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Abstract

This paper investigates whether stock market liquidity has an impact on banks' risk-taking behaviour. Using the Tick Size Pilot Program of the Securities and Exchanges Commission (SEC) to identify liquidity shocks, I show that banks with less liquid stocks take more risk, as reflected in lower Z-scores, higher earnings volatility and non-performing loan ratios, and lower capital adequacy ratios. I examine the two mechanisms through which reduced stock liquidity increases banks' risk-taking: dampening the governance effect of discipline trading by stockholders and reducing the price informativeness for managers to obtain feedback on investment decisions. The result suggests the governance channel has greater explanatory power than the feedback channel.

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1 Introduction

The liquidity of a stock refers to how quickly its shares can be bought or sold without having a significant impact on the stock price. Recent studies provide empirical evidence that stock market liquidity has real effects on firm fundamentals (Fang et al., 2009, 2014; Brogaard et al., 2017). On the other hand, banks' excessive risk-taking is widely recognised as a main cause of the financial crisis of 2008. Do liquidity shocks in the stock market affect publicly traded banks' risk-taking? The answer to this question helps to explain the channel through which the stock market microstructure affects the stability of the banking system, which in turn affects the development of the economy (Levine and Zervos, 1998).

Stock liquidity can affect banks' risk-taking for several reasons. Increased liquidity can make it easier for banks to issue seasoned common stock to raise additional funds in the stock market, and higher levels of funding liquidity increase banks' risk-taking (Wagner, 2007; Acharya and Naqvi, 2012; Khan et al., 2017). Meanwhile, increased liquidity might also decrease banks' risk-taking. A liquid market allows investors to gather information and form discipline trading or exit threats to regulate firm managers' behaviour, and also to provide feedback for bank managers to evaluate investment decisions (Bharath et al., 2013). Banks facing more disciplinary trading pressures and with better evaluative feedback could be less likely to take excessive risks. Brogaard et al. (2017) exclude banks and other financial firms and show that higher stock liquidity lowers default risk. Compared to non-financial firms, banks are systematically more important due to their role as financial intermediaries and monitors of the governance of their borrowers; therefore, banks are more intensively regulated to prevent negative externalities (Ahn and Choi, 2009; Pathan, 2009). Stock market liquidity as an explanatory variable would be valuable for policymakers to assess the financial stability of banks.

This paper examines the effect of stock market liquidity on banks' risk-taking behaviour. Identifying the effect of liquidity on banks' risk-taking is challenging because risk-taking could also affect stock liquidity. For instance, excessive bank risk-taking can be a source of financial turmoil, and the turmoil can trigger fly-to-quality episodes that lead to significant declines in stock market liquidity. To address concerns about reverse causality, I use a controlled experiment from the Securities and Exchanges Commission (SEC), the Tick Size Pilot Program (hereafter the "Pilot"). The Pilot uses stratified random sampling to split firms with similar characteristics into treatment and control groups, and mechanically increases the tick size for the treatment stocks. The change in tick size (the minimum price variation) is often used in the literature as an instrument for liquidity shocks (Fang et al., 2009, 2014; Brogaard et al., 2017; Albuquerque et al., 2020). Therefore, the Pilot provides a unique opportunity to identify causal effects, as the liquidity shocks can be viewed as randomly given and independent of banks' risk-taking. Such an arrangement is well suited for difference-in-difference (DID) analysis.

The Pilot consists of three treatment groups, each with approximately 400 treated stocks, and a control group with 1,200 stocks. Stocks in the control group quote and trade at their current tick size of \$0.01. Stocks assigned to Group 1 (hereafter G1) follow a Quote (Q) rule, which means increasing the minimum *quote* from \$0.01 to \$0.05. Group 2 securities (hereafter G2) observe both Q and Trade (T) rule, the latter of which means *trade* in \$0.05 increments. Group 3 stocks (hereafter G3) follow the Q and T rules plus a Trade-At (TA) rule. The TA rule is a *trade-at* requirement that increases trading costs for non-displayed liquidity and dark pool trades. I form a sample of 252 banks from the Pilot, and the data period is from January 2014 to December 2018. The data period covers around two years before and after the start date of the program.

Banks can take a variety of risks. The Z-score is the key indicator in this study. Z-score is a commonly used indicator of banks' risk-taking, describing banks' distance to insolvency (Laeven and Levine, 2009; Pathan, 2009; Delis and Staikouras, 2011; Khan et al., 2017). As a robustness check, I also check the responses of earnings volatility, net charge-off ratio (NCO), and Capital Adequacy Ratio (CAR). Earnings volatility is the standard deviation of banks' earnings. Net charge-off ratio (NCO) is widely used for bank stress testing by regulators and credit rating firms (Grover and McCracken, 2014; Fang and Yeager, 2020). The Capital Adequacy Ratio (CAR) is another regulator-monitored measure that shows whether a bank can withstand a reasonable level of loss while also meeting statutory capital requirements. These four metrics provide a relatively comprehensive description of banks' risk-taking behaviour.

My estimates are based on the DID method, in which I compare the impact of the Pilot treatments on treated banks with control banks. I first identify the validity of Pilot treatments as an instrument to stock liquidity. The results show that the Q rule (i.e., increasing the minimum quote increment from \$0.01 to \$0.05) leads to a decline in stock liquidity. The T rule and the TA rule—i.e., increasing the minimum trade increment and the trade-at restriction, respectively—do not have significant effects on stock liquidity. Deploying the Q rule as an instrument of stock liquidity, I find that the reduced liquidity caused by the Q rule increases banks' risk-taking 2 years later. This is reflected in their significantly lower Z-scores, higher earnings volatility and net charge-off ratio, and lower CAR. The result is robust after controlling for the inverse of price, stock turnover, bank size, income, capital asset ratio, funding liquidity, and firm and quarterly fixed effects.

How is the liquidity of bank stocks related to risk-taking? I try to explain the increase in bank risk-taking behaviour through a governance channel and a feedback channel. Bharath et al. (2013) postulates a threat-of-exit channel available to shareholders in the market. The governance channel operates when investors gather information and form discipline trades to govern bank managers' behaviour. Banks that face less disciplinary trading pressure are more inclined to take excessive risks. The efficiency with which stock prices absorb and reflect traders' information influences the effectiveness of the governance channel. I measure the price efficiency with correlation and price delay measures following Brogaard et al. (2017) and find empirical evidence that the Q rule reduces price efficiency. Using the Q rule as an instrument for price efficiency, I find that lower price efficiency is related to increased risk-taking.

The feedback channel occurs when bank managers use information from a bank's stock price to evaluate investment decisions. Banks with less informative stocks may make worse decisions and appear to be more risk-taking. The effectiveness of the feedback channel depends on the informativeness of the stock price, that is, the private information that is valuable for banks' business decisions. Following Chen et al. (2007), I use price non-synchronicity to measure the amount of private information in the stock price. However, I have not found substantial evidence that the Q rule is related to price non-synchronicity.

The remainder of this paper is arranged as follows. Section 2 introduces the literature. Section 3 describes the data, sample, and variable measurements. Section 4 contains the empirical estimates. Section 5 discusses possible explanations for the results and section 6 concludes.

2 Literature

This paper contributes to the growing literature that looks at the link between stock liquidity and firm fundamentals. This field of study has exploded in popularity in recent years. Liquidity is found to promote firm value (Fang et al., 2009), reduce future innovation (Fang et al., 2014), decrease default risk (Brogaard et al., 2017), raise stock price crash risk (Chang et al., 2017), increase the proportion of equity-based compensation (Jayaraman and Milbourn, 2012), enhance the probability of blockholders' activism (Norli et al., 2015), and improve corporate governance through institutional ownership (Cheung et al., 2015). Stocks with higher liquidity are less likely to offer dividends (Banerjee et al., 2007), have fewer acquirer gains (Roosenboom et al., 2014), engage in less accrual-based and real earnings management (Chen et al., 2015), and engage less in extreme tax avoidance (Chen et al., 2019). In this paper, I show that liquidity can influence banks' risk-taking behaviours.

In explaining the increased risk-taking induced by an adverse liquidity shock, I emphasise the role of the governance channel raised by Bharath et al. (2013). The channel is available to blockholders through the threat of exit. Bharath et al. (2013) claim that higher liquidity increases the effectiveness of the channel and vice versa. Most research on fundamentals considers the threat of blockholder exit as one of the main control channels through which increased stock liquidity positively affects firm fundamentals. For example, Chen et al. (2015) show that this channel increases blockholder monitoring, prevents opportunistic earnings management, and mitigates short-term managerial behaviour. An exception is Roosenboom et al. (2014), which supports the hypothesis that stock liquidity weakens institutions' incentives to monitor managerial decisions.

My work is also related to studies of bank risk-taking and supervision. Flannery (1998) reviews the previous literature and concludes that market investors could usefully exercise additional supervision over large financial firms. Laeven and Levine (2009) find that the effectiveness of bank regulation on bank risk-taking depends on the specific governance structure of each bank. Delis and Staikouras (2011) find that market discipline is an important and complementary mechanism to government supervision to reduce bank fragility. Berger et al. (2014) show that the composition of management teams affects bank risk-taking. Nguyen et al. (2016) suggest that active and better supervision by bank boards can prevent misconduct. In summary, researchers acknowledge the important effects of market discipline and governance on bank risk-taking.

3 Data

3.1 The Tick Size Program

The Pilot is issued by SEC and implemented by National Securities Exchanges and Financial Industry Regulatory Authority (FINRA). The purpose of the program is to assess the impact of larger tick sizes on the liquidity and trading of shares of small capitalization companies.

[Table I to be here]

As summarized in Table I, Pilot Securities was divided into a control group and three test groups. The three treatment groups include about 400 Pilot Securities respectively, and the remaining 1200 Pilot Securities are included in the control group. All stocks in the three treatment groups are subjected to the Q rule, quoting in the minimum increment of $0.05, compared to $0.01 in the control group. G2 and G3 must additionally follow the T rule, trading in $0.05 increments. G3 is additionally subject to the TA rule, which prevents brokers from trading on non-public platforms such as dark pools unless they can execute the trades at a significantly better price than in the public market. The Q rule applies to G1, G2, and G3; the T rule applies to G2 and G3; and the TA rule applies only to G3.

To assign stocks to each group, the Pilot uses a stratified random selection procedure based on three variables: market capitalization, volume-weighted average price, and consolidated average daily volume. The Pilot's entire securities space is divided into 27 distinct parts, each with a "score" of low, medium, or high on the three variables. Each variable in turn divides the population into three subsets. To fill each test group with 400 stocks, securities are randomly selected from each of the parts. Stratified random selection thus ensures that the population in each test group is similarly distributed among the parts.

The exchanges posted the preliminary list of pilot stocks on their websites on September 2, 2016, while all stocks are included in the control group. The official implementation of the Pilot began on October 3, 2016 and was activated gradually throughout October. During this process, securities were moved to their respective test groups and subjected to the groups' treatments. As of October 31, 2016, all securities were in use and active. In my quarterly sample, the last quarter of 2016 is considered the start of treatments.

The Pilot lasted two years (eight quarters) and ended on September 28, 2018, during which time the securities list underwent several changes. After October 1, 2018, all pilot securities were shifted back to the control groups to quote and trade at a minimal increment of 0.01. The last quarter of 2018 is considered the end in my quarterly sample. In this work, I focus on risk-taking toward the end of the program, which is eight quarters after the Pilot began.

3.2 Variable Construction

3.2.1 Treatment Dummies and Liquidity Measures

Tick size change is associated with liquidity in the literature. Several studies use the change in tick size as an instrument for the change in liquidity (Fang et al., 2009, 2014; Brogaard et al., 2017; Albuquerque et al., 2020). I construct three dummies to measure the Q, T, and TA rules that apply to the three treatment groups of the Pilot. The dummies equal one if the corresponding rule is active for a stock, and zero otherwise.

I use the logarithm of the quoted spread and the effective spread to calculate stock liquidity. The quoted spread is the difference between the end-of-day ask and bid prices divided by the mid-quote. The effective spread is the absolute difference between the end-of-day price and mid-quote divided by the mid-quote. Because my sample is on a quarterly basis, I average the daily log values of the quoted spread and effective spread throughout each quarter and use the averaged log spreads as my liquidity measurements.

3.2.2 Risk-taking Measures

I measure bank risk-taking primarily using the Z-score, a widely used measure in the literature to assess bank risk-taking behaviour (Laeven and Levine, 2009; Duchin and Sosyura, 2014; Khan et al., 2017). The Z-score is equal to the return on assets (ROA) plus the capital asset ratio divided by the standard deviation of ROA. The capital asset ratio is the total common equity divided by total asset. The Z-score is an accounting-based risk measure that assesses the distance to insolvency. A higher value of the Z-score implies a lower probability of default (see Laeven and Levine (2009) for details). I calculate the standard deviations of ROA separately before and after the Pilot starts. I also use earnings volatility as an alternative risk-taking measure following Laeven and Levine (2009). The volatility of earnings is the standard deviation of the earnings ratio, which is equal to total pre-tax earnings divided by total assets. Volatility is also calculated separately before and after the starting quarter of the Pilot.

Excessive risk-taking decreases bank stability. To assess banks' stability, I also examine the impact of treatment on net charge-offs of loans (NCO) and the capital adequacy ratio (CAR). Net charge-offs of loans are equal to the difference between gross charge-offs and any recoveries of past-due loans and reveal important information about banks' credit standards toward their borrowers on an ex-post basis (Berger and Udell, 1990). I calculate the net charge-offs rate as the net charge-offs divided by total assets. I expect a riskier bank to have looser credit standards, which is reflected in a higher net charge-off ratio.

The CAR reflects a bank's ability to absorb adverse shocks and maintain stability during financial downturns. The ratio is calculated by dividing risk-weighted assets by the sum of Tier 1 and Tier 2 capital. Under the revised regulatory environment envisaged by Basel III, the CAR is closely monitored in accordance with the minimum capital requirement. Basel III aims to enhance the resilience and stability of the international banking system, and the adequacy of capital is a core requirement. In the US, the phased implementation of the minimum capital requirement to increase the CAR begins on January 1, 2014, and ends on January 1, 2019, so it is more likely that the ratio will increase to follow the requirement rather than decrease during the sample period.

3.2.3 Control variables

I include a set of control variables, including the inverse of daily closing price, daily stock turnover, bank size, return on asset, capital asset ratio, and funding liquidity ratio of the banks. Firm size is measured with the total assets of the bank. Return on asset is net income divided by the total assets. The capital asset ratio is the total common equity divided by total assets. The funding liquidity ratio captures the cash flow of a bank, equal to the sum of cash due from banks and US treasury securities, divided by total assets. The control variables capture various dimensions of banks' performance, which can be influential on bank risk-taking.

I use three control variables to proxy for the regulatory inspections across banks to control for the influence of regulators: the total non-interest income scaled by total asset, total deposit scaled by total liabilities, and CAR. Non-interest income captures the restrictions of regulators on non-traditional bank activities. In the same vein, Cubillas et al. (2012) use banks activities in the securities, insurance, real estate, and bank ownership of non-financial firms to measure regulatory hurdles to banks. The deposit measure, on the other hand, is a proxy capturing the effect of deposit insurance required by the regulator, used by Cubillas et al. (2012) as well. CAR, as discussed in the risk-taking measure part, is the core ratio monitored under Basel II and III. The three regulatory variables control different types of regulatory supervision.

Firm and quarter fixed effects are also taken into account. Firm fixed effects control is used to account for firm-specific and time-invariant factors that influence bank risk-taking, whereas quarterly fixed effects control is used to account for time effects such as the macroeconomic environment. The quarterly fixed effects are particularly important because banks have experienced significant changes in the macroeconomic environment, including regulatory reform, which reforms banks' risk management practices, and Fed Fund Rate fluctuation, which changes banks' access to funding and, as a result, risk-taking behaviour. The quarterly fixed effects control for such issues that influence all banks [1].

3.3 Sample Selection

Following the definition of the FAMA 49 industry, I define banks as firms with SIC codes from 6000 to 6199. I obtain daily stock prices and returns from the Center for Research in Security Prices (CRSP), and quarterly balance sheet data from Compustat. I get the list of pilot securities produced at the start of the program and the list of securities changed during the Pilot from FINRA's website [2]. For all firms in the Pilot, I exclude firms that were originally included but later removed during the execution of the Pilot. I winsorize the return on asset (ROA) ratio at 1% and 99% to eliminate the influence of outliers[3]. The final sample contains 252 bank stocks in the Pilot, with 127 control stocks, 37 banks in G1, 45 in G2, and 43 in G3.

[Table II to be here]

Table II describes the summary statistics, including mean, minimum, maximum, standard deviation, and number of observations. In this paper, I focus on the change in risk behaviours at the end of the

[1] All time-varying but firm-invariant factors are controlled by the quarterly fixed effect. Macroeconomic time series such as the one-month T-bill rate and/or the fed funds rate are perfectly collinear with the quarterly fixed effect and are automatically omitted.

[2] http://www.finra.org/sites/default/files/Tick_Size_Pilot_Rollout_List.xlsx

[3] Since the plot of ROA strongly implies the existence of outliers, and the calculation of the Z-score requires both the level and the standard deviation of ROA, I winsorize the ROA instead of the Z-score itself.

program, i.e., eight quarters after the start of the Pilot. Thus, the sample covers observations from January 2014 to December 2018, roughly two years before and after the start of the Pilot.

4 Empirical Results

In this study, I use the Pilot treatments as a market liquidity instrument and use DID estimation to investigate the impact of liquidity on bank risk-taking. For the instrument to be valid, two assumptions must be met: first, the instrument must be distributed independently of the dependent variable's error process. Second, the instrument is sufficiently correlated with the endogenous variable that is included. The treatments can be considered independent of the data generation process of banks' risk-taking because the Pilot's treatment groups are generated by stratified random sampling. But whether the Pilot treatment are significantly related to liquidity needs further discussion. In the section below, I first check whether the Pilot treatment and liquidity are significantly correlated and then analyse the relationship between liquidity and banks' risk-taking behaviour.

4.1 Stock Liquidity

In this section, I examine the relationship between the Pilot treatment and liquidity. Several studies have examined the effect of changing tick size on liquidity. Fang et al. (2009) consider decimalisation as a quasi-experiment and show that a smaller tick size leads to higher liquidity and vice versa. Compared with decimalization, which changes the quote and trade tick size altogether, the Pilot separates the treatment of the quote (Q rule) and trade (T rule) tick size, and only the Q rule applies to all treatment groups. Albuquerque et al. (2020) find that for G1, G2, and G3, liquidity decreases for all stocks relative to stocks in the control group, as shown by a number of measures, including quoted spreads, effective spreads, and the increase in price impact and trading volume. Chung et al. (2020) find that the Q rule reduces quoted spreads and effective spreads, but the T and TA rules do not consistently have such an impact. I expect the bank stocks to exhibit a similar pattern and therefore hypothesise:

Hypothesis 1 (Tick size and liquidity): For bank stocks, the Q rule reduces stock liquidity.

To test the hypothesis, I estimate the following model in the entire sample:

$$Liquidity_{it} = \alpha + \beta_1 Q_i \times post_t + \beta_2 T_i \times post_t + +\beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it} \quad (1)$$

where $Liquidity_{it}$ is the quarterly averaged liquidity measure of stock at quarter t, which is quoted spread or effective spread. Q_i, T_i and TA_i are the quote, trade, and trade-at rule dummy variables. $Post_t$ is the Pilot dummy variable, which is equal to one after the launch time (2016q4) and zero otherwise. X_{it} are the control variables, including the inverse of daily closing price, daily stock turnover, bank size, ROA, bank capital asset ratio, and banks' funding liquidity, which equals the sum of cash due from banks and US treasury securities divided by the total assets. Firm fix effect γ_i and quarter fix effects θ_t are included to control for any firm- or quarter-invariant factors. Because the firm fix effects and Q_i, T_i and TA_i are perfectly collinear, and so are the quarter fix effects and $Post_t$, the coefficients of Q_i, T_i, TA_i and $Post_i$ are not displayed after including the fix effects. Following Albuquerque et al. (2020), I report the robust standard errors clustered by stock and quarter to account for any residual correlation within the firm or within the quarter.

The results in columns (1) and (2) of the Table III confirm Hypothesis 1. The results show that the Q rule leads to significantly lower liquidity as measured by both the log of quoted spread and the effective spread. The treatment of the Q rule significantly increases *Log_QSprd* and *Log_ESprd* by 0.497 and 0.513, respectively. The T and TA rules have no significant effect on *Log_QSprd* and *Log_ESprd*. For the control variables, banks with greater turnover, size, and capital asset rates have smaller quoted and effective spreads, i.e., higher liquidity. The results suggest that for the Q, T, and TA treatments produced by the Pilot, only the Q rule treatment is an effective instrument for liquidity.

[Table III to be here]

4.2 Bank Risk-Taking

4.2.1 The Q rule and Bank Risk-Taking

The estimation in previous section indicates that the Q rule is a valid instrument of market liquidity. In this part, I test whether the treatment of the Q rule affects banks' risk-taking. Using the change in tick size in decimalization as an instrument of liquidity change, Fang et al. (2009) find that smaller tick size leads to higher liquidity and better firm performance and vice versa. Similarly, Brogaard et al. (2017) show that a smaller tick size leads to higher liquidity and lower default risk for non-financial firms. I expect banks to take more risk when liquidity in the stock market falls. Among the three treatment rules, only the Q rule reduces liquidity, so I expect the Q rule to increase banks' risk-taking in the future.

Hypothesis 2 (Tick size and Bank Risk-Taking): For bank stocks, the Q rule increases banks' risk-taking in the future.

Hypothesis 3 (Liquidity and Bank Risk-Taking): The decreased liquidity increases banks' risk-taking in the future.

Because the impact of the liquidity shocks on banks' risk-taking may take some time to manifest, I focus on the shift in bank risk-taking at the end of the program, i.e., eight quarters after the program began. As a result, the dependent variable is the risk-taking measure eight quarters later. For the entire sample, I estimate the following model to test Hypothesis 2:

$$RiskTak_{i,t+8} = \alpha + \beta_1 Q_i \times post_t + \beta_2 T_i \times post_t + +\beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it} \tag{2}$$

As explained in the section on risk measures, I use the Z-score as the primary measure of risk-taking, as well as the volatility of earnings, the net charge-off rate, and the capital adequacy ratio. The results in columns (3) through (6) of Table III confirm Hypothesis 2. The Q rule treatment decreases the Z-score by 17.789 on average over the eight-quarter period, significantly at the 1% level. Earnings volatility significantly increases by 0.016 on average at the 10% level. The Q rule increases the net charge-off ratio by 0.012 and reduces the capital adequacy ratio by 0.585, both significant at the 1% level.

The T rule has the opposite effect of the Q rule, boosting the Z-score, reducing earnings volatility, and improving the capital adequacy ratio, implying that while the T rule does not affect stock liquidity, it does limit banks' risk-taking behaviour in the future. The TA rule has no substantial effect on the Z-score, earnings volatility, or the CAR. However, the TA rule reduces NCO significantly. Larger banks with weaker funding liquidity have higher Z-scores for the control variables.

4.2.2 The Q rule as an Instrument of Liquidity

The most straightforward way to formally test the impact of liquidity on banks' risk-taking behaviour is by regressing the various liquidity measures on banks' risk-taking measures and controlling for other potential variables (X_{it}) and bank and time fix effects:

$$RiskTak_{i,t+8} = \alpha + Liquidity_{it} + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{i,t+8} \tag{3}$$

The issue is that there may be potential market or bank mechanisms that affect liquidity and future risk-taking at the same time. This indicates that the slope coefficient calculated using OLS to estimate the above equation is not an unbiased measure of the causal effect of future risk-taking on liquidity. To find the causal effect, an instrumental variable (IV) that affects future risk-taking but is unrelated to the residual must be found. The results in previous sections show that the Q rule, the wider minimum quote increment, has an influence on stock liquidity. Since the formulation of treatment groups in the Pilot is random and independent of banks' risk-taking, the Q rule can be regarded as a valid instrument of liquidity. In this section, I use the Q rule treatment $Q_i \times post_t$ as an instrument for liquidity and estimate the following model with two-stage least squares (2SLS) regression method:

$$RiskTak_{i,t+8} = \alpha + Liquidity_{it} + \beta_2 T_i \times post_t + \beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{i,t+8} \tag{4}$$

Table IV shows the instrument regression results for *Log_QSprd* in panel (a) and *Log_ESprd* in panel (b). In panel (a), the IV-estimate of -31.154 suggests that a one-unit increase in *Log_QSprd* means that the Z-score decreases by 29.906 on average. Since the average within-stock standard deviation for the Z-score is 195, the Z-score decrease caused by one unit of liquidity represents about 15% of the standard deviation. At the same time, earnings volatility and the net charge-off rate increase by 0.027 and 0.021, respectively, and the CAR decreases by -0.972, which is statistically distinguishable from zero. The results for *Log_ESprd* in panel (b) coincide with those in panel (a). The findings suggest that greater quoted and effective spreads, which imply less liquidity, increase banks' risk-taking in the future.

4.2.3 Robustness Check: Alternative Treatment Dummies

In the DID estimates in the previous sections, I use the rule-based dummies of Q, T, and TA to measure the treatment and find that only the Q rule significantly affects liquidity. The estimates are conducted over the full sample, covering the three test groups and the control groups. As a robustness check, I construct three alternative dummies to capture the group-level treatment effects for G1, G2, and G3 relative to the control group: *Gi* is a dummy variable that equals 1 if a stock is in Group i, equals 0 if it is in the control group, and is missing otherwise, for i = 1, 2, and 3. For G1, only the Q rule is active. Since the stocks in the three treatment groups are randomly selected using the same stratified random sampling procedure, G1 itself is a valid treatment group and excludes the influence of the T and Q rules. I use G1 as an alternative Q rule dummy and repeat the OLS and instrument variable estimations in Table III and IV respectively. Specifically, I estimate the following models with OLS regression:

$$RiskTak_{i,t+8} = \alpha + \beta_1 G_1 + \beta_2 Post_t + \beta_3 G_1 \times Post_t + \delta' X_{it} + \varepsilon_{it} \tag{5}$$

And the model below with 2SLS regression:

$$RiskTak_{i,t+8} = \alpha + \beta Liquidity_{it} + \delta' X_{it} + \varepsilon_{it} \tag{6}$$

where the G1 treatment ($G1 \times post_t$) is the instrumental variable of liquidity. Panel (a) of Table V shows the estimation results of the Z-score and other risk-taking measures for the G1 treatment. The signs and scales of the slope coefficients are relatively similar to the results in Table III for the Q rule dummy. Panel (b) presents the results of the instrumental variable estimation. While all signs of the coefficients of *Log_QSprd* are consistent with the results in Table IV, the scale of the liquidity measure on the Z-score is -31.154, smaller than the -32.306 in Panel (a) of Table IV.

[Table IV to be here]

5 Interpretation

In this section, I investigate possible explanations for why the decreased liquidity brought on by the Q rule increases banks' risk-taking. I try to explain the results through a governance channel and a feedback channel.

5.1 The Governance Channel

In the governance channel, the stock market plays a role in monitoring the management of banks. Edmans (2009) shows that blockholders have incentives to monitor a firm's fundamentals and sell their shares when they receive negative information. When managers sacrifice long-term value for short-term earnings goals, blockholders without monitoring rights can exert control through trading. Several small blockholders can form the threat of disciplinary trading by trading competitively and incorporating more information into prices to regulate managers' behaviour (Edmans and Manso, 2011). Banks facing less disciplinary trading pressure are therefore more likely to take excessive risk [4].

The efficiency with which stock prices absorb and reflect information from traders determines the effectiveness of the governance channel. In this section, I measure price efficiency using correlation and price delay and examine the role of price efficiency in bank risk-taking. The first measure *Corr* is the absolute value of the first-order autocorrelation of weekly stock returns. A low *Corr* implies that the stock-price process is closer to a random walk, and hence the price is more efficient (Brogaard et al., 2017). The second measure of price efficiency, as suggested by Hou and Moskowitz (2005), is price delay, i.e., an estimate of how quickly prices incorporate public information. Price delay is calculated as 1-(R^2 of restricted model / R^2 of non-restricted model). The non-restricted model is specified as

$$r_{i,t} = \beta_{i,0} + \beta_{i,m} \times r_{m,t} + \sum_{n=1}^{4} \delta_i^{(-n)} \times r_{m,t-n} + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of bank i at time t, and $r_{m,t}$ is the market return at time t. The restricted model constrains that $\delta_i^{(-n)} = 0$. This measure reflects how much of the difference in individual stock returns can be explained by lagged market returns over a relatively long horizon. A longer price delay signifies a less efficient stock price, in the sense that it takes longer for the stock to assimilate market-wide information.

[Table VI to be here]

Panel (a) of Table VI shows how the Pilot treatments affect price efficiency. The Q rule treatment significantly reduces price efficiency, as reflected in larger *Corr* and *PriceDelay*. Using the Q rule treatment as an instrumental variable, liquidity also increases *Corr* and *PriceDelay*, suggesting that lower liquidity hinders the price discovery process in the stock market. The results imply that the Q rule impairs price efficiency, which echoes the finding of Albuquerque et al. (2020).

[4] One concern is whether banks can really increase risk without facing stock return and volatility consequences. In the appendix I regress the pilot treatments on quarterly averaged stock returns and historical volatility simultaneously and eight quarters later and found no significant results. The insignificant results suggest that banks face no stock return and volatility consequences though they have taken more risks.

The TA rule, which prohibits investors from trading on non-public exchanges, promotes price efficiency instead. Informed traders, according to Nimalendran and Ray (2014), use both dark and bright exchanges to trade strategically. Under the TA rule, informed trading that is not permitted on dark exchanges might move to the lit exchanges, increasing the lit markets' price efficiency. Improved price efficiency suggests a stronger governance channel, which means banks will take fewer risks. Result in Table III showing that the TA rule reduces NCO, i.e., banks take less risk, provide evidence of the governance channel.

I further investigate whether price inefficiency leads to increased bank risk-taking and report the results in panel (b) of Table VI. Panel (b) reports the results of the instrumental variable regression of the price efficiency measures on bank risk-taking, employing the treatment of the Q rule as the instrument. As shown in the table, *Corr* and *PriceDelay* decrease the Z-score and increase earnings volatility, suggesting that pricing inefficiency caused by the Q rule treatment is positively associated with banks' risk-taking behaviour.

[Table VI to be here]

5.2 The Feedback Channel

In the feedback channel, as firm managers use information from the firm's stock price to evaluate investment decisions (Chen et al., 2007; Bakke and Whited, 2010), a bank with less informed stocks may make poorer lending decisions and appear to be more risk-taking. The market can be better informed about the firm's non-investor stakeholders, such as customers, employees, and suppliers (Subrahmanyam and Titman, 2001). Better-informed traders improve firm performance and alleviate the firm's financial constraints (Khanna and Sonti, 2004). An uninformed trader may instead cause firms to allocate resources inefficiently (Goldstein and Guembel, 2008). Increasing liquidity could stimulate informed investors, make price more informative, and lead to more efficient investment (Subrahmanyam and Titman, 2001).

The effectiveness of the feedback channel depends on the informativeness of the stock price, that is, the information that is valuable for the bank to make business decisions. I expect banks with less informative stocks to make worse decisions and appear more risk-taking. Following Chen et al. (2007), I use *price-nonsynchronicity* to measure the amount of private information in the stock price and to examine how the treatments of the test groups affect price informativeness and hence risk-taking. This measure reflects the firm-specific variation in stock price. It is estimated by $1-R^2$, where R^2 is the R-squared from the following regression:

$$r_{i,t} = \beta_{i,0} + \beta_{i,m} \times r_{m,t} + \beta_{i,b} \times r_{b,t} + \varepsilon_{i,t}$$

$r_{i,t}$ is the return on bank i at time t, $r_{m,t}$ is the market return at time t, and $r_{b,t}$ is the return on the banking industry at time t. The residual of the regression is considered orthogonal to the market and industry-wide variation, and thus it captures the firm-specific variation in returns that is correlated with private information. I calculate *price-nonsynchronicity* on weekly individual and market stock returns.

[Table VII to be here]

The results in Table VII show that the Q rule treatments have no significant effect on *price-nonsynchronicity*, but the T rule significantly increases *price-nonsynchronicity*; that is, larger minimum trade sizes improve price informativeness. The instrumental variable regression result in column (2) suggests that when the Q rule is treated as an instrument of liquidity, the effect of liquidity on *price-nonsynchronicity* is not significantly different from zero. Therefore, the feedback channel does not appear to be the reason that reduced liquidity affects banks' risk-taking behaviour.

The T rule treatments, on the other hand, result in a considerable rise in *price-nonsynchronicity*, implying a stronger feedback channel and less risk-taking. Table III shows that the T rule treatments reduce banks' risk-taking behaviour, as seen by significantly higher Zscore, decreased earning volatility, and greater CAR, corroborating the existence of the feedback channel.

6 Conclusion

How do liquidity shocks affect banks' risk-taking behaviour? To answer this question, I refer to the laboratory-like experiment the Tick Size Pilot Program and provide causal evidence that lower liquidity leads to higher bank risk-taking. The result is robust to various measures of risk-taking and alternative treatment dummies, and it remains unchanged after controlling for inverse of price, turnover, bank size, income, capital asset ratio, and funding liquidity.

The effect is interpreted through a governance channel through which bank blockholders can use discipline trading to monitor and regulate managers' risk behaviour. Lower liquidity reduces the effectiveness of the governance channel and provides less monitoring of bank managers' behaviour. Reduced price efficiency supports the argument that the effectiveness of the governance channel is impaired. On the other hand, although the feedback channel, where managers gather information from the stock market to make decisions, is emphasised by Fang et al. (2009) and Brogaard et al. (2017), I find no evidence that this channel affects my results.

My study helps clarify the role of the publicly traded bank in transmitting stock market liquidity shocks to bank loans. Brogaard et al. (2017) find that the negative liquidity shocks in the stock market increase the default risk of non-financial firms. My results show that banks subject to adverse liquidity shocks, with potentially weaker market-based governance, can become more risk-taking. Regulators could take this into consideration when supervising banks to uphold financial stability.

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Table I
Treatments of the Tick Size Program

This table describes the number of stocks and treatments in each test group in the Pilot. The program creates three test groups and one control group and applies progressive treatments on G1, G2, and G3, respectively. Three rules are applied to the three test groups. The Q rule is to quote at a minimum increment of \$0.05. The T rule is to trade at a minimum increment of \$0.05. The TA rule prevents the stock from trading in the off-exchange trading systems. My sample contains 252 bank stocks in the Pilot, with 127 control stocks, 37 banks in G1, 45 in G2, and 43 in G3.

Group Name	Stock Num	Bank Stocks	Minimum Increment of Quote	Minimum Increment of Trade	Trade-at Prohibition	Rules
Control group	1200	127	0.01	0.01	No	No
G1	400	37	0.05	0.01	No	Q
G2	400	45	0.05	0.05	No	Q, T
G3	400	43	0.05	0.05	Yes	Q, T, TA

Table II
Summary Statistics

The tables show the summary statistics of the main variables over the period from 2014 to 2018. *QSprd* is the price spread, i.e., the daily difference between the bid and ask prices at the end of the day divided by the mid-quote, averaged over each quarter. *ESprd* is the effective spread, which is the daily difference between the end-of-day price and the mid-quote divided by the mid-price, averaged over each quarter. *Zscore* is ROA plus the capital asset ratio divided by the standard deviation of the ROA, calculated before and after the start quarter of the Pilot. Capital asset ratio equals to total equity divided by total assets. *Vearn* is the standard deviation of the earnings ratio, which is equal to total earnings before income taxes divided by total assets. *NCO* is net charge-off divided by total assets. *CAR* is the CAR calculated by Compustat. *Corr* is the absolute value of the first-order auto-correlation of weekly stock returns. *PriceDelay* is a price efficiency measure raised by Hou and Moskowitz (2005). *PriceNonSyn* is price non-synchronicity, which is the $1-R^2$ of stock return explained by FAMA 49 bank industry portfolio return and CRSP Total Return Value-Weighted Index, reflecting firm-specific return variation that captures private firm information. *InversePrice* is the inverse of the daily closing price. *Turnover* is the log of the daily stock turnover, averaged across each quarter. *Size* is measured by the log of total assets. *ROA* is the ROA. *FundLqdt* measures bank funding liquidity and equals the sum of cash and due from banks and U.S. Treasury securities divided by total assets. *Leverage* is the debt to asset ratio which equals to total debt divided by total assets. *NonItrs* is the total non-interest income scaled by total asset. *Deposit* is total deposit scaled by total liabilities.

	Mean	St.Dev	Min	Max	Count
QSprd	0.1942	0.3564	0.0098	6.0676	4785
ESprd	0.0034	0.0042	0.0001	0.0431	4785
Zscore	146.6813	112.3570	-0.3816	1766.8086	4785
Vearn	0.0020	0.0023	0.0001	0.0219	4785
NCO	-0.0002	0.0007	-0.0139	0.0141	4784
CAR	15.5250	4.4977	7.3600	67.5100	4785
Corr	0.0998	0.0777	0.0001	0.5089	3840
PriceDelay	0.3796	0.3346	-0.5993	0.9999	3840
PriceNonSyn	0.7641	0.2110	0.2082	0.9998	4785
InversePrice	0.0638	0.0744	0.0045	2.6882	4785
Turnover	13.0650	2.5017	1.6715	20.6144	4785
Size	7.7371	1.0623	4.4869	10.4238	4785
ROA	0.0022	0.0012	-0.0091	0.0054	4785
FundLqdt	0.0890	0.0857	0.0032	0.7525	4785
Leverage	0.0287	0.0446	0.0000	0.5044	4785
NonItrs	0.0024	0.0018	-0.0046	0.0266	4785
Deposit	0.8870	0.0760	0.3524	0.9978	4785

Table III
Tick size, Liquidity and Z-score

This table gives the regression results of the model $RiskTak_{it} = \alpha + \beta_1 Q_i \times post_t + \beta_2 T_i \times post_t + \beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$, where $RiskTak_{it}$ represents *Log_QSprd*, *Log_ESprd*, $Zscore_{t+8}$, $Vearn_{t+8}$, NCO_{t+8}, CAR_{t+8}. *Log_QSprd* is the quarterly average of the log quoted spread, which is the difference between the daily ask and bid prices divided by the mid-quote. *Log_ESprd* is the quarterly average of the log of the effective spread, which is equal to the difference between the end-of-day ask and mid-quote divided by the mid-quote. $Zscore_{t+8}$ equals the ROA plus the capital asset ratio, divided by the standard deviation of ROA. $Vearn_{t+8}$ is the standard deviation of the earnings ratio, which equals the total earnings before income tax divided by the total assets. NCO_{t+8} is the gross charge-offs minus any recoveries of delinquent debts divided by the total assets. CAR_{t+8} equals the sum of Tier 1 and Tier 2 capital divided by the risk-weighted asset. Q_i, T_i and TA_i are the quote, trade, and trade-at rule dummy variables. I include a set of control variables: *InversePrice* is the inverse of the daily closing price. *Turnover* is the log of the daily stock turnover. *Size* is measured by the log of total assets. *ROA* is return on asset. *Leverage* is the debt to asset ratio which equals to total debt divided by total assets. *FundLqdt* measures bank funding liquidity and equals the sum of cash and due from banks and U.S. Treasury securities divided by total assets. *NonItrs* is the total non-interest income scaled by total asset. *Deposit* is total deposit scaled by total liabilities. The sample includes quarterly observations between 2014 and 2018. Firm and quarterly fixed effects γ_i and θ_t are included. Robust t-statistics clustered by firm and quarter are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Liquidity		Risk-Taking Measures			
	(1)	(2)	(3)	(4)	(5)	(6)
	Log_QSprd	*Log_ESprd*	$Zscore_{t+8}$	$Vearn_{t+8}$	NCO_{t+8}	CAR_{t+8}
Q × post	0.497***	0.513***	-17.789***	0.016*	0.012**	-0.584***
	(3.92)	(4.27)	(-3.74)	(1.93)	(2.85)	(-4.24)
T × post	0.126	0.002	23.835**	-0.009*	-0.002	0.526***
	(1.02)	(0.01)	(3.09)	(-1.92)	(-0.51)	(3.28)
TA × post	0.009	0.112	8.037	-0.010	-0.022*	0.063
	(0.09)	(0.95)	(1.46)	(-1.45)	(-2.09)	(0.56)
InversePrice	-1.868**	0.452	-74.875	0.156	0.005	0.540
	(-2.52)	(1.64)	(-1.32)	(1.25)	(0.12)	(0.67)
Turnover	-0.072***	-0.085***	0.964	0.001	0.000	0.002
	(-6.61)	(-8.39)	(0.54)	(0.56)	(0.06)	(0.10)
Size	-0.750***	-0.774***	164.432***	-0.058	0.016	1.833*
	(-5.41)	(-5.91)	(3.42)	(-1.25)	(1.11)	(2.17)
ROA	0.759	-18.487	2190.848	-10.746*	3.369	-121.784*
	(0.07)	(-1.39)	(0.53)	(-1.88)	(0.63)	(-1.91)
FundLqdt	0.722*	0.139	-314.675*	-0.092	0.018	2.925
	(1.73)	(0.38)	(-2.14)	(-0.83)	(0.47)	(0.94)
Leverage	-0.173	-0.520	211.266	-0.048	0.107	1.342
	(-0.38)	(-1.12)	(0.90)	(-0.44)	(1.18)	(0.93)
NonItrs	1.059	2.718	2179.826	2.754	0.449	-20.616
	(0.08)	(0.21)	(1.20)	(0.98)	(0.22)	(-0.61)
Deposit	-0.540	-0.876*	155.633	-0.133	0.161*	3.891
	(-1.18)	(-1.82)	(1.01)	(-1.10)	(2.05)	(1.40)
CAR	-0.027***	-0.018***	-1.732	0.004	-0.002*	0.075
	(-5.33)	(-3.60)	(-0.80)	(1.54)	(-2.17)	(0.62)
Firm Fix	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4785	4785	2748	2752	2755	2701
Adjusted R^2	0.898	0.898	250.621	0.588	0.279	0.893

Table IV
Tick size, Liquidity and Z-score: Instrument Regression

This table gives the instrument regression results of the model $VAR_{it} = \alpha + Liquidity_{it} + \beta_2 T_i \times post_t$ + $\beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$, where VAR_{it} represents risk-taking measures $Zscore_{t+8}$, $Vearn_{t+8}$, NCO_{t+8}, CAR_{t+8} and $Liquidity_{it}$ denotes liquidity measures *Log_QSprd* and *Log_ESprd* in panel (a) and (b) respectively. The Q rule treatment $Q_i \times post_t$ is the instrument for liquidity measures. *Log_QSprd* is the quarterly average of the log quoted spread, which is the difference between the daily ask and bid prices divided by the mid-quote. *Log_ESprd* is the quarterly average of the log of the effective spread, which is equal to the difference between the end-of-day ask and the mid-quote divided by the mid-quote. $Zscore_{t+8}$ equals the ROA plus the capital asset ratio, divided by the standard deviation of the ROA. $Vearn_{t+8}$ is the standard deviation of the earnings ratio, which equals the total earnings before income tax divided by the total assets. NCO_{t+8} is the gross charge-offs minus any recoveries of delinquent debts divided by the total assets. CAR_{t+8} equals the sum of Tier 1 and Tier 2 capital divided by the risk-weighted asset. Q_i, T_i and TA_i are the quote, trade, and trade-at rule dummy variables. I include a set of control variables: *InversePrice*, *Turnover*, *Size*, *ROA*, *Leverage*, *FundLqdt*, *NonItrs*, *Deposit* and *CAR*. The sample includes quarterly observations over 2014-2018. Firm and quarterly fixed effects γ_i and θ_t are included. Robust t-statistics clustered by firm and quarter are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(a) Quote Spread

	(1)	(2)	(3)	(4)
	$Zscore_{t+8}$	$Vearn_{t+8}$	NCO_{t+8}	CAR_{t+8}
Log_QSprd	-31.154***	0.027**	0.021***	-0.972***
	(-6.26)	(2.01)	(3.65)	(-4.92)
T × post	26.339***	-0.012**	-0.004	0.600***
	(3.10)	(-2.25)	(-1.23)	(3.69)
TA × post	4.860***	-0.007***	-0.019**	-0.072
	(3.91)	(-2.78)	(-2.11)	(-0.64)
Controls	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes
Observations	2749	2753	2755	2702
Adjusted R^2	-0.088	-0.103	-0.124	-0.120

(b) Effective Spread

	(1)	(2)	(3)	(4)
	$Zscore_{t+8}$	$Vearn_{t+8}$	NCO_{t+8}	CAR_{t+8}
Log_ESprd	-32.306***	0.028**	0.022***	-1.015***
	(-6.09)	(2.00)	(3.63)	(-4.63)
T × post	24.869***	-0.010**	-0.003	0.555***
	(3.02)	(-2.31)	(-0.98)	(3.44)
TA × post	7.442**	-0.010**	-0.021**	0.008
	(2.35)	(-2.10)	(-2.30)	(0.07)
Controls	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes
Observations	2749	2753	2755	2702
Adjusted R^2	-0.086	-0.095	-0.123	-0.142

Table V
Tick size, Liquidity and Z-score: Alternative Treatment Dummies

This table reports the OLS regression results of the model $RiskTak_{i,t+8} = \alpha + \beta_1 G_1 + \beta_2 Post_t + \beta_3 G_1 \times Post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in panel (a), and instrument variable estimation result of the model $RiskTak_{i,t+8} = \alpha + \beta Liquidity_{jt,i} + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in panel (b), where $RiskTak_{it}$ represents $Zscore_{t+8}$, $Vearn_{t+8}$, NCO_{t+8}, and CAR_{t+8} and $Liquidity_{it}$ denotes liquidity measures *Log_QSprd* and *Log_ESprd*. G1 equals 1 if a stock belongs to Group 1, equals 0 if it belongs to the control group, and is missing otherwise. For G1, only the Q rule is active. The G1 treatment $G1 \times post_t$ is the instrument for liquidity measures in panel (b). The liquidity measure *Log_Qsprd* is the quarterly average of the log daily quoted spread. I include a set of control variables: *InversePrice*, *Turnover*, *Size*, *ROA*, *Leverage*, *FundLqdt*, *NonItrs*, *Deposit* and *CAR*. The sample includes quarterly observations between 2014 and 2018. Firm and quarterly fixed effects γ_i and θ_t are included. Robust t-statistics clustered by firm and quarter are reported in parentheses. * p0.1, ** p0.05, *** p0.01.

(a) OLS Regression

	(1) $Zscore_{t+8}$	(2) $Vearn_{t+8}$	(3) NCO_{t+8}	(4) CAR_{t+8}
G1 × post	-17.480**	0.018*	0.013**	-0.576***
	(-2.91)	(2.07)	(2.86)	(-4.03)
Controls	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes
Observations	1769	1769	1773	1729
Adjusted R^2	0.605	0.651	0.192	0.879

(b) Instrumental Variable Estimation

	(1) $Zscore_{t+8}$	(2) $Vearn_{t+8}$	(3) NCO_{t+8}	(4) CAR_{t+8}
Log_QSprd	-29.790***	0.031**	0.021***	-0.933***
	(-5.58)	(2.11)	(3.92)	(-5.34)
Controls	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes
Observations	1770	1770	1773	1730
Adjusted R^2	-0.084	-0.109	-0.127	-0.095

Table VI
Price Efficiency, Liquidity, and Z-score

This table reports the OLS regression results of the model $PriceEf_{it} = \alpha + \beta_1 Q_i \times post_t + \beta_2 T_i \times post_t + \beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in columns (1) and (2) of panel (a), and instrument variable estimation results for model $PriceEf_{it} = \alpha + \beta Liquidity_{jt,i} + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in columns (3) to (6), where $PriceEf_{it}$ means price efficiency measures *Corr* or *PriceDelay* and $Liquidity_{it}$ denotes liquidity measures *Log_QSprd* and *Log_ESprd*. Panel (b) shows results for instrument variable estimation of the model $RiskTak_{i,t} = \alpha + \beta PriceEf_{jt,i} + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$, where $RiskTak_{it}$ represents $Zscore_{t+8}$ and $Vearn_{t+8}$. The Q rule treatment $Q_i \times post_t$ is the instrument for liquidity measures and price efficiency measures. The liquidity measure *Log_Qsprd* is the quarterly average of the log daily quoted spread. I include a set of control variables: *InversePrice*, *Turnover*, *Size*, *ROA*, *Leverage*, *FundLqdt*, *NonItrs*, *Deposit* and *CAR*. The sample includes quarterly observations between 2014 and 2018. Firm and quarterly fixed effects γ_i and θ_t are included. Robust t-statistics clustered by firm and quarter are reported in parentheses. * p0.1, ** p0.05, *** p0.01.

(a) Price Efficiency

	(1) *Corr*	(2) *PriceDelay*	(3) *Corr*	(4) *PriceDelay*	(5) *Corr*	(6) *PriceDelay*
Q × post	0.014**	0.048**				
	(2.41)	(2.10)				
Log_Qsprd			0.027**	0.093**		
			(2.37)	(2.23)		
Log_Esprd					0.027**	0.093**
					(2.35)	(2.25)
T × post	0.005	0.041	0.004	0.038	0.005	0.042*
	(0.75)	(1.60)	(0.56)	(1.45)	(0.77)	(1.72)
TA × post	-0.034***	-0.152***	-0.036***	-0.159***	-0.036***	-0.159***
	(-5.82)	(-6.83)	(-6.22)	(-7.57)	(-6.21)	(-7.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3785	3785	3785	3785	3785	3785
Adjusted R^2	0.514	0.684	-0.103	-0.015	-0.106	-0.001

(b) Zscore

	(1) *Zscore*	(2) *Zscore*	(3) *Vearn*	(4) *Vearn*
Corr	-5.0e+03**		0.049**	
	(-2.19)		(2.57)	
PriceDelay		-1.4e+03**		0.014**
		(-2.09)		(2.10)
T × post	100.666**	133.760**	-0.001	-0.001
	(2.31)	(2.23)	(-1.62)	(-1.59)
TA × post	-142.265*	-189.061*	0.001	0.001
	(-1.75)	(-1.78)	(1.38)	(1.37)
Controls	Yes	Yes	Yes	Yes
Firm Fix	Yes	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes	Yes
Observations	3785	3785	3785	3785
Adjusted R^2	0.514	-0.103	0.684	-0.015

Table VII
Price Informativeness and Liquidity

This table reports the OLS regression results of the model $PriceNonSyn_{i,t+8} = \alpha + \beta_1 Q_i \times post_t + \beta_2 T_i \times post_t + \beta_3 TA_i \times post_t + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in column (1), and instrument variable estimation results for model $PriceNonSyn_{i,t} = \alpha + \beta Liquidity_{jt,i} + \delta' X_{it} + \gamma_i + \theta_t + \varepsilon_{it}$ in columns (2) and (3), where $Liquidity_{it}$ denotes liquidity measures *Log_QSprd* and *Log_ESprd*. The Q rule treatment $Q_i \times post_t$ is the instrument for liquidity measures. *Log_Qsprd* is the quarterly average of the log daily quoted spread. *Log_ESprd* is the quarterly average of the log of the effective spread. I include a set of control variables: *InversePrice*, *Turnover*, *Size*, *ROA*, *Leverage*, *FundLqdt*, *NonItrs*, *Deposit* and *CAR*. The sample includes quarterly observations between 2014 and 2018. Firm and quarterly fixed effects γ_i and θ_t are included. Robust t-statistics clustered by firm and quarter are reported in parentheses. * p0.1, ** p0.05, *** p0.01.

	(1)	(2)	(3)
		PriceNonSyn	
Q × post	0.003		
	(1.03)		
Log_QSprd		0.006	
		(1.07)	
Log_ESprd			0.006
			(1.07)
T × post	0.011**	0.010**	0.011**
	(2.21)	(1.98)	(2.30)
TA × post	-0.005	-0.005	-0.006
	(-1.06)	(-1.11)	(-1.23)
InversePrice	0.047**	0.059**	0.044**
	(2.12)	(2.12)	(2.12)
Turnover	-0.004***	-0.004***	-0.003***
	(-7.50)	(-5.20)	(-4.79)
Size	-0.107***	-0.102***	-0.102***
	(-17.99)	(-14.77)	(-14.80)
ROA	-1.324***	-1.338***	-1.329***
	(-2.67)	(-2.77)	(-2.79)
FundLqdt	0.111***	0.106***	0.110***
	(5.72)	(5.54)	(5.94)
Leverage	-0.071**	-0.070**	-0.067**
	(-2.48)	(-2.54)	(-2.42)
NonItrs	0.785	0.783	0.804
	(1.20)	(1.24)	(1.27)
Deposit	-0.018	-0.014	-0.012
	(-0.71)	(-0.58)	(-0.48)
CAR	0.001	0.001**	0.001*
	(1.51)	(1.99)	(1.90)
Firm Fix	Yes	Yes	Yes
Quarter Fix	Yes	Yes	Yes
Observations	4785	4785	4785
Adjusted R^2	0.962	0.080	0.083