is the increase in an alternative market leverage ratio during an investment spike ($\Delta MLEV_{j,\tau=0}$). Accordingly, $BLEV_{j,\tau=-1}$ is used as a lagged leverage ratio in columns (1)-(2), whereas $MLEV_{j,\tau=-1}$ is used in columns (3)-(4). Note that $SPIKESIZE1_{j,\tau=0}$ is used in in columns (1)-(2) while $SPIKESIZE2_{j,\tau=0}$ is used in in columns (3)-(4). $SPIKESIZE1_{j,\tau=0}$ represents abnormal investment as a proportion of book value of total assets at the beginning of the year with an investment spike, while $SPIKESIZE2_{j,\tau=0}$ represents abnormal investment as a proportion of the sum of book value of financial liabilities and market value of equity at the beginning of the year with an investment spike[23]. See Table 1 Panel B for details.

In all of the models, the coefficient of an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE1_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ or $SPIKESIZE1_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$ or $SPIKESIZE2_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ or $SPIKESIZE2_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$) is positive and significant at the 1% level of significance. These results support Hypothesis **H1** once again, since share liquidity has a positive effect on abnormal borrowing at the time of an investment spike. It is noteworthy that coefficients of interaction terms are somewhat larger in models with market leverage measures. Note also that the share liquidity measures do not have any significant effect on target leverage in all columns. I therefore conclude that firms with higher share liquidity tend to use substantially more debt finance when they are faced with unusually large investment requirements, although share liquidity does not have a significant effect on target leverage ratio in the spike periods. The positive effect of share liquidity on the propensity to raise debt finance to fund investment spikes is robust to the choice of leverage measures.

[Insert Table 7 Here.]

[23]Note that the denominators used to construct $SPIKESIZE1_{j,\tau=0}$ and $SPIKESIZE2_{j,\tau=0}$ are the same as the denominators used to construct $BLEV_{j,\tau=-1}$ and $MLEV_{j;\tau=-1}$, respectively.

5 Using the whole sample rather than the investment spikes sample

One might suspect that a positive effect from share liquidity on the change in leverage is driven by the use of the investment spikes sample instead of the whole sample. Therefore, I test this possibility by implementing a dynamic leverage change model similar to Equation (12) and Equation (13) with the whole sample. Table 8 reports the results for the regressions designed to investigate whether share liquidity has a positive effect on target leverage and abnormal borrowing during an investment spike in the whole sample. The dependent variables in all regressions are the change in leverage (ΔLEV_{it}). The liquidity measure based on the Gibbs spread is used as a measure of liquidity in columns (1)-(4), whereas the liquidity measure based on the Amihud measure is used in columns (5)-(8). Odd-numbered columns present the OLS estimation results, whereas even-numbered columns present the fixed effects (FE) regression results. All the models reported in columns (1)-(8) have a dummy variable for a year with investment spikes (D_SPIKE_{it}) to see if more debt finance is used in the year with investment spikes compared with other periods. The models reported in columns (3), (4), (7), and (8) include a spike size measure ($SPIKESIZE_{it}$) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE_{it} \times D\_HLIQ^{G}_{i,t-1}$ or $SPIKESIZE_{it} \times D\_HLIQ^{A}_{i,t-1}$), as well as a dummy variable for acquisitions (D_AQC_{it}). Table 1 Panel B provides details on how to construct those variables. Note that the spike size measure ($SPIKESIZE_{it}$) and its interaction terms ($SPIKESIZE_{it} \times D\_HLIQ^{G}_{i,t-1}$ or $SPIKESIZE_{it} \times D\_HLIQ^{A}_{i,t-1}$) have a value of zero if the firm-year is not categorized as an investment spike. The industry dummies defined as in Fama and French's (1997) study and year dummies are included in each regression.

[Insert Table 8 Here.]

Main results

The results of this analysis are summarized as follows. First, note that a dummy variable for a year with investment spikes (D_SPIKE_{it}) is positive and significant at the 1% level, regardless of model specifications and estimation methods. This suggests that a substantial amount of debt finance is raised during a year with investment spikes. Based on column (1), on average firms increase leverage in such a year by about 6.1% points more than in normal periods. Second, the coefficients of D_AQC_{it} have positive signs regardless of estimation methods, meaning that investment spending involving acquisitions tends to be more debt-financed compared with investment spending with capital expenditures only. Third, an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($SPIKESIZE_{it} \times D\_HLIQ^G_{it-1}$ or $SPIKESIZE_{it} \times D\_HLIQ^A_{it-1}$) is positive and significant at the 1% level, regardless of the estimation method used. In addition, the magnitude of the positive effect of share liquidity is very similar to that found in the investment spikes sample. This analysis also shows that the addition of investment spikes information increases the explanatory power of the model. Note that R-squared increases from 0.186 (column (1)) to 0.202 (column (3)) and the coefficients of all additional variables are significant at the 1% level.

Effect of share liquidity on target leverage

This whole sample analysis can be also used to identify the effect of share liquidity on target or normal leverage ratio[24]. This analysis shows that the effect of share liquidity on target leverage is positive and significant at the 1% level, regardless of model specifications and estimation methods. In the models with a liquidity measure based on Gibbs spread, the coefficient of the linear liquidity term ($LIQ^G_{i,t-1}$) has a value between 0.006 and 0.012; in the models with a liquidity measure based on Amihud measure, the

[24]Note that the model used in Table 8 is the reduced-form partial adjustment model often used to estimate the speed of adjustment (SOA) of actual leverage to target leverage (Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007; Leary and Roberts, 2005; Lemmon *et al.*, 2008; Huang and Ritter, 2009).

coefficient of the linear liquidity term ($LIQ^A_{i,t-1}$) has a value between 0.004 and 0.007. This contrasts with the results based on the spikes sample. Recall that in the spikes sample share liquidity has a weakly positive effect on target leverage ratio, but the effects are not always significant in the spikes sample. This is driven by the fact that within-firm variations as well as cross-sectional variations are exploited in the whole sample analysis, while within-firm variations are not exploited in the spikes sample analysis. In a partial adjustment model used to study the effects of various variables on target leverage and to estimate the speed of leverage adjustment, the within-firm variations rather than crosssectional variations can be more informative about the effects of various variables on target leverage and the speed of leverage adjustment. Thus, I can conclude that share liquidity has a positive and significant effect on target leverage.

In summary, the results in the previous section are not just driven by the use of the investment spikes sample, although using the years with investment spikes gives us more pronounced results. In addition, I have found that firms with higher share liquidity tend to have higher target ratios. I therefore conclude that firms with more liquid shares have a higher propensity to raise debt finance.

6 Mechanisms through which share liquidity increases debt finance

Having established the positive effect of share liquidity on the propensity to raise debt finance, I turn to the assessment of the mechanisms through which share liquidity increases the propensity to raise debt finance. To assess whether each of the two mechanisms works, I compare the observed correlation coefficients of the share liquidity measures ($LIQ^G_{j,\tau=-1}$ and $LIQ^A_{j,\tau=-1}$) and the two key variables[25] with the correlation coefficients predicted in those mechanisms. Then, we check whether the magnitude or

[25]The key variables used are $MALTMANZ_{j,\tau=-1}$ for the credit ratings mechanism and $NUMMGRS_{j,\tau=-1}$ for the information spillover mechanism. Those variables are defined in Section 3.3.2.

significance of the coefficient of an interaction term[26] between a spike size measure ($SPIKESIZE_{j,\tau=0}$) and a dummy variable for high-liquidity firms ($SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ or $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$) is weakened when a key variable and an interaction term between the spike size measure and a dummy variable based on the key variable are included as explanatory variables in the regression.

Information spillover mechanism

First, the *information spillover mechanism* (**H1A**) is based on the argument that banks can monitor high-liquidity firms more efficiently by supplementing their own information with more informative stock prices, as more information is available for those firms and such information spills over into the debt market (Sunder, 2004; Saunders and Steffen, 2011). Although the amount of information prevailing in the stock market is hard to measure, it is proxied by the number of institutional managers for each firm-year ($NUMMGRS_{j,\tau=-1}$). The information spillover mechanism predicts that the shares of high-liquidity firms are owned by a larger number of institutional managers. Table 3 Panel C shows that $NUMMGRS_{j,\tau=-1}$ is positively correlated with two liquidity measures at the 1% level, as predicted by this mechanism.

[Insert Table 9 Here.]

Table 9 reports the results of the regression models designed to evaluate the information spillover mechanism. First, column (1) shows that the interaction term between the spike size measure and a dummy variable for firms with high information production ($SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$) is positive and statistically significant at the 1% level of significance. The magnitude of the coefficient is 0.071, so this is similar to the coefficients of two dummy variables for high-liquidity firms. Columns (2) and (4) show that the coefficients for $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ and $SPIKESIZE_{j,\tau=0} \times$

[26]Recall that this was defined as θ_D in Section 4.1.

$D\_HLIQ^{A}_{j,\tau=-1}$ are 0.063 and 0.071, respectively. Then, we investigate whether the positive effect of share liquidity on abnormal borrowing during an investment spike is attenuated after the inclusion of the number of institutional managers ($NUMMGRS_{j,\tau=-1}$) as a proxy for the information produced in the stock market and the inclusion of an interaction term between the spike size measure and a dummy variable for firms with high information production ($SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$). Columns (3) and (5) show that the positive effect of share liquidity on the propensity to raise debt finance vanishes when additional variables related to information production in the stock market are included in the regression. In the case of both liquidity measures, the magnitude of θ_D gets smaller and its significance disappears. It seems that share liquidity measures also capture the amount of information available in the stock market. Thus, based on both correlation analysis and regression analysis, I conclude that the information spillover mechanism works.

Credit ratings mechanism

Second, the *credit ratings mechanism* (**H1B**) is based on the argument that credit ratings and share liquidity capture the same adverse selection risk, although they are measured in different markets, i.e. debt market and stock market (Odders-White and Ready, 2006). A modified Altman's Z-score ($MALTMANZ_{j,\tau=-1}$) is often used to measure adverse selection risk instead of credit ratings data[27]. Thus, the credit ratings mechanism predicts a positive correlation between share liquidity and $MALTMANZ_{j,\tau=-1}$. Table 3 Panel C shows that correlations between $MALTMANZ_{j,\tau=-1}$ and both liquidity measures are positive and significant at the 1% level in the investment spikes sample. Chava *et al.* (2009) also show that $MALTMANZ_{j,\tau=-1}$ has a significantly negative effect on the loan spread, after controlling for various firm and loan characteristics.

[27] A dummy variable for an investment-grade bond is highly correlated with the modified Altman's Z-score, but this dummy variable is not used because sample size drops in this case.

[Insert Table 10 Here.]

Table 10 reports the results of the regressions designed to evaluate the credit rating mechanism. First, column (1) shows that the interaction term between the spike size measure and a dummy variable for firms with high credit ratings ($SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$) is positive and statistically significant at the 1% level of significance. The magnitude of the coefficient is 0.090, so this is slightly larger than the coefficients of two dummy variables for high-liquidity firms. Columns (2) and (4) show that the coefficients for $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ and $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$ are 0.079 and 0.083, respectively. Then, we investigate whether the positive effect of share liquidity on abnormal borrowing during an investment spike is attenuated after the inclusion of an interaction term between the spike size measure and a dummy variable for firms with high credit ratings ($SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$). Columns (3) and (5) show that the positive effect of share liquidity on the propensity to raise debt finance vanishes when additional variables related to information production in the stock market are included in the regression. In the case of both liquidity measures, the magnitude of θ_D gets smaller and its significance disappears. It seems that share liquidity measures also capture the adverse selection risk reflected in credit ratings. Thus, based on both correlation analysis and regression analysis, I conclude that the credit ratings mechanism also works.

In this section, I have shown that the credit ratings mechanism and information spillover mechanism work. Those two mechanisms provide interesting explanations as to why a firm with more liquid shares have a higher propensity to raise debt finance. Firms with more liquid shares are less likely to have severe asymmetric information problems between informed investors, including managers, and uninformed investors. Thus, firms with more liquid shares are likely to have more informative share prices. In addition, more information on those firms is available because those firms are followed by a large number of financial analysts and shares of those firms are owned by many financial institutions. Banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices. Hence, firms with more liquid shares face a lower cost of debt and are likely to have a higher propensity to raise debt finance. Moreover, firms with more liquid shares also tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, firms with more liquid shares incur lower costs when raising debt finance in subsequent periods and are likely to raise more debt finance to satisfy large investment requirements.

7 Conclusions

This study has investigated whether firms with a more liquid market for their shares would prefer debt to equity more than firms with a less liquid market for their shares. This topic has not received sufficient attention in empirical studies of corporate finance, although there are conflicting views about the effect of share liquidity on how firms finance investment activities. I have found that firms with more liquid shares rely more on net debt issuances and less on net equity issuances in comparison with firms with less liquid shares. I have also found that firms with more liquid shares tend to have higher target leverage ratios. One interpretation of these results is that the information spillovers from the presence of more informative share prices as well as more active information production in the stock market allow firms with more liquid shares to borrow on more favourable terms in normal times, as well as to obtain additional debt finance at lower costs when taking advantage of unusually large investment opportunities. This paper makes a substantial contribution to several branches of finance literature. First, this paper contributes to the security design literature represented by authors such as Boot and Thakor (1993). Boot and Tharkor (1993) provide a theory which explains why a firm raising external capital would wish to simultaneously issue multiple types of financial claims such as debt and equity against its cash flows. This paper is the first to consider share liquidity as a determinant of the sources used to finance firms' large investment activities. My empirical findings can trigger some theoretical research on the relation between share liquidity and the way firms finance their investment activities. Second, this paper contributes to the literature on the interaction of market microstructure and corporate finance; this strand of literature includes authors such as Fang, Noe and Tice (2009), who investigate the effect of share liquidity on corporate performance and financing behavior. Unlike conventional views predicting a negative effect of share liquidity on the propensity to raise debt finance, this paper finds a positive effect of share liquidity on the propensity to raise debt finance and shows that explanations based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2011) and the shared information content in share liquidity and credit ratings (Odders-White and Ready, 2006) work very well. Finally, this paper contributes to the empirical literature on the way in which firms meet exceptional financing needs in relation to investment spikes, as studied by authors such as DeAngelo, DeAngelo, and Whited (2011) and Mayer and Sussman (2005). Although my findings are very robust to the choice of various empirical specifications, my research does not take into account the possibility that the liquidity-sensitivity of bank debt and bonds could be different and the possibility that the way acquisitions are funded might be different to the way capital expenditures are financed. These extensions are fruitful agendas for future research.

A Appendix

A.1 Liquidity measures

In this paper, I construct two share liquidity measures $LIQ^{G}_{j,\tau=-1}$ and $LIQ^{A}_{j,\tau=-1}$ by multiplying Hasbrouck's Gibbs spread measure and Amihud's price impact measure by (-1) respectively. The following shows how to construct Hasbrouck's (2009) Gibbs spread measure and Amihud's (2002) price impact measure.

1. Gibbs spread measure

Hasbrouck (2009) introduces a Gibbs sampler estimation of the Roll (1984) model using prices from all days in each year. In his model, the "efficient price" (m_t) is assumed to follow a Gaussian random walk:

$$m_t = m_{t-1} + u_t, \tag{14}$$

where $u_t \sim N(0, \sigma_u^2)$. The transaction price is given by

$$p_t = m_t + cq_t, \tag{15}$$

where c is the effective cost parameter and q_t is the trade direction indicator, which takes the value +1 (for a buy) or -1 (for a sale) with equal probability. The disturbance, u_t, reflects public information and is assumed to be uncorrelated with q_t. The transaction prices are observed but q_t and m_t are not. Taking first differences gives:

$$\Delta p_t = m_t + cq_t - (m_{t-1} + cq_{t-1}) = c\Delta q_t + u_t, \tag{16}$$

Note that this equation would be a simple linear regression if Δq_t were known. However, Δq_t is unobserved. In this situation, a Bayesian method called Gibbs sampling provides a way to estimate the model parameters $\{c, \sigma_u^2\}$ along with the latent buy/sell indicators $q = \{q_1, q_2, \cdots, q_T\}$, where T is the number of days in the year. The parameter c estimated for firm i during year y gives us the effective trading cost for firm i during year y, $Gibbs_{iy}$. I use the SAS programming codes on Joel Hasbrouck's website without any modification. To see economic significance of the measure, I normalize the Gibbs spread measure so that its mean equals 0 and its standard deviation equals 1.

2. Amihud measure

The price impact measure developed by Amihud (2002) captures the "daily price response associated with one dollar of trading volume." Specifically, he uses the ratio

$$Amihud_{iy} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} \left(\frac{|R_{iyd}|}{DVOL_{iyd}} \right), \tag{17}$$

where D_{iy} is the number of days for which data are available for stock i in year y, R_{iyd} is firm i's stock return on day d in year y, and $DVOL_{iyd}$ is firm i's dollar volume on day d in year y. The average is calculated over all positive-volume days, since the ratio is undefined for zero-volume days. The Amihud measure is also normalized so that its mean equals 0 and its standard deviation equals 1.

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Table 1: Variable definitions

This table shows the definitions of variables used in the study. Panel A describes major variables used in regression analyses, Panel B describes additional variables related to the size of investment spikes, and Panel C describes dummy variables used in this paper. The definitions of variables in Panel A closely follow those of Flannery and Rangan (2006), Lemmon *et al.* (2008), and Rajan and Zingales (1995). Unless otherwise stated, all the Compustat variables are measured at the end of year t. The variables in ratios are winsorized at the 1-st and 99-th percentiles. The italicized codes in the brackets ([ ]) represent item codes in Compustat North America.

Panel A. Major variables used in regression analyses

Abbreviation	Description	Formula
LEV	A baseline leverage measure	Book value of total liabilities [*lt*] / (Book value of total liabilities [*lt*] + Market value of equity [*prcc_c* × *csho*])
BLEV	A book leverage measure	See 3.3.1.
MLEV	An alternative market leverage measure	See 3.3.1.
ΔLEV	Change in market leverage	LEV_t - LEV_{t-1}
LnTA	Log(firm size)	Natural logarithm of Total assets [*at*]
EBIT_TA	Profitability	(Income before extraordinary items [*ib*] + Total interest and related expenses [*xint*] + Total income taxes [*txt*]) / Total assets at the beginning of the year [at_{t-1}]
MV_BV	Market-to-Book	(Total long-term debt [*dltt*] + Total debt in current liabilities [*dlc*] + Liquidation value of preferred stock [*pstkl*] + Close price at the end of calendar year [*prcc_c*] × Number of common shares outstanding [*csho*]) / Total assets [*at*]
FA_TA	Tangibility of assets	Total property, plant and equipment [*ppent*] / Total assets [*at*]
RD_TA	R&D intensity	R&D expenses [*xrd*] / Total assets at the beginning of the year [at_{t-1}]
LIQ^G	Liquidity based on *Gibbs*	$(-1)\times$ Standardized Hasbrouck's Gibbs spread
LIQ^A	Liquidity based on *Amihud*	$(-1)\times$ Standardized Amihud's price impact

Panel B. Investment spike size measures

Abbreviation	Description	Formula
$SPIKESIZE_{j,\tau=0}$	Abnormal investment as a proportion of market value of total assets at the beginning of the year with an investment spike	$(I_{j,\tau=0} - BASE_j)$/(Book value of total liabilities at the beginning of the year [$lt_{j,\tau=-1}$] + Close price at the beginning of calendar year [$prcc\_c_{j,\tau=-1}$] × Number of common shares outstanding [$csho_{j,\tau=-1}$]); *SPIKESIZE* and its interaction terms with D_HLIQ^G or D_HLIQ^A have a value of zero if the firm-year is not categorized as an investment spike.
$SPIKESIZE1_{j,\tau=0}$	Abnormal investment as a proportion of book value of total assets at the beginning of the year with an investment spike	$(I_{j,\tau=0} - BASE_j)$/(Book value of total assets at the beginning of the year [$at_{j,\tau=-1}$])
$SPIKESIZE2_{j,\tau=0}$	Abnormal investment as a proportion of the sum of book value of financial liabilities and mark value of equity at the beginning of the year with an investment spike	$(I_{j,\tau=0} - BASE_j)$/(Book value of long-term liabilities [$dltt_{j,\tau=-1}$] + Book value of short-term liabilities [$dlc_{j,\tau=-1}$] + Market value of equity[$prcc\_c_{j,\tau=-1}$ × $csho_{j,\tau=-1}$])

Table 1 (Continued): Variable definitions

Panel C. Dummy variables used in this paper

Abbreviation	Description	Formula
$D\_AQC_{j,\tau=0}$	Dummy variable for acquisitions	1 if a firm reports positive acquisitions [$aqc_{j,\tau=0}$], and 0 otherwise.
$D\_HLIQ^{G}_{j,\tau=-1}$	High liquidity dummy based on Hasbrouck's (2009) Gibbs spread	1 if $LIQ^{G}_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HLIQ^{A}_{j,\tau=-1}$	High liquidity dummy based on Amihud's (2002) price impact	1 if $LIQ^{A}_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_LARGE_{j,\tau=-1}$	Dummy variable for large firms	1 if $LnTA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HLEV_{j,\tau=-1}$	Dummy variable for high leverage firms	1 if $LEV_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HPRF_{j,\tau=-1}$	Dummy variable for high profitability firms	1 if $EBIT\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HMB_{j,\tau=-1}$	Dummy variable for high market-to-book firms	1 if $MV\_BV_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HTAN_{j,\tau=-1}$	Dummy variable for high asset tangibility firms	1 if $FA\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HRD_{j,\tau=-1}$	Dummy variable for high R&D intensity firms	1 if $RD\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HNMGRS_{j,\tau=-1}$	Dummy variable for firms with high number of institutional managers	1 if $NUMMGRS_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HMALTZ_{j,\tau=-1}$	Dummy variable for firms with high $MALTMANZ_{j,\tau=-1}$	1 if $MALTMANZ_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.

Table 2: Summary statistics

Panel A reports summary statistics for the whole sample whereas Panel B reports summary statistics for the investment spikes sample. Section 3.2 describes how the investment spikes sample is constructed. The variables are defined as in Table 1. The identifier i represents the firm code, whereas the identifier j represents the investment spike code. The time index t represents the fiscal year reported in Compustat, whereas the time index τ represents the time in relation to an investment spike. For example, $\tau = 0$ indicates the year categorized as an investment spike, whereas $\tau = -1$ indicates the year before an investment spike. The subscripts (i,t) are used in the whole sample, whereas the subscripts (j,τ) are used in the investment spikes sample.

Panel A. Summary statistics: Whole sample

Variable	N	Mean	SD	Q1	Median	Q3
ΔLEV_{it}	89936	0.014	0.148	-0.047	0.006	0.074
LEV_{it}	103093	0.359	0.259	0.137	0.313	0.541
$\Delta BLEV_{it}$	103350	0.001	0.295	-0.036	0.000	0.036
$BLEV_{it}$	117106	0.303	0.432	0.033	0.208	0.398
$\Delta MLEV_{it}$	89784	0.010	0.142	-0.032	0.000	0.050
$MLEV_{it}$	102947	0.229	0.252	0.013	0.140	0.368
$LnTA_{it}$	117471	4.558	2.630	2.842	4.551	6.306
$EBIT\_TA_{it}$	100807	-0.108	0.787	-0.063	0.068	0.143
MV_BV_{it}	102400	2.669	5.367	0.840	1.282	2.308
FA_TA_{it}	117210	0.281	0.238	0.090	0.210	0.414
RD_TA_{it}	112278	0.071	0.171	0.000	0.000	0.062
LIQ^G_{it}	66922	0.016	0.969	-0.163	0.368	0.571
LIQ^A_{it}	66922	0.010	0.838	0.095	0.119	0.121

Panel B. Summary statistics: Investment spikes sample

Variable	N	Mean	SD	Q1	Median	Q3
$\Delta LEV_{j,\tau=0}$	5872	0.073	0.150	-0.005	0.050	0.141
$LEV_{j,\tau=0}$	6123	0.354	0.242	0.147	0.319	0.527
$LEV_{j,\tau=-1}$	5905	0.285	0.227	0.094	0.232	0.429
$\Delta BLEV_{j,\tau=0}$	6383	0.039	0.245	-0.007	0.019	0.104
$BLEV_{j,\tau=0}$	6402	0.269	0.298	0.049	0.224	0.395
$BLEV_{j,\tau=-1}$	6396	0.230	0.334	0.014	0.148	0.326
$\Delta MLEV_{j,\tau=0}$	5860	0.070	0.149	0.000	0.028	0.129
$MLEV_{j,\tau=0}$	6114	0.232	0.236	0.023	0.162	0.373
$MLEV_{j,\tau=-1}$	5897	0.165	0.205	0.004	0.084	0.256
$LnTA_{j,\tau=-1}$	6415	4.729	2.376	3.117	4.672	6.295
$EBIT\_TA_{j,\tau=-1}$	5964	-0.078	0.844	0.008	0.101	0.175
$MV\_BV_{j,\tau=-1}$	5878	2.827	4.756	0.954	1.516	2.746
$FA\_TA_{j,\tau=-1}$	6406	0.249	0.217	0.076	0.184	0.360
$RD\_TA_{j,\tau=-1}$	6418	0.090	0.203	0.000	0.002	0.082
$LIQ^G_{j,\tau=-1}$	4103	0.075	0.867	-0.114	0.360	0.558
$LIQ^A_{j,\tau=-1}$	4103	0.034	0.885	0.105	0.119	0.121

Table 3: Correlation matrix for variables used in regression analysis

This table shows the correlation matrix between the major variables used in this study. Panel A is based on the whole sample, whereas Panel B and Panel C are based on the investment spikes sample. Definitions of variables used in panels A and B are in Table 1 Panel A. Panel C shows the correlation coefficients between two share liquidity measures and additional variables defined in Section 3.3.2. The time index τ represents the time in relation to an investment spike. Pearson correlation coefficients are reported. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Correlation matrix: Whole sample

	ΔLEV_{it}	$LEV_{i,t-1}$	$LnTA_{i,t-1}$	$EBIT\_TA_{i,t-1}$	$MV\_BV_{i,t-1}$	$FA\_TA_{i,t-1}$	$RD\_TA_{i,t-1}$	$LIQ^G_{i,t-1}$
$LEV_{i,t-1}$	-0.2652***							
$LnTA_{i,t-1}$	-0.0196***	0.1766***						
$EBIT\_TA_{i,t-1}$	-0.0436***	0.0743***	0.3754***					
$MV\_BV_{i,t-1}$	0.0742***	-0.2804***	-0.3963***	-0.5343***				
$FA\_TA_{i,t-1}$	-0.0211***	0.2177***	0.2318***	0.1092***	-0.1178***			
$RD\_TA_{i,t-1}$	0.0326***	-0.2946***	-0.2218***	-0.4572***	0.2965***	-0.2407***		
$LIQ^G_{i,t-1}$	0.0709***	-0.1899***	0.5298***	0.1432***	0.0724***	0.0079*	-0.0115***	
$LIQ^A_{i,t-1}$	0.0513***	-0.1092***	0.1623***	0.0297***	0.0422***	-0.0157***	0.0217***	0.5445***

Panel B. Correlation matrix: Investment spikes sample

	$\Delta LEV_{j,\tau=0}$	$LEV_{j,\tau=-1}$	$LnTA_{j,\tau=-1}$	$EBIT\_TA_{j,\tau=-1}$	$MV\_BV_{j,\tau=-1}$	$FA\_TA_{j,\tau=-1}$	$RD\_TA_{j,\tau=-1}$	$LIQ^G_{j,\tau=-1}$
$LEV_{j,\tau=-1}$	-0.2279***							
$LnTA_{j,\tau=-1}$	0.0086	0.2212***						
$EBIT\_TA_{j,\tau=-1}$	0.0085	0.1181***	0.3264***					
$MV\_BV_{j,\tau=-1}$	-0.0083	-0.3371***	-0.3270***	-0.4858***				
$FA\_TA_{j,\tau=-1}$	0.0184	0.2669***	0.2547***	0.1347***	-0.1551***			
$RD\_TA_{j,\tau=-1}$	-0.0154	-0.3309***	-0.2372***	-0.5698***	0.3381***	-0.2675***		
$LIQ^G_{j,\tau=-1}$	0.0553***	-0.1563***	0.5201***	0.1075***	0.0726***	0.0294*	-0.0228	
$LIQ^A_{j,\tau=-1}$	0.0510***	-0.1009***	0.1292***	0.0237	0.0355**	-0.0401**	0.0131	0.5974***

Panel C. Correlation coefficients between share liquidity and additional variables

	$MALTMANZ_{j,\tau=-1}$	$NUMMGRS_{j,\tau=-1}$
$LIQ^G_{j,\tau=-1}$	0.1204***	0.3680***
$LIQ^A_{j,\tau=-1}$	0.0496***	0.1080***

Table 4: Share liquidity, other firm characteristics and debt/equity issuances

This table shows summary statistics for debt finance dependence and equity finance dependence measured in the investment spikes sample. Both debt finance dependence ($DFD_{j,\tau=0}$) and equity finance dependence ($EFD_{j,\tau=0}$) are constructed as follows:

$$
\begin{aligned}
DFD_{j,\tau=0} &= \frac{LTDEBT_{j,\tau=0}}{(I_{j,\tau=0} - OPR_{j,\tau=0})} \\
EFD_{j,\tau=0} &= \frac{EQUITY_{j,\tau=0}}{(I_{j,\tau=0} - OPR_{j,\tau=0})},
\end{aligned}
$$

where I measures investment outlays on tangible assets, intangible assets and acquisitions [*capx-sppe+aqc*], OPR measures after-tax cash flow from operating activities [*ibc+dpc-dv*], $LTDEBT$ measures funds from issuances of long-term debt capital net of retirements [*dltis-dltr*], and $EQUITY$ measures funds from issuances of ordinary and preferred shares net of retirements [*sstk-prstkc*]. The italicized codes in the brackets ([ ]) represent item codes in Compustat North America.

Panel A. Share liquidity and debt/equity issuances

	Debt Finance Dependence ($DFD_{j,\tau=0}$)			Equity Finance Dependence ($EFD_{j,\tau=0}$)		
Category	N	Mean	Median	N	Mean	Median
Low share liquidity (Gibbs)	2049	0.336	0.053	2045	0.176	0.013
High share liquidity (Gibbs)	2043	0.496	0.411	2044	0.113	0.009
Low share liquidity (Amihud)	2049	0.300	0.103	2048	0.173	0.010
High share liquidity (Amihud)	2043	0.532	0.324	2041	0.115	0.011

Panel B. Firm characteristics and debt/equity issuances

	Debt Finance Dependence ($DFD_{j,\tau=0}$)			Equity Finance Dependence ($EFD_{j,\tau=0}$)		
Category	N	Mean	Median	N	Mean	Median
Small firms	3206	0.225	0.000	3202	0.334	0.019
Large firms	3196	0.524	0.450	3200	0.127	0.004
Low profitability	2973	0.290	0.047	2972	0.331	0.016
High profitability	2972	0.476	0.351	2973	0.122	0.003
Low Market/Book	2926	0.448	0.393	2930	0.067	0.001
High Market/Book	2933	0.349	0.000	2927	0.286	0.042
Low tangibility of assets	3197	0.202	0.000	3191	0.302	0.023
High tangibility of assets	3187	0.544	0.517	3193	0.158	0.003
Low R&D intensity	1746	0.447	0.325	1744	0.267	0.009
High R&D intensity	4650	0.347	0.050	4652	0.216	0.011

Panel C. Information-related and credit-related variables and debt/equity issuances

	Debt Finance Dependence ($DFD_{j,\tau=0}$)			Equity Finance Dependence ($EFD_{j,\tau=0}$)		
Category	N	Mean	Median	N	Mean	Median
Without 13f filing	3243	0.326	0.033	3245	0.336	0.011
With 13f filing	3159	0.424	0.269	3157	0.122	0.009
Low institutional holdings	1565	0.291	0.085	1563	0.174	0.009
High institutional holdings	1594	0.554	0.408	1594	0.070	0.009
Low modified Altman's Z	3085	0.329	0.029	3082	0.363	0.027
High modified Altman's Z	3082	0.442	0.257	3085	0.110	0.003
Non-investment-grade ratings	534	0.495	0.589	536	0.128	0.006
Investment-grade ratings	674	0.604	0.612	673	0.016	0.000

Table 5: Effects of share liquidity on the propensity to raise debt finance

This table reports the results of the regressions designed to investigate whether share liquidity increases abnormal borrowing during an investment spike. The dependent variable is the change in leverage during an investment spike ($\Delta LEV_{j,\tau=0}$). The explanatory variables are defined as in Table 1 Panel A. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ($LIQ^{G}_{j,\tau=-1}$) is used as a measure of liquidity in columns (1)-(2), whereas the liquidity measure based on Amihud's (2002) price impact ($LIQ^{A}_{j,\tau=-1}$) is used in columns (3)-(4). Odd-numbered columns present the regression results without investment spike characteristics, whereas even-numbered columns present the regression results with investment spike characteristics. One of the following interaction terms are used in columns (2) and (4), respectively: $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$ or $SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$. Table 1 Panel B describes how to construct $D\_AQC_{j,\tau=0}$, $SPIKESIZE_{j,\tau=0}$, $D\_HLIQ^{G}_{j,\tau=-1}$, and $D\_HLIQ^{A}_{j,\tau=-1}$. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

	Liquidity based on *Gibbs*		Liquidity based on *Amihud*	
VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)
$LEV_{j,\tau=-1}$	**-0.173*****	**-0.184*****	**-0.181*****	**-0.187*****
	(0.013)	(0.012)	(0.013)	(0.013)
$LnTA_{j,\tau=-1}$	**-0.005*****	**-0.005*****	**-0.003****	**-0.004*****
	(0.001)	(0.001)	(0.001)	(0.001)
$EBIT\_TA_{j,\tau=-1}$	**-0.019*****	**-0.016****	**-0.019*****	**-0.015****
	(0.006)	(0.006)	(0.006)	(0.006)
$MV\_BV_{j,\tau=-1}$	**-0.003*****	**-0.002****	**-0.003*****	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.059*****	**0.051*****	**0.060*****	**0.052*****
	(0.015)	(0.013)	(0.015)	(0.014)
$RD\_TA_{j,\tau=-1}$	**-0.059*****	**-0.024**	**-0.058*****	**-0.024**
	(0.022)	(0.021)	(0.022)	(0.021)
$LIQ^{G}_{j,\tau=-1}$	**0.010*****	**0.006**		
	(0.004)	(0.004)		
$LIQ^{A}_{j,\tau=-1}$			**0.005**	**0.003**
			(0.003)	(0.003)
$D\_AQC_{j,\tau=0}$		**0.023*****		**0.024*****
		(0.005)		(0.005)
$SPIKESIZE_{j,\tau=0}$		**0.162*****		**0.164*****
		(0.017)		(0.017)
$SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{G}_{j,\tau=-1}$		**0.080*****		
		(0.022)		
$SPIKESIZE_{j,\tau=0} \times D\_HLIQ^{A}_{j,\tau=-1}$				**0.085*****
				(0.023)
Constant	**0.117*****	**0.077*****	**0.109*****	**0.076*****
	(0.030)	(0.024)	(0.030)	(0.024)
Observations	3,728	3,728	3,728	3,728
R-squared	0.174	0.281	0.173	0.281

Table 6: Controlling for other firm characteristics

This table reports the results of the regressions designed to investigate whether the effect of share liquidity on abnormal borrowing during an investment spike remains after controlling for firm characteristics. The same variables used in column (2) of Table 5 are used in each model. Additionally, the interaction terms between $SPIKESIZE_{j,\tau=0}$ and the following dummy variables are used: $D\_LARGE_{j,\tau=-1}$ *(large firms dummy)*; $D\_HLEV_{j,\tau=-1}$ *(high-leverage firms dummy)*; $D\_HPRF_{j,\tau=-1}$ *(high profitability dummy)*; $D\_HMB_{j,\tau=-1}$ *(high market-to-book dummy)*; $D\_HTAN_{j,\tau=-1}$ *(high assets tangibility dummy)*; and $D\_HRD_{j,\tau=-1}$ *(high R&D intensity dummy)*. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Liquidity measure based on Hasbrouck's Gibbs spread measure

VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)	$\Delta LEV_{j,\tau=0}$ (6)	$\Delta LEV_{j,\tau=0}$ (7)
$LEV_{j,\tau=-1}$	**-0.183*** **	**-0.161*** **	**-0.177*** **	**-0.171*** **	**-0.184*** **	**-0.183*** **	**-0.152*** **
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
$LnTA_{j,\tau=-1}$	**-0.004*** **	**-0.004*** **	**-0.005*** **	**-0.005*** **	**-0.005*** **	**-0.005*** **	**-0.004*** **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$EBIT\_TA_{j,\tau=-1}$	**-0.016** **	**-0.014** **	**-0.020*** **	**-0.015** **	**-0.015** **	**-0.016** **	**-0.019*** **
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$MV\_BV_{j,\tau=-1}$	**-0.002** **	**-0.002** **	**-0.002** **	**-0.002*** **	**-0.002** **	**-0.002** **	**-0.002** **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.052*** **	**0.051*** **	**0.052*** **	**0.051*** **	**0.058*** **	**0.052*** **	**0.049*** **
	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.013)	(0.015)
$RD\_TA_{j,\tau=-1}$	**-0.023**	**-0.016**	**-0.028**	**-0.019**	**-0.023**	**-0.026**	**-0.024**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
$LIQ^G_{j,\tau=-1}$	**0.006**	**0.006***	**0.006***	**0.006***	**0.006**	**0.006**	**0.006***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$D\_AQC_{j,\tau=0}$	**0.023*** **	**0.022*** **	**0.022*** **	**0.022*** **	**0.023*** **	**0.022*** **	**0.021*** **
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SPIKESIZE_{j,\tau=0}$	**0.168*** **	**0.224*** **	**0.128*** **	**0.144*** **	**0.175*** **	**0.148*** **	**0.132*** **
	(0.019)	(0.030)	(0.017)	(0.016)	(0.022)	(0.017)	(0.034)
$SPIKESIZE_{j,\tau=0}$	**0.101*** **	**0.074*** **	**0.051** **	**0.061** **	**0.080*** **	**0.081*** **	**0.044***
$\times D\_HLIQ^G_{j,\tau=-1}$	(0.027)	(0.023)	(0.024)	(0.025)	(0.022)	(0.022)	(0.027)
$SPIKESIZE_{j,\tau=0}$	**-0.032**						**-0.011**
$\times D\_LARGE_{j,\tau=-1}$	(0.028)						(0.024)
$SPIKESIZE_{j,\tau=0}$		**-0.092*** **					**-0.057** **
$\times D\_HLEV_{j,\tau=-1}$		(0.029)					(0.027)
$SPIKESIZE_{j,\tau=0}$			**0.090*** **				**0.088*** **
$\times D\_HPRF_{j,\tau=-1}$			(0.025)				(0.022)
$SPIKESIZE_{j,\tau=0}$				**0.085*** **			**0.057***
$\times D\_HMB_{j,\tau=-1}$				(0.033)			(0.030)
$SPIKESIZE_{j,\tau=0}$					**-0.021**		**0.015**
$\times D\_HTAN_{j,\tau=-1}$					(0.025)		(0.024)
$SPIKESIZE_{j,\tau=0}$						**0.049***	**0.055** **
$\times D\_HRD_{j,\tau=-1}$						(0.028)	(0.023)
Constant	**0.075*** **	**0.065*** **	**0.074*** **	**0.071*** **	**0.075*** **	**0.076*** **	**0.063** **
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Observations	3,728	3,728	3,728	3,728	3,728	3,728	3,728
R-squared	0.282	0.287	0.288	0.286	0.282	0.283	0.297

Table 6 (Continued): Controlling for other firm characteristics

Panel B. Liquidity measure based on Amihud's measure

VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)	$\Delta LEV_{j,\tau=0}$ (6)	$\Delta LEV_{j,\tau=0}$ (7)
$LEV_{j,\tau=-1}$	**-0.186*****	**-0.164*****	**-0.181*****	**-0.175*****	**-0.187*****	**-0.187*****	**-0.156*****
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
$LnTA_{j,\tau=-1}$	**-0.004*****	**-0.004*****	**-0.004*****	**-0.004*****	**-0.004*****	**-0.004*****	**-0.003****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$EBIT\_TA_{j,\tau=-1}$	**-0.015****	**-0.013****	**-0.019*****	**-0.015****	**-0.014****	**-0.015****	**-0.018*****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$MV\_BV_{j,\tau=-1}$	**-0.002****	**-0.002****	**-0.002****	**-0.002****	**-0.002****	**-0.002****	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.053*****	**0.053*****	**0.053*****	**0.052*****	**0.058*****	**0.053*****	**0.049*****
	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)	(0.015)
$RD\_TA_{j,\tau=-1}$	**-0.024**	**-0.016**	**-0.028**	**-0.020**	**-0.023**	**-0.027**	**-0.024**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
$LIQ^A_{j,\tau=-1}$	**0.004**	**0.004**	**0.003**	**0.004**	**0.004**	**0.003**	**0.003**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$D\_AQC_{j,\tau=0}$	**0.024*****	**0.023*****	**0.023*****	**0.023*****	**0.023*****	**0.023*****	**0.021*****
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SPIKESIZE_{j,\tau=0}$	**0.169*****	**0.226*****	**0.125*****	**0.145*****	**0.175*****	**0.151*****	**0.129*****
	(0.019)	(0.030)	(0.017)	(0.016)	(0.022)	(0.017)	(0.034)
$SPIKESIZE_{j,\tau=0}$	**0.100*****	**0.082*****	**0.063****	**0.065****	**0.085*****	**0.085*****	**0.058****
$\times D\_HLIQ^A_{j,\tau=-1}$	(0.030)	(0.023)	(0.025)	(0.026)	(0.023)	(0.023)	(0.027)
$SPIKESIZE_{j,\tau=0}$	**-0.022**						**-0.013**
$\times D\_LARGE_{j,\tau=-1}$	(0.030)						(0.025)
$SPIKESIZE_{j,\tau=0}$		**-0.093*****					**-0.059****
$\times D\_HLEV_{j,\tau=-1}$		(0.029)					(0.027)
$SPIKESIZE_{j,\tau=0}$			**0.093*****				**0.092*****
$\times D\_HPRF_{j,\tau=-1}$			(0.024)				(0.022)
$SPIKESIZE_{j,\tau=0}$				**0.086****			**0.055***
$\times D\_HMB_{j,\tau=-1}$				(0.033)			(0.030)
$SPIKESIZE_{j,\tau=0}$					**-0.018**		**0.018**
$\times D\_HTAN_{j,\tau=-1}$					(0.026)		(0.025)
$SPIKESIZE_{j,\tau=0}$						**0.045**	**0.053****
$\times D\_HRD_{j,\tau=-1}$						(0.029)	(0.024)
Constant	**0.075*****	**0.064*****	**0.073*****	**0.069*****	**0.075*****	**0.076*****	**0.061****
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	3,728	3,728	3,728	3,728	3,728	3,728	3,728
R-squared	0.281	0.287	0.288	0.285	0.281	0.282	0.296

Table 7: Alternative definitions of leverage

This table reports the results of the regressions designed to investigate whether the effect of share liquidity on the propensity to raise debt finance during investment spikes is robust to the use of alternative leverage measures. The dependent variable is the increase in a book leverage measure during an investment spike ($\Delta BLEV_{j,\tau=0}$) in columns (1)-(2), whereas the dependent variable is the increase in an alternative market leverage measure during an investment spike ($\Delta MLEV_{j,\tau=0}$) in columns (3)-(4). See Section 3.3.1 for how to construct those book leverage and alternative market leverage ratios. The major explanatory variables are defined as in Table 1 Panel A. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ($LIQ^G_{j,\tau=-1}$) is used as a measure of share liquidity in columns (1) and (3), whereas the liquidity measure based on Amihud's (2002) price impact ($LIQ^A_{j,\tau=-1}$) is used in columns (2) and (4). Table 1 Panel B and Panel C describes how to construct $SPIKESIZE1_{j,\tau=0}$, $SPIKESIZE2_{j,\tau=0}$, $D\_AQC_{j,\tau=0}$, $D\_HLIQ^G_{j,\tau=-1}$, and $D\_HLIQ^A_{j,\tau=-1}$. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

	Book Leverage		Alternative Market Leverage	
VARIABLES	$\Delta BLEV_{j,\tau=0}$ (1)	$\Delta BLEV_{j,\tau=0}$ (2)	$\Delta MLEV_{j,\tau=0}$ (3)	$\Delta MLEV_{j,\tau=0}$ (4)
$BLEV_{j,\tau=-1}$	**-0.267*** **	**-0.264*** **		
	(0.043)	(0.043)		
$MLEV_{j,\tau=-1}$			**-0.155*** **	**-0.155*** **
			(0.015)	(0.015)
$LnTA_{j,\tau=-1}$	**0.001**	**-0.001**	**-0.005*** **	**-0.005*** **
	(0.003)	(0.002)	(0.001)	(0.001)
$EBIT\_TA_{j,\tau=-1}$	**0.001**	**0.001**	**-0.005**	**-0.004**
	(0.007)	(0.007)	(0.005)	(0.005)
$MV\_BV_{j,\tau=-1}$	**-0.006*** **	**-0.007*** **	**-0.002*** **	**-0.002*** **
	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.094*** **	**0.095*** **	**0.079*** **	**0.081*** **
	(0.018)	(0.019)	(0.014)	(0.014)
$RD\_TA_{j,\tau=-1}$	**0.001**	**-0.007**	**-0.029***	**-0.030***
	(0.022)	(0.022)	(0.017)	(0.017)
$LIQ^G_{j,\tau=-1}$	**-0.008**		**0.003**	
	(0.005)		(0.004)	
$LIQ^A_{j,\tau=-1}$		**0.002**		**0.004**
		(0.002)		(0.003)
$D\_AQC_{j,\tau=0}$	**0.021*** **	**0.022*** **	**0.024*** **	**0.025*** **
	(0.005)	(0.005)	(0.005)	(0.005)
$SPIKESIZE1_{j,\tau=0}$	**0.068*** **	**0.074*** **		
	(0.019)	(0.021)		
$SPIKESIZE1_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$	**0.074*** **			
	(0.020)			
$SPIKESIZE1_{j,\tau=0} \times D\_HLIQ^A_{j,\tau=-1}$		**0.061*** **		
		(0.020)		
$SPIKESIZE2_{j,\tau=0}$			**0.144*** **	**0.148*** **
			(0.022)	(0.022)
$SPIKESIZE2_{j,\tau=0} \times D\_HLIQ^G_{j,\tau=-1}$			**0.103*** **	
			(0.022)	
$SPIKESIZE2_{j,\tau=0} \times D\_HLIQ^A_{j,\tau=-1}$				**0.096*** **
				(0.023)
Constant	**0.045**	**0.065****	**0.037**	**0.040**
	(0.029)	(0.028)	(0.026)	(0.026)
Observations	3,730	3,730	3,725	3,725
R-squared	0.290	0.283	0.298	0.295

Table 8: Use of whole sample with investment spike characteristics

The regressions are designed to investigate whether share liquidity has a positive effect on target leverage and abnormal borrowing during an investment spike in the whole sample. The dependent variables are the change in leverage (ΔLEV_{it}). All the models reported in columns (1)-(8) include a dummy for the year with investment spikes (D_SPIKE_{it}). The models reported in columns (3), (4), (7), and (8) include a spike size measure ($SPIKESIZE_{it}$) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ($(SPIKESIZE \times D\_HLIQ^G)_{it}$ or $(SPIKESIZE \times D\_HLIQ^A)_{it}$) as well as a dummy variable for acquisitions (D_AQC_{it}). The industry dummies and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

	Liquidity based on *Gibbs*				Liquidity based on *Amihud*			
VARIABLES	ΔLEV_{it} (1)	ΔLEV_{it} (2)	ΔLEV_{it} (3)	ΔLEV_{it} (4)	ΔLEV_{it} (5)	ΔLEV_{it} (6)	ΔLEV_{it} (7)	ΔLEV_{it} (8)
$LEV_{i,t-1}$	**-0.157*****	**-0.446*****	**-0.156*****	**-0.440*****	**-0.162*****	**-0.459*****	**-0.161*****	**-0.452*****
	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.008)	(0.003)	(0.008)
$LnTA_{i,t-1}$	**0.000**	**0.036*****	**-0.001**	**0.037*****	**0.002*****	**0.039*****	**0.001****	**0.040*****
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)
$EBIT\_TA_{i,t-1}$	**-0.023*****	**-0.019*****	**-0.023*****	**-0.018*****	**-0.022*****	**-0.018*****	**-0.022*****	**-0.017*****
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$MV\_BV_{i,t-1}$	**-0.001*****	**-0.000**	**-0.001*****	**-0.000**	**-0.001*****	**-0.000**	**-0.001*****	**-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$FA\_TA_{i,t-1}$	**0.008****	**0.062*****	**0.010****	**0.060*****	**0.008****	**0.063*****	**0.010****	**0.061*****
	(0.004)	(0.011)	(0.004)	(0.011)	(0.004)	(0.011)	(0.004)	(0.011)
$RD\_TA_{i,t-1}$	**-0.055*****	**-0.037*****	**-0.048*****	**-0.033*****	**-0.054*****	**-0.034*****	**-0.047*****	**-0.031*****
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
$LIQ^G_{i,t-1}$	**0.007*****	**0.012*****	**0.006*****	**0.011*****				
	(0.001)	(0.002)	(0.001)	(0.002)				
$LIQ^A_{i,t-1}$					**0.005*****	**0.007*****	**0.004****	**0.007*****
					(0.002)	(0.002)	(0.002)	(0.002)
D_SPIKE_{it}	**0.061*****	**0.049*****	**0.028*****	**0.018*****	**0.062*****	**0.049*****	**0.028*****	**0.019*****
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
D_AQC_{it}			**0.013*****	**0.009*****			**0.013*****	**0.008*****
			(0.001)	(0.002)			(0.001)	(0.002)
$SPIKESIZE_{it}$			**0.174*****	**0.163*****			**0.178*****	**0.169*****
			(0.017)	(0.017)			(0.017)	(0.017)
$(SPIKESIZE \times D\_HLIQ^G)_{it}$			**0.079*****	**0.089*****				
			(0.021)	(0.021)				
$(SPIKESIZE \times D\_HLIQ^A)_{it}$							**0.078*****	**0.081*****
							(0.022)	(0.023)
$Constant$	**0.123*****	**-0.077*****	**0.117*****	**-0.091*****	**0.117*****	**-0.086*****	**0.111*****	**-0.099*****
	(0.010)	(0.011)	(0.009)	(0.011)	(0.010)	(0.011)	(0.009)	(0.011)
Number of firms	5,976	5,976	5,953	5,953	5,976	5,976	5,953	5,953
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	38,598	38,598	38,351	38,351	38,598	38,598	38,351	38,351
R-squared	0.186	0.331	0.202	0.343	0.185	0.330	0.201	0.342

Table 9: Testing the information spillover mechanism

This table reports the results of the regressions designed to investigate whether share liquidity increases abnormal borrowing during an investment spike through the information spillover mechanism. The dependent variable is the change in leverage during an investment spike ($\Delta LEV_{j,\tau=0}$). Most explanatory variables are defined as in Table 1 Panel A and Panel B. Section 3.3.2 describes how to construct $NUMMGRS_{j,\tau=-1}$ (Number of institutional managers) and $D\_HNMGRS_{j,\tau=-1}$ (Dummy variable for high number of institutional managers). Column (1) presents the regression results with $NUMMGRS_{j,\tau=-1}$ and $SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$. Columns (2) and (4) present the regression results with liquidity-related variables and without information-related variables in the subsample in which information-related variables are observed. Columns (3) and (5) present the regression results with liquidity-related terms as well as information-related variables. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

	Baseline	Liquidity based on *Gibbs*		Liquidity based on *Amihud*	
VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)
$LEV_{j,\tau=-1}$	**-0.174*** **	**-0.159*** **	**-0.155*** **	**-0.153*** **	**-0.152*** **
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
$LnTA_{j,\tau=-1}$	**-0.002**	**-0.005*** **	**-0.007*** **	**-0.005*** **	**-0.006** **
	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
$EBIT\_TA_{j,\tau=-1}$	**-0.017***	**-0.018***	**-0.018***	**-0.016***	**-0.016***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
$MV\_BV_{j,\tau=-1}$	**-0.002*** **	**-0.003*** **	**-0.003*** **	**-0.003*** **	**-0.003*** **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.047*** **	**0.045*** **	**0.046*** **	**0.044*** **	**0.045*** **
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
$RD\_TA_{j,\tau=-1}$	**-0.018**	**-0.017**	**-0.017**	**-0.017**	**-0.017**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
$LIQ^G_{j,\tau=-1}$		**0.014** **	**0.015*** **		
		(0.006)	(0.006)		
$LIQ^A_{j,\tau=-1}$				**0.041*** **	**0.042*** **
				(0.009)	(0.009)
$D\_AQC_{j,\tau=0}$	**0.024*** **	**0.023*** **	**0.023*** **	**0.024*** **	**0.024*** **
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SPIKESIZE_{j,\tau=0}$	**0.180*** **	**0.179*** **	**0.178*** **	**0.181*** **	**0.179*** **
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)
$NUMMGRS_{j,\tau=-1}$	**-0.000**		**0.000**		**0.000**
	(0.000)		(0.000)		(0.000)
$SPIKESIZE_{j,\tau=0}$	**0.071*** **		**0.038**		**0.039**
$\times D\_HNMGRS_{j,\tau=-1}$	(0.027)		(0.031)		(0.039)
$SPIKESIZE_{j,\tau=0}$		**0.063** **	**0.040**		
$\times D\_HLIQ^G_{j,\tau=-1}$		(0.027)	(0.033)		
$SPIKESIZE_{j,\tau=0}$				**0.071*** **	**0.041**
$\times D\_HLIQ^A_{j,\tau=-1}$				(0.026)	(0.038)
Constant	**0.027**	**0.038**	**0.043**	**0.040**	**0.042**
	(0.027)	(0.026)	(0.027)	(0.026)	(0.026)
Observations	2,891	2,891	2,891	2,891	2,891
R-squared	0.299	0.303	0.304	0.307	0.307

Table 10: Testing the credit ratings mechanism

This table reports the results of the regressions designed to investigate whether share liquidity increases abnormal borrowing during an investment spike through the credit ratings mechanism. The dependent variable is the change in leverage during an investment spike ($\Delta LEV_{j,\tau=0}$). Most explanatory variables are defined as in Table 1 Panel A and Panel B. Section 3.3.2 describes how to construct $MALTMANZ_{j,\tau=-1}$ (Modified Altman's Z-score) and $D\_HMALTZ_{j,\tau=-1}$ (Dummy variable for high $MALTMANZ_{j,\tau=-1}$). Column (1) presents the regression results with $MALTMANZ_{j,\tau=-1}$ and $SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$. Columns (2) and (4) present the regression results with liquidity-related variables and without credit-ratings-related variables in the subsample in which credit-ratings-related variables are observed. Columns (3) and (5) present the regression results with liquidity-related terms as well as credit-ratings-related variables. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

	Baseline	Liquidity based on *Gibbs*		Liquidity based on *Amihud*	
VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)
$LEV_{j,\tau=-1}$	**-0.190*****	**-0.183*****	**-0.180*****	**-0.187*****	**-0.184*****
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$LnTA_{j,\tau=-1}$	**-0.001**	**-0.004*****	**-0.004*****	**-0.003****	**-0.003****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$EBIT\_TA_{j,\tau=-1}$	**-0.018*****	**-0.016****	**-0.019*****	**-0.015****	**-0.018*****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$MV\_BV_{j,\tau=-1}$	**-0.002****	**-0.002****	**-0.002****	**-0.002****	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$FA\_TA_{j,\tau=-1}$	**0.053*****	**0.052*****	**0.053*****	**0.053*****	**0.055*****
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$RD\_TA_{j,\tau=-1}$	**-0.026**	**-0.025**	**-0.026**	**-0.025**	**-0.026**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
$LIQ^G_{j,\tau=-1}$		**0.006**	**0.006***		
		(0.004)	(0.004)		
$LIQ^A_{j,\tau=-1}$				**0.003**	**0.004**
				(0.003)	(0.003)
$D\_AQC_{j,\tau=0}$	**0.021*****	**0.023*****	**0.021*****	**0.023*****	**0.021*****
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SPIKESIZE_{j,\tau=0}$	**0.155*****	**0.167*****	**0.144*****	**0.169*****	**0.144*****
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
$MALTMANZ_{j,\tau=-1}$	**0.001***		**0.001***		**0.001****
	(0.000)		(0.000)		(0.000)
$SPIKESIZE_{j,\tau=0}$	**0.090*****		**0.077*****		**0.081*****
$\times D\_HMALTZ_{j,\tau=-1}$	(0.027)		(0.027)		(0.027)
$SPIKESIZE_{j,\tau=0}$		**0.079*****	**0.059****		
$\times D\_HLIQ^G_{j,\tau=-1}$		(0.023)	(0.024)		
$SPIKESIZE_{j,\tau=0}$				**0.083*****	**0.069*****
$\times D\_HLIQ^A_{j,\tau=-1}$				(0.025)	(0.026)
Constant	**0.058****	**0.073*****	**0.065****	**0.072*****	**0.063****
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	3,632	3,632	3,632	3,632	3,632
R-squared	0.283	0.281	0.286	0.280	0.286