The Effect of Stock Liquidity on Default Risk

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Abstract

Corporate bankruptcy prediction has long been a widely studied topic. In this paper, we examine the impact of stock liquidity on firm's bankruptcy risk. We show that firms with more liquid stocks have lower default risk. The result is robust to different bankruptcy models and various measures of liquidity. We identify causality using decimalization as an exogenous shock to stock liquidity. We examine the mechanisms and show that stock liquidity reduces firm default risk through enhancing the informational efficiency of stock prices and facilitating corporate governance by blockholders. We last show there is spillover effect on bond market that firms with more liquid stocks have smaller corporate bond yield spread.

JEL Classifications: G12; G14; G33; G34

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1. Introduction

Bankruptcy prediction has been a popular area of research for over half a century. It is an important issue for creditors, investors, and rating agencies. Earlier studies focus on using accounting ratios to predict default probability (Altman 1968; Zmijewski 1984). Recent work indicates that market-driven variables (Shumway 2001; Bharath and Shumway 2008) and industry effects (Chava and Jarrow 2004) have better predictive power. In this paper, we intend to investigate whether stock market liquidity has any impact on bankruptcy probability.

First, stock liquidity affects firm default risk through its impact on firm value and future cash flow. On one hand, higher stock liquidity is associated with higher firm value and better cash flow due to the feedback effects from stock price to firm investments. Higher liquidity leads to more informed stock prices since it permits informed investors to profit more from their private information, thus incentivizes investors to acquire more information (Kyle, 1984; Holden and Subrahmanyam, 1992; Holmström and Tirole 1993; Subrahmanyam and Titman 2001). Stock price is a useful source of information, embodying the aggregate information of different investors (Hayek 1945). Although managers are most informed of their own firms' fundamentals and investment opportunities, they are less likely to have perfect information on every decision-relevant factor, such as macroeconomic conditions, future prospects of the industry, and competitors' strategies. Such important information, however, is collectively possessed by outside investors who might have no intention to directly communicate with managers and intervene, but choose to trade on their private information to maximize trading profits, in turn transmitting their information into stock prices. As a result, managers are able to learn from stock prices the new information, and incorporate it to improve their decision making (Dow and Gorton 1997; Subrahmanyam and Titman 2001; Chen, Goldstein, and Jiang 2007; Luo 2005; Bakke and Whited 2010). In turn, it leads to better investment decision, generates higher cash flows and reduces cash flow volatility, resulting in lower bankruptcy risk consequently. Second, stock liquidity facilitates corporate governance by blockholders through increased likelihood of block formation, direct intervention and threat of exit. (Maug 1998; Edmans 2009; Edmans and Manso 2011). Although blockholders are less incentivized to intervene in corporate governance when liquidity is high, higher liquidity increases the likelihood of accumulating a bock in a firm. The overall effect of liquidity on direct intervention is positive (Edmans, Fang and Zur 2013). Moreover, higher liquidity makes it easier for blockholders to sell stocks. The sales impose a downward pressure on stock price, hurting the manager who is compensated through equity-based compensation. Ex-ante, the thread of exit serves as an effective corporate governance mechanism (Admati and Pfleiderer, 2009;

Edmans 2009; Edmans and Manso 2011). Good corporate governance disciplines managers, urging them to engaging in value-enhancing investments and guarding against opportunistic management behavior, leading to lower bankruptcy probability. Fulghieri and Lukin (2001), Sunder (2004), and Baker, Stein, and Wurgler (2003) find evidence that feedback can also result from the effect of the stock price on the firm's access to capital when lenders learn from stock prices as they make investment decisions. There is also evidence that even random movements in stock prices affect firms' real investment decisions (Gilchrist, Himmelberg, and Huberman 2005; Polk and Sapienza 2009).

In addition, firms with more liquid stocks are less likely to miss its debt obligation due to improved access to capital market, and lower direct cost of issuing. Butler and Wan (2010) show that higher liquidity not only leads to better chance of issuing public debt, it also significantly reduces direct issuing cost. Bulter, Grullon, and Weston (2005) examine seasoned equity offerings and find a large and robust inverse relationship between the total fees paid to investment banks and the stock market liquidity of the issuing firm. Odders-White and Ready (2006) examine the link between credit ratings and stock liquidity, and show firms with liquid stock have better credit quality than illiquid ones. Moreover, Denis and Mihov (2003) show that firms with better credit quality are more likely to issue public debt.

On the contrary, some argue that the feedback effect from financial market to firm value might create a negative relation between liquidity and firm real activities. Goldstein and Guembel (2008) argue that high liquidity creates an incentive for uninformed investors to manipulate stock price through sell orders and drives down price. Managers might mistakenly interpret the artificially depressed stock price as investor disapproval, and respond to it by cancelling good investment projects, which results in lower future cash flow and increased risk of default. Using insights from global game, Ozdenoren and Yuan (2008) construct a model to show strong feedback effect could lead to higher excess volatility due to high sensitivity of price to non-fundamental shocks. Higher volatility implies higher chance that the value of a firm's asset will fall to such an extent that it is unable to repay the debt.

However, to our knowledge, there is no empirical literature studying the relationship between stock liquidity and bankruptcy risk. We would like to fill this gap in literature by investigating the effect of stock liquidity on firm bankruptcy risk.

We first show that firms with higher stock liquidity have lower bankruptcy risk. We employ two default risk models: the Cox proportional hazard model, a semi-parametric regression model that is used to estimate the effect of explanatory variables on time to failure, and the expected default frequency (EDF) regression in which we use the default risk measure (EDF) derived from Merton DD model as the dependent variable. The results indicate that higher stock liquidity is associated with lower default probability.

Next, we perform a test to shed light on the issue of the causal effect of stock liquidity on firm default risk using decimalization as a natural experiment. Early in 2001, the Securities and Exchange Commission (SEC) ordered the equity markets to convert from trading in discrete price fractions (sixteenths of a dollar) to a smoother decimal format with one penny The prior studies document that decimalization improves market liquidity significantly, especially among actively traded stocks (Goldstein and A Kavajecz 2000; Bessembinder 2003). On the other hand, it is unlikely that the decimalization was introduced as a result of change in firm bankruptcy risk; We rely on the framework of Fang, Tian, and Tice (2013) to conduct difference-in-difference tests and show that firms with larger increase in stock liquidity due to the decimalization event have larger drop in EDF than those with smaller increase in liquidity.

Having established the causality between stock liquidity and corporate default risk, we would like to pin down the mechanisms through which stock liquidity affects firms' default risk. First, we use two natural experiments, decimalization and brokerage terminations, to examine the price efficiency channel and find that the stock liquidity increases stock price efficiency and that the increase in price efficiency decreases EDF. Second, we use blockholder ownership and the number of blockholders to explore the corporate governance channel and show that both the blockholder ownership and the number of blockholders significantly increase after the decimalization event and that the increased blockholder ownership significantly decreases firm's default probability.

Finally, we extend our study to corporate bond market. We add stock liquidity measures into the corporate bond yield spread linear regression used by Chen, Lesmond, and Wei (2007) and Bharath and Shumway (2008) and find that higher stock liquidity can reduce corporate bond yield spread.

Our work is the first empirical study to cast light on the research question concerning whether stock liquidity reduces or increases corporate bankruptcy risk. It is the first study to test the causal effect of stock liquidity on firm bankruptcy risk. Our empirical results support the argument that stock liquidity can reduce corporate bankruptcy risk.

Our paper adds to the bankruptcy literature by showing that stock liquidity has potential predictive power for corporate default risk. The earlier studies focus on predicting default risk using accounting ratios, pioneered by Altman (1996). Shumway (2001) employs a hazard model and argues that market-driven variables have more predictive power for bankruptcy risk than accounting ratios. Chava and

Jarrow (2004) find that industry effects are important in forecasting bankruptcy probability. Vassalou and Xing (2004), on the other hand, propose a default measure based on Merton's (1974) option pricing model. Similarly, Bharath and Shumway (2008) show that default measure based on Merton's is useful for forecasting defaults.

Our paper is also related to the growing literature examines the relationship between stock liquidity and corporate real economic activities. Fang, Noe, and Tice (2009) show that stock liquidity improves firm value measured by Tobin's Q. Bharath, Jayaraman, and Nagar (2013) argue stock liquidity magnifies the effect of block ownership on firm value. In contrast, Fang, Tian, and Tice (2013) find that the higher liquidity leads to a decline in firm innovation. We further show the effect of liquidity on firm real economic activities is extended to the likelihood of bankruptcy. Moreover, we provide direct causal evidence of the informational efficiency channel by using two natural experiments, decimalization and brokerage terminations, while Fang, Noe, and Tice (2009) only present indirect evidence.

The remainder of this paper is organized as follows. Section 2 reviews related literature. In section 3, we describe the sample selection and the data. Section 4 presents the empirical results. In section 5, we examine the mechanisms. In section 6, we test whether stock liquidity can affect corporate bond yield spread. Section 7 concludes.

2. Literature Review

2.1 Bankruptcy Literature

Our study relates to bankruptcy literature. Since Altman (1968) applies the multiple discrimination analysis to predict firm bankruptcy, researchers have developed different bankruptcy predicting models. Merton (1974) considers the equity of the firm as a call option on the underlying value of the firm and builds an option pricing model which is later widely used to measure default probability. Shumway (2001), arguing that the hazard model is superior to other static models in predicting bankruptcy risk, employs a hazard model to forecast bankruptcy and suggests that market-driven variables, such as past stock returns and the idiosyncratic standard deviation of stock returns, have more predictive power for bankruptcy risk than accounting ratios. Chava and Jarrow (2004) add four industry dummies into the hazard model and find that industry effects are important in forecasting bankruptcy probability. Vassalou and Xing (2004) first use Merton (1974)'s model to measure firms' distance to default (DD). Bharath and Shumway (2008) then use the hazard model to test the accuracy of the expected default frequency (EDF) in forecasting default risk and suggest that EDF is a useful variable to measure default risk.

In our study, we would like to add stock liquidity measures into the bankruptcy risk models to see whether stock liquidity has predictive power for default risk.

2.2 Liquidity and Stock Price Efficiency

To build the relationship between stock liquidity and bankruptcy risk, we first investigate the role of stock liquidity in affecting price efficiency: One line of research suggests a positive relationship between stock liquidity and price efficiency. While the other line of research demonstrates a negative relationship in which the selling actions of uninformed speculators are studied.

On one hand, stock liquidity can induce traders to acquire information. Kyle (1984) models the relationship between informed trading and price behavior. He demonstrates that high liquidity allows informed traders to better camouflage their trading, thus permits them to benefit more from their private information. The higher potential profits create incentives for traders to acquire more private information and trade on it. This causes price to become more informative as more information is revealed through trading by the larger number of informed traders. Building on Kyle (1984), Holden and Subrahmanyam (1992) show competition among informed traders induces them to trade more aggressively, causing more information to be revealed earlier, and resulting higher price efficiency. Furthermore, Subrahmanyam and Titman (2001) argue that higher stock liquidity will increase the importance of this feedback effect and make stock price more informative by stimulating more informed trading.

In contrast to Subrahmanyam and Titman (2001), Goldstein and Guembel (2008) show that the feedback effect from stock prices to a firm’s investment decisions induces an uninformed speculator to sell the stock. When this uninformed speculator drives down the stock price by selling, the manager may cancel the investment project due to the reason that the decreasing price is thought as a signal of negative information about the project. As this information is misleading, investment decision is inefficient and the firm’s future cash flow will decrease, enabling the uninformed speculator to profit. Since higher stock liquidity makes it easier for uninformed traders to sell stocks, stock prices become even more misleading and less efficient.

Having investigated the effects of stock liquidity on price efficiency, we should build the relationship between informational efficiency of stock prices and the efficiency of real investment decisions which is one of the central steps to study the real effect of stock market. Stock market is the place where traders use their information to profit from trading. Traders’ actions lead to the changes in stock prices, incorporating their information in stock prices. Dow and Gorton (1997) identify two roles of stock price in improving the efficiency of managers’ investment decisions: a prospective role and a retrospective role. First, managers tend to learn from the stock market and base their decisions on price as the market contains information they do not have, such as macroeconomic conditions, future prospects of the industry, and competitors' strategies. Then traders have incentive to produce information about expected profitability of the investment project and trade on it. Second, stock prices can be used to evaluate past investment decisions, inducing managers to make efficient decisions. Subrahmanyam and Titman (2001) construct a model of feedback in which a firm's stakeholders make decisions based on the information contained in stock prices, leading to fluctuations of firms' future cash flows. They argue that this feedback effect from stock prices to firm fundamentals can greatly affect mangers' incentives to collect information from stock market to guide their real decisions. Since the information contained in stock prices affects managers' real decisions, more informative prices can enhance the efficiency of investment decisions.

If stock liquidity enhances price efficiency, then managers tend to make more efficient investment decisions based on the information incorporated in stock prices. Since manager's decision making can affect a firm's future cash flow which determines whether or not a firm can afford debt service costs and principal payments, the more efficient investment decisions can reduce firms' bankruptcy risk by generating higher cash flows. Hence, in this logic, we can suspect a negative relationship between stock liquidity and firm default risk.

If higher stock liquidity induces uninformed traders to manipulate stock prices, stock prices will be more misleading and distort the firm investment decisions, leading to lower cash flows which weaken a firm's ability to afford debt service costs and principal payments. Thus, stock liquidity may increase firm default risk.

2.3 Liquidity and Corporate Governance

Another channel through which stock market liquidity affects firm default risk is corporate governance. Stock liquidity can impel blockholders to exert governance through two different approaches: monitoring and stock trading. Maug (1998) builds a model of intervention by large shareholders who may reap profits by either monitoring the firm or trading on their private information in stock markets. The model demonstrates that large shareholders will engage in more monitoring if the stock market is more liquid, the reason being that the higher stock liquidity allows those large investors to benefit more from informed stock trading so as to cover the cost of monitoring. Edmans (2009) shows that blockholders can cause stock price to reflect firm fundamental value by gathering and trading on their private information, this in turn can induce managers to invest for long-term growth. The model constructed by Edmans and Manso (2011) implies that stock market liquidity can improve blockholders' power in exerting governance through stock trading, this kind of threat of disciplinary trading will promote higher managerial effort. When the high stock market liquidity improves the power of corporate governance, managers tend to make more efforts in increasing firm's future cash flow, thus leading to lower bankruptcy risk.

2.4 Empirical Studies

Empirical studies find distinct evidences on the effect of stock liquidity on firm performance. Fang, Noe, and Tice (2009) show that stock liquidity improves firm value as measured by Tobin's Q. Bharath, Jayaraman, and Nagar (2013) study the role of liquidity in blockholder's threat of exit and conclude that stock liquidity magnifies the effect of block ownership on firm value. In contrast, Fang, Tian, and Tice (2013) employ a difference-in-difference method based on the decimalization event and find that the increase in liquidity leads to decrease in firm innovation.

However, the above mentioned empirical literature does not directly linked stock liquidity to firm's bankruptcy risk. In this paper, we would like to test the relationship between stock liquidity and firm bankruptcy risk.

3. Data, sample, variable construction and statistics

3.1 Data and sample

The sample construction starts with a comprehensive list of U.S. common stocks between 1993 and 2008[1], which appears in both the Compustat Industrial file and the Center for Research in Security Prices (CRSP) stock return file. We obtain intraday trades and quotes from the Trade and Quote (TAQ) database to construct the high-frequency liquidity stock liquidity measure. The bankruptcy dataset is assembled by Chava (Chava and Jarrow, 2004; Chava, Stefanescu, and Turnbull, 2011; and Alanis and Chava, 2012)[2]. The comprehensive dataset includes the bankruptcy cases between January 1993 and July 2008 filed under both Chapter 7 and Chapter 11 by US public firms listed on NYSE, AMEX and NASDAQ. The database consolidates cases reported in four different sources including the Wall Street Journal Index, SEC Filings, the SDC Database and the CCH Capital Changes Reporter. We exclude from our sample financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 9000 and 9999) because their accounting numbers are subject to statutory capital requirements. Moreover, to assure there are enough data points to compute liquidity measures, we exclude firm-year observations with less than 50 active trading days in a year[3]. The accounting data are obtained from the Compustat quarterly tapes. If the accounting data is missing for one year, the previous

[1] Our sample period starts from 1993 because the TAQ's coverage starts from 1993. The sample stops in July 2008 because the bankruptcy database, which is kindly provided by Sudheer Chava ends in July 2008.

[2] We thank Sudheer Chava for providing to us the bankruptcy dataset.

[3] Alternatively, we restrict the sample to stock-year observations with at least 200 active trading days in a year. Our results are not sensitive to the choice of the cut-off point.

non-missing observation is used. The resulting sample comprises 47,169 firm-year observations.

3.2 Variable construction

3.2.1 Stock Liquidity Measures

We capture stock liquidity using both low-frequency and high-frequency measures. The first two measures are based on daily trading information, which are commonly used in studies involving a relatively long timeframes. Our first measure $Amihud_{iy}$ is the Amihud illiquidity ratio (2002), defined as absolute value of daily stock return divided by daily dollar trading volume. The measure is based on an idea that, everything else equal, illiquid stocks should experience a larger change in the stock price for the same amount of trading, and thus a high value corresponds to lower liquidity. Specifically, $AMIHUD_{it}$ is calculated as:

$$\mathrm{AMIHUD_{it}} = \frac{1}{\mathrm{D_{it}}} \times \sum_{\mathrm{d=1}}^{\mathrm{D}} \frac{|\mathrm{RET_{id}}|}{|\mathrm{VOLUME_{id}}|} ;$$

where RET_{id}, and $VOLUME_{id}$ are, respectively, the returns and dollar trading volume on day d for stock i, and D_{it} is the number of trading days for stock i in year t.

Following Lesmond, Ogden, and Trzcinka (1999), we calculate our second liquidity measure $ZEROs_{it}$, which is the proportion of days with zero returns. Intuitively, illiquid stocks are more likely to experience trading days with zero returns due to either no trading interesting or high trading cost. Therefore, a high value is associated with low liquidity. It is computed as follows:

$$\mathrm{ZEROs}_{\mathrm{it}} = \frac{\text{\# of days with zero returns}}{\mathrm{D}_{\mathrm{it}}} \;;$$

where D_{it} is the number of trading days for stock *i* in year *t*.

The two other measures are calculated using intraday trade and quote data from the TAQ database, which provides a better and more precise measure of trading cost (Goyenko, Holden, and Trzcinka, 2009). We consider both quoted spread and effective spread. The percentage quoted spread ($RQSPR_{i,t}$) captures the cost of making a round-trip trading (buy and sell), if trades are executed at the quoted prices. To compute $RQSPR_{i,t}$, we first calculate the daily average percentage quoted spread, which is the time-weighted average of all intraday spread records, and average across all trading days in a year to construct an annual measure.

Each intraday percentage quoted spread is calculated as follows:

$$\mathrm{RQSPR} = \frac{ASK - BID}{(ASK+BID)/2}$$

where ASK and BID are, respectively, the quoted ask and bid price.

Although quoted spread is a good starting point, in the US, trades often occur at prices other than the inside quotes due to hidden liquidity, large orders ‘walking up the book’ or price improvement provided by specialists. As a result, we compute percentage effective spread ($RESPR_{i,t}$), which is a better measure for trading cost when trades occur either within or outside the quotes. For each intraday trade record, we compute percentage effective spread, defined as twice the difference between the execution price and the midpoint of the prevailing best quotes divided by the midpoint of the prevailing best bid-ask quote. The formula is as follows:

$$RESPR = 2 \times \mathrm{LR} \times \frac{(P - M)}{M}$$

where LR is an indicator which equals 1 for buyer-initiated trade and -1 for seller-initiated trade, P is the price of the trade, and M is the midpoint price at the time of order submission. The daily average quoted effective spread is the volume-weighted average of all intraday effective spread records, which is then averaged across all trading days in a year to compute $RESPR_{i,t}$.

We apply several filters to the TAQ data before computing the two spread measures. We follow Hasbrouck (2010) to derive the National Best Bid and Offer (NBBO)[4]. Following Chordia, Roll, and Subrahmanyam (2001), we exclude records for which the quoted spread is larger than \$ 5, the dollar (relative) effect spread is more than 4 times larger than the dollar (relative) quoted spread, or quoted spread is more than 40% of the trade price. We classify trades using the widely-used Lee and Ready (1991) algorithm. Specifically, a trade is considered buyer-initiated

[4] The SAS program suggested by Hasbrouck (2010) can be found on WRDS website. See https://wrds-web.wharton.upenn.edu/wrds/.

(seller-initiated) if it is executed at a price above (below) its matching quote midpoint[5]. For trades occur at the midpoint price, a 'tick test' is used to classify the trade as buyer-initiated (seller-initiated) if the last price change before the trade is positive (negative).

3.2.2 Expected default frequency

We employ a Cox proportional hazard model and a regression analysis to analyze the impact of equity market liquidity on firm default risk. We will discuss the Cox proportional hazard model in the 'Methodology' session, and focus this session on the construction of a default risk measure used in the regression analysis.(perhaps delete it)

We follow Bharath and Shumway (2008) to construct a measure expected default frequency ($EDF_{i,t}$), which is a simplified version of Merton (1974) structural default model. Merton (1974) considers that a firm's equity is a call option on the underlying value of the firm's assets with a strike price equal to the face value of the firm's debt, and a firm defaults when its asset value falls below the face value of the firm's debt. To compute the probability, the model first calculates a distant-to-default (DD) measure by subtracting the face value of the firm's debt from an estimate of firm's assets divided by an estimate of the volatility of the firms' assets. The resulting DD

[5] A matching quote is defined as the first quote at least five seconds prior to the trade for trades between 1993 and 1998 inclusive, and the first quote prior to the trade for trades occurring after 1998.

measure is then substituted in to a cumulative standard normal distribution to compute the probability that the value of firm's assets will be less than the face value of its debt. Although the Merton model is widely used in academic studies and by practitioners (Crosbie and Bohn, 2001, Kealhofer and Kurbat 2001, Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007), its original formula involves a complicated iterative procedure and is difficult to calculate. Bharath and Shumway (2008) show that Merton model's predictive power mainly comes from its functional form, rather than the actual default probability produced by the model. Campbell, Hilscher and Szilagyi (2008) reach a similar conclusion. Bharath and Shumway (2008) further propose a 'naive' default probability measure which retains Merton model's structural form and same basic inputs while greatly simplifies the calculation. Bharath and Shumway (2008) compare the two methods, and show that their 'native' measure performs surprisingly well. The measure is calculated as follows:

$$\mathrm{EDF}_{i,t} = \mathrm{N}(-\mathrm{DD}_{i,t});$$

$$\mathrm{DD}_{it} = \frac{\log\left(\frac{\mathrm{E}_{i,t} + \mathrm{F}_{i,t}}{\mathrm{FF}_{i,t}}\right) + \left(\mathrm{r}_{i,t-1} - \frac{\sigma^2_{\mathrm{V}i,j}}{2}\right) \times T_{i,t}}{\sigma_{\mathrm{V}i,j} \times \sqrt{T_{i,t}}}$$

$$\sigma_{\mathrm{V}i,t} = \frac{\mathrm{E}_{i,t}}{\mathrm{E}_{i,t} + \mathrm{F}_{i,t}} \times \sigma_{\mathrm{E}i,t} + \frac{\mathrm{E}_{i,t}}{\mathrm{E}_{i,t} + \mathrm{F}_{i,t}} \times \left(0.05 + 0.25 \times \sigma_{\mathrm{E}i,t}\right);$$

where $E_{i,t}$ is the market value of equity (in millions of dollars) at the end of year. $F_{i,t}$ is the face value of debt computed as the sum of debt in current liabilities and one-half of long-term debt. r_{it-1} is the annual return for firm i and year t-1. $\sigma_{Ei,t}$ is the stock return volatility for firm i and year t estimated using the monthly stock return from the previous year. $\sigma_{Vi,t}$, calculated from $\sigma_{Ei,t}$, is an approximation of the volatility of firm assets; $T_{i,t}$ is set to one year. We construct $DD_{i,t}$ of all sample firms as of the last day of each year. $N(.)$ is the cumulative standard normal distribution function.

3.2.3 Control Variables

We follow Bharath and Shumway (2008) to construct the control variables. *ln(E)* is the natural log of market value of equity at the end of year. *ln(F)* is the natural log of face value of debt. $1/\sigma_E$ is the inverse of the annualized stock return volatility. *EXRET*, the excess return, is calculated as the different before the stock's annual return and the CRSP value-weighted return for the previous year. *NITA* is the ratio of net income to total asset.

To avoid any outlier effects, we winsorize all variables at the 0.5% and 99.5% level.

3.3 Descriptive statistics

Panel B of Table I reports summary statistics. RESPR (Amihud (multiplied by 106), RQSPR, and Zeros) ranges from 0.0441% (0.0001, 0, and 0.0327%) to 5.3433% (8.6982, 35.7724%, and 7.8108%) with a mean value of 1.4424% (0.4406, 8.4470%, and 1.2343%). With a mean of 0.5475, stock volatility ranges from 0.1168 to 2.0837.

Ranging from -99.13% to 363.37%, excess return has a mean of 4.91%. The average market value of equity and face value of debt are 2387.98 (in million dollars) and 354.69 (in million dollars) respectively. The mean of EDF is 0.05. To make sure that the empirical results are not driven by outliers, we have winsorized all the variables except EDF at the 1st and 99th percentile.

[Insert Table I here]

4. Empirical Results

Our empirical analysis employs two

To investigate whether stock liquidity affects firm's bankruptcy risk, we employ two popular default risk models. The first one is a Cox proportional hazard model, which is widely used in literature (Shumway 2001; Chava and Jarrow 2004; Bharath and Shumway 2008) to predict bankruptcy risk. The second one is called expected default frequency (EDF), which is derived from Merton DD model to measure firm's default probability.

To identify the causal effect of stock liquidity on firm's bankruptcy risk, we use the decimalization event as an exogenous shock to stock liquidity and do a series of difference-in-difference tests.

4.1 Summary Statistics

4.2 Univariate Analysis

In the univariate analysis, we compute the expected default probability (EDF) for groups of stocks formed on the basis of stock illiquidity measure. First, in year t, we assign stocks into five groups based on their illiquidity measures which are estimated in year t-1. Specifically, the most liquid stocks (with lowest illiquidity measure) are assigned into the first group and the least liquid stocks (with highest illiquidity measure) are assigned into the fifth group. In this step, we use four illiquidity measures, RESPR, RQSPR, Amihud, and Zeros, to form stock groups. Second, for each group, we compute the average of EDF in year t. In other words, each group has its EDF value every year. Third, we calculate the time-series mean of these averages of EDF for each group.

The results of the univariate analysis are presented in Table II. Based on relative effective spread, we can find that the EDF for the first group (with the highest liquidity) is only 0.63% which is 9.86% lower than the EDF of 10.48% for the fifth group (with the lowest liquidity). The difference between the EDF of the fifth group and that of the first group is significant at 1% level. As liquidity drops from the first group to the fifth group, the EDF increases. The results hold for all the other three illiquidity measures. Thus, the results indicate a negative relationship between stock liquidity and firm default risk.

[Insert Table II here]

4.3 Multivariate Analyses

4.3.1 Hazard Model Results

To investigate the relationship between bankruptcy risk and stock liquidity, we first estimate the Cox proportional hazard model in which we add liquidity measures. Developed by Cox (1972), the proportional hazard model is a semi-parametric regression model that is used to estimate the effect of explanatory variables on time to failure, t. The Cox model is as follows[6]:

$$h(t|\mathbf{X}, \boldsymbol{\beta}) = h_0(t)\exp(\mathbf{X}'\boldsymbol{\beta})\,;$$

where $h_0(t)$ is referred to as the baseline hazard function, **X** and **β** are vectors of covariates and regression coefficients. In this model, the baseline hazard function $h_0(t)$ is common to all corporations, no prior estimation of the baseline hazard function is required before the model is estimated. The covariates **X** may affect the probability of

[6] See Cox (1972) for the detailed deduction of the Cox model.

failure and vary with time. The coefficients $\boldsymbol{\beta}$ are the model's estimates.

In our analysis, we lag all the explanatory variables by one year so as to ensure that they are available both at the start of each year and at the time of estimation. The hazard model is actually as follows:

$$h(t|\mathbf{X}_{it-1}, \boldsymbol{\beta}) = h_0(t)\exp\left(\mathbf{X}_{it-1}{}'\boldsymbol{\beta}\right).$$

where t is time-to-default which equals the number of days from the beginning of the sample period till the default time (if the firm go bankrupt at time t) or till the end of the sample period (if the firm does not go bankrupt at time t). X_{it-1} includes liquidity measure (RESPR, RQSPR, Amihud, and Zeros) and the control variables used in Bharath and Shumway (2008).

[Insert Table III here]

Table III contains the likelihood estimates for Cox proportional hazard model with both industry and year fixed effects. There are 38,129 firm-year observations and 482 bankruptcies in this model. We use five specifications. Specification 1 contains no liquidity measure. We add liquidity measures in the following four specifications. The liquidity measures from Specification 2 to 5 are Relative Effective Spread, Relative Quoted Spread, Amihud measure, and Zeros respectively. The table shows that the coefficients for the four liquidity measures are all positive and significant at 1% level. Specifically, compared to the sample bankruptcy probability of 1.26%, the marginal effect of RESPR (RQSPR, Amihud, and Zeros) on firm's bankruptcy is 0.25% (0.44%, 0.11%, and 0.05%). These results suggest that lower stock liquidity (high illiquidity measure) is associated with higher bankruptcy risk. The results for other control variables are similar to Bharath and Shumway (2008)'s findings. Firms with higher equity value, less debt, lower stock return volatility, higher excess return, and greater net income to asset ratio are less likely to go bankrupt.

To test whether stock liquidity significantly predicting the bankruptcy risk, we also report -2 of the logarithm of the likelihood of model which is used to conduct a likelihood ratio test. The first specification without liquidity measure is considered as the constrained model. Other specifications with liquidity measure are considered as the unconstrained models. The Chi-statistic, which equals 2 of the difference between the logarithms of the likelihoods of the constrained and unconstrained models, is asymptotically distributed according to the Chi-square distribution. The Chi-square statistics for the four models are all significant, implying that stock liquidity is an important factor in the bankruptcy prediction model.

4.3.2 EDF regression Results

In addition to the Hazard model, we also run regressions with expected default probability (EDF) as dependent variable and standard errors clustered by both firm and year. The specification we use is as follows:

$$\text{EDF} = \alpha_0 + \alpha_1 \text{Liquidity} + \alpha_2 \text{Ln(E)} + \alpha_3 \text{Ln(F)} + \alpha_4 \left(\frac{1}{\sigma_E}\right) + \alpha_5 \text{EXRET} + \alpha_6 \text{NITA}.$$

Table IV contains the regression results with EDF as dependent variable and the same control variables as in prior hazard model. There are totally 36,967 firm-year observations in this regression.

[Insert Table IV here]

The first regression is estimated without liquidity measure. RESPR, RQSPR, Amihud measure, and Zeros are added in the following four regressions respectively. The coefficients for the four liquidity measures are all positive and significant at 1% level, suggesting that higher stock liquidity is associated with lower default probability. More specifically, a 1% decrease in RESPR (a 1% increase in stock liquidity) leads to a 2.03% decrease in default probability. We observe similar results for other liquidity measures (Amihud, RQSPR, and Zeros). The coefficients for other control variables are consistent with the results in the Cox proportional hazard model. We also run the regression with year dummies and with standard errors clustered by firm. The results are similar.

[Insert Table V here]

4.4 Decimalization Test Results

It is possible that firm bankruptcy risk can affect stock traders' trading behaviors so as to induce changes in stock liquidity. Even though we have introduced one-year lag between illiquidity measure and EDF, the reverse causality problem still exists.

We intend to use the decimalization as an exogenous shock to stock liquidity so as to identify the causal effect of stock liquidity on firm bankruptcy risk. The decimalization event has been widely used in prior literature[7]as an exogenous shock to stock market liquidity. The decimalization event happened in 2001. The U.S. Securities and Exchange Commission (SEC) regulated that all stock markets within the U.S. should convert all stock price quotes into decimal trading format by April 9, 2001. More specifically, prior to decimalization in 2001, the smallest price change was1/16 of one dollar in a price quote. With the effectiveness of decimalization, the minimum price change is reduced to $0.01, which allows for tighter spreads between the bid and the ask prices for stock trading. As a result, the trading costs are much lower and stock liquidity becomes higher after the decimalization event (Bessembinder 2003). Moreover, the decimalization is unlikely to affect firm bankruptcy risk. Thus, the decimalization provides a proper candidate to generate exogenous shocks to stock liquidity.

4.4.1 OLS Regression

In the first test, we regress the change in EDF surrounding decimalization year 2001

[7] See, for example, Chordia, Roll, and Subrahmanyam (2008), Fang, Noe, and Tice (2009), Chordia, Roll, and Subrahmanyam (2011), Fang, Tian, and Tice (2013), and Edmans, Fang, and Zur (2013).

on the change in liquidity from 2000 (the year prior to decimalization) to 2002 (the year after decimalization) and the changes in other control variables. The decimalization test model is as follows:

$$\begin{aligned}\Delta \mathrm{EDF}_{i,t-1\ \mathrm{to}\ t+1} &= \alpha_0 + \alpha_1 \Delta \mathrm{Liquidity}_{i,t-1\ \mathrm{to}\ t+1} + \alpha_2 \Delta \mathrm{Ln(E)}_{i,t-1\ \mathrm{to}\ t+1} \\ &+ \alpha_3 \Delta \mathrm{Ln(F)}_{i,t-1\ \mathrm{to}\ t+1} + \alpha_4 \Delta\left(\frac{1}{\sigma_E}\right)_{i,t-1\ \mathrm{to}\ t+1} + \alpha_5 \Delta \mathrm{EXRET}_{i,t-1\ \mathrm{to}\ t+1} \\ &+ \alpha_6 \Delta \mathrm{NITA}_{i,t-1\ \mathrm{to}\ t+1} + \mathrm{error}_{i,t-1\ \mathrm{to}\ t+1}\end{aligned}$$

where Δ presents the change of variables, t is the decimalization year 2001, t-1 to t+1 indicates that the change is from prior decimalization year to after decimalization year.

Table VI displays the results of the OLS regression of the decimalization test model. The coefficients for the changes in liquidity measures are all positive and significant at 1% level, suggesting that a raise in stock liquidity surrounding decimalization will lead to drops in expected default probability (EDF). Since the change of stock liquidity is exogenous, we can safely suggest a causal effect of stock liquidity on firm default risk.

[Insert Table VI here]

4.4.2 Difference-in-Difference Estimator

In the second test, we conduct a difference-in-difference analysis. First, we calculate the change in relative effective spread (ΔRESPR) from the pre-decimalization year (2000) to post-decimalization year (2002). Second, we assign the 2,882 sample firms into tertiles based on their $\Delta \text{RESPR}_{2000 \text{ to } 2002}$ and only retain the firms in the first tertile and third tertile. Specifically, firms in the first tertile experience the highest increase in stock liquidity (largest drop in RESPR) and firms in the third tertile experience the lowest increase in stock liquidity (smallest drop in RESPR). We are left with 1,921 firms and denote the first tertile as treatment group and the third tertile as control group. Third, we use a propensity score matching approach to match firms in treatment group with firms in control group. Specifically, we first run a probit model based on firms in the treatment and the control groups. The dependent variable of the probit model equals one if the firm belongs to the treatment group and zero if the firm comes from the control group. The independent variables of the probit model are the control variables we used in the Hazard model and EDF regression measured in the pre-decimalization year (2000). We include these control variables to rule out the factors that affect firm's default probability and make the treatment and control groups more comparable. The probit model is as follows:

$$D_i = \alpha_0 + \alpha_1 \text{RESPR}_{i,t-1} + \alpha_2 \text{Ln(E)}_{i,t-1} + \alpha_3 \text{Ln(F)}_{i,t-1} + \alpha_4 \left(\frac{1}{\sigma_E}\right)_{i,t-1}$$
$$+ \alpha_5 \text{EXRET}_{i,t-1} + \alpha_6 \text{NITA}_{i,t-1} + \text{error}_{i,t-1} ;$$

where D_i is a dummy variable which equals one if firm i belongs to the treatment group and zero otherwise. The results of the probit regression are reported in column (1) of Table VII Panel A. From the probit model estimation, we obtain the propensity scores that is the predicted probability for firms in treatment and control groups. Each firm in the treatment group is then matched to a control firm with the closest propensity score and within a difference of 0.01. If a control firm is matched with more than one firm in treatment group, we retain all the matched pairs. We finally get a new sample containing 753 pairs of matched firms.

[Insert Table VII here]

Before doing difference-in-difference (DID) estimation, we conduct three diagnose tests to verify that our matched sample complies with the parallel trend assumption required by DID approach. In the first diagnose test, we make a comparison between the propensity scores of the treatment group and those of the control group. Panel B of Table VII reports the statistical distributions of the propensity scores of the treatment and control groups and their differences. The differences are quite trivial, suggesting that our matching procedure is accurate.

In the second diagnose test, we run the same probit model as in the propensity score matching step but with the matched sample. The results of the probit model are presented in column (2) of Table VII Panel A. The results show that none of the control variables are significant and the likelihood ratio is much lower than that in the prior probit model results, implying that there is no significant difference in EDF between the treatment and control groups in the pre-decimalization year.

In the last diagnose test, we use t-test to examine the differences between the control variables of the treatment group and those of the control group in the pre-decimalization year. Table VII Panel C reports variable means for both treatment and control group, the differences in means of each variable, and the corresponding t-statistics. The insignificant t-statistics suggest that there are no significant differences between the treatment and control firm's characteristics that affect firm's EDF.

The above three diagnose tests suggest that the parallel trend assumption is not violated. As we have control the factors that may affect firm's EDF, the changes in EDF surrounding the decimalization are more likely to be caused by the changes in stock liquidity. In order to verify this statement, we calculate the difference-in-difference estimators and do significance tests. Specifically, we first calculate the changes of EDF from pre-decimalization year to post-decimalization year ($\Delta EDF_{2000\text{ to }2002}$) for both treatment and control firms in our matched sample. Then we calculate the difference-in-difference estimators by subtracting the average ΔEDF of the control firms from the average ΔEDF of the treatment firms. Finally, we run a t-test to examine whether there is significant difference between the ΔEDF of the treatment firms and that of the control firms. Panel D of Table VII reports the DID estimators and the corresponding t-statistics. Results show that the treatment firms experience a larger drop of 9.44% in EDF than the control firms around decimalization event (i.e., 1.89 times the sample average EDF)[8] and the difference between the ΔEDF of the two groups are statistically significant at 1% level.

5. Mechanisms

In this section, we examine the mechanisms through which stock market liquidity decreases firms' default probability.

5.1 Price Informational Efficiency

In this part, we examine whether stock liquidity decreases firms' default risk by improving the informational efficiency of stock prices. Higher stock liquidity can enhance the informational efficiency of share prices by inducing more informed trading (Subrahmanyam and Titman 2001). Since the information from the financial markets is more accessible and much cheaper, managers tend to 'listen' to this information (Dow and Gorton 1997) and make more informative decisions if the stock

[8] The average of the control firms experience drops in liquidity (increase in RESPR) and result in increase in EDF, thus the drop in EDF from treatment firms relative to control firms is higher than the sample average. The relative effective spread (RESPR) for the treatment firms drops by 3.0554 more than the RESPR for the control firms. For a similar drop in RESPR (3.15 times the median sample RESPR of 0.9701), the EDF regression estimates a 6.5% drop in EDF.

price is more efficient. Manager's decision making can affect a firm's future cash flow which determines whether or not a firm can afford debt service costs and principal payments. Thus, the informational efficiency of stock prices forms a channel through which the stock liquidity affects firms' default risk.

We employ two measures of price efficiency. The first measure is stock return autocorrelation (Corr) which is the absolute value of the correlation between contemporaneous weekly stock returns and the one week lagged weekly stock returns. A smaller autocorrelation indicates that the stock price process is much closer to a random walk and thus the price is more efficient. When constructing this measure, we use the CRSP daily stock price data and calculate the weekly returns from the last day's closing price in a given week t, i.e., $return_t=\ln(P_t/P_{t-1})$. After getting the weekly returns, we compute the absolute value of the autocorrelation coefficients for each stock per calendar year. The second measure, |VRx-1|, is the absolute value of the variance ratio minus one. The variance ratio, VRx, is calculated by dividing variance of x weeks compound returns by x times the variance of weekly returns. We use 3 and 4 weeks (VR3 and VR4) variance ratio in the analysis. If stock prices follow a random walk, the variance ratio should be equal to one. Since variance ratios below or above one indicates deviation from random walk, we subtract the variance ratio by one and calculate the absolute value (Griffin, Kelly, and Nardari 2010; Saffi and Sigurdsson

2011). Thus, |VR3-1| and |VR4-1| should be equal to zero under the null hypothesis of random walk.

To pin down this informational efficiency channel, we use two natural experiments. The first is the decimalization event and the second is brokerage terminations.

5.1.1 Decimalization Test for Informational Efficiency Channel

In the first part, we employ the difference-in-difference method to examine the effect of stock liquidity on the price informational efficiency based on the matched sample constructed in Part 4.4.2. Specifically, we calculate the changes of price efficiency measures from pre-decimalization year to post-decimalization year ($\Delta Corr_{2000\ to\ 2002}$ and $\Delta|VRx\text{-}1|_{2000\ to\ 2002}$) for each stock. The difference-in-difference estimators are computed by subtracting the changes of price efficiency measure of the control firms from the changes of price efficiency measure of the treatment firms. We then run a t-test to examine whether there is significant difference between the changes of price efficiency measure (ΔCorr and Δ|VRx-1|) of the treatment firms and that of the control firms[9]. Panel A of Table VIII reports the DID estimators and the corresponding t-statistics. Results show that the treatment firms experience a significantly larger drop of 2.86%, 2.93%, and 3.37% in Corr, |VR3-1| and |VR4-1| respectively than the control firms.

[9] Before doing the DiD estimation, we also conduct the three diagnostic tests to verify that we do not violate the parallel trends assumption. The results of the tests suggest that the assumption is not violated. To save space we do not put the results here.

Next, to test whether the increase of stock price informational efficiency surrounding the decimalization could cause a drop in the firm's expected default frequency (EDF), we run the following regression on the matched sample constructed in section 3.4:

$$
\begin{aligned}
\Delta \mathrm{EDF}_{i,t-1\text{ to }t+1} \\
&= \alpha_0 + \alpha_1 \Delta \text{Price Efficiency}_{i,t-1\text{ to }t+1} + \alpha_2 \Delta \mathrm{Ln(E)}_{i,t-1\text{ to }t+1} \\
&+ \alpha_3 \Delta \mathrm{Ln(F)}_{i,t-1\text{ to }t+1} + \alpha_4 \Delta\left(\frac{1}{\sigma_E}\right)_{i,t-1\text{ to }t+1} + \alpha_5 \Delta \mathrm{EXRET}_{i,t-1\text{ to }t+1} \\
&+ \alpha_6 \Delta \mathrm{NITA}_{i,t-1\text{ to }t+1} + \mathrm{error}_{i,t-1\text{ to }t+1}
\end{aligned}
$$

Panel B of Table VIII displays the results of the OLS regression. The coefficients for ΔCorr, Δ|VR3-1| and Δ|VR4-1| are all positive and significant; suggesting that a raise in stock price informational efficiency surrounding decimalization will lead to drops in expected default probability (EDF).

[Insert Table VIII here]

In sum, by showing that the exogenous shock of decimalization to stock liquidity leads to the increase of stock price informational efficiency and that the increase in informational efficiency of price surrounding decimalization decreases EDF, we reach the conclusion that the informational efficiency of price may be the channel through which stock liquidity affects firm's default risk.

5.1.2 Brokerage Terminations Test for Informational Efficiency

Channel

The second natural experiment is brokerage terminations, which bring about exogenous reduction in analyst coverage of certain stocks. Kelly and Ljungqvist (2012) list 43 U.S. brokerage firms that terminated research sections due to both broker closure and broker merger during the year 2000 to 2008. They also argue that the brokerage terminations affect the analyst coverage of firm's stocks, but are exogenous to firm fundamental value. After the brokerage terminations, the retail investors who are uninformed and more dependent on sell-side analyst research may reduce their demand for the affected stocks and even drop out of the market due to the brokerage terminations. According to O'hara (1995)'s argument, when the number of informed traders is endogenous, reduction in the uninformed trading will decrease the potential gains of informed traders, and this will decrease the entry of informed traders and even cause some of the existing informed traders to drop out of the market, resulting in the decrease in the amount of informed trading. This causes prices to become less informative as the number of informed traders participate in the stock market is less and less information is revealed in stock market. Kelly and Ljungqvist (2008) empirically show that stock price informational efficiency deteriorates following the brokerage terminations. In addition, Hong and Kacperczyk (2010) use the brokerage terminations as exogenous source of the reduction in competition among analysts and find that less competition lead to an increase in analyst optimism bias. In sum, the brokerage termination can not only decrease the amount of information revealed in the market but also deteriorate the quality of information, both resulting in the decrease in the informational efficiency of stock price.

Since the brokerage termination will influence informational efficiency of stock price and are unlikely to affect firm fundamental characteristics, we can use this natural experiment to examine the causal effect of price informational efficiency on firm default risk. Specifically, we use the list of brokerage terminations between Q1, 2000, and Q1, 2008, provided in Kelly and Ljungqvist (2012). We merge the list with I/B/E/S unadjusted historical detail dataset to find the affected stocks and restrict that the affected stocks stay in the I/B/E/S dataset in t+1 (the year after the event). After obtaining the sample of affected stocks, we merge the sample with CRSP and Compustat data, excluding financial and utility firms, and restrict that the affected firms have data both in pre-event year and post-event year. We keep the pre-event and post-event firm-year observations in the sample of affected firms, which contains 2,170 unique firms and 4,340 firm-year observations (the number of unique firms is similar to the terminations sample constructed by Kelly and Ljungqvist (2012)). We then merge the sample with TAQ data and restrict that a stock must trade at least 200 days in a year.

After all the merging steps, we conduct difference-in-difference analysis using a matched sample. To construct the matched sample, we employ the propensity score matching approach as we used in previous sections. Specifically, we first run a probit model based on both the affected and unaffected firms in pre-event years. The dependent variable of the probit model equals one if the firm is affected by the brokerage terminations and zero otherwise. The independent variables of the probit model are the control variables we use in the Hazard model and EDF regression measured in the pre-event years, i.e. Ln(E), Ln(F), 1/σE, EXRET, and NITA. After obtaining the propensity scores for each firm from the probit regression, we match each affected firm to an unaffected firm with the closest propensity score and within a difference of 0.01. Finally, we are left with a matched sample containing 1,317 pairs of matched firms and define the affected firms as treatment firms and unaffected firms as control firms. We then compare changes in EDF, Amihud, RESPR, RQSPR, Zeros, Corr, |VR3-1|, and |VR4-1|of treatment firms to those of control firms. The difference-in-difference results are reposted in Table IX.

[Insert Table IX here]

We find that the average increase of EDF for affected firms is significantly higher than that for unaffected firms at 5% level, implying that the firms that affected by brokerage terminations tend to have higher default risk after the events. For Amihud, RESPR, and RQSPR[10], there are also significant higher increases for affected firms, meaning that the affected stocks experience more drops in market liquidity than the unaffected stocks. The informational inefficiency, measured by |VR3-1| and |VR4-1|[11], of treatment firms increases more than that of control firms. Overall, the results, which are consistent with our previous analysis, suggest that the brokerage terminations decrease the price informational efficiency of affected stocks, resulting in higher default risk of the affected firms.

5.2 Stock Liquidity and Corporate Governance

Another possible channel through which stock liquidity reduces default risk is corporate governance. To test the governance channel, we employ two measures, blockholder ownership (BLOCK) and the number of blockholders (NBLOCK). The institutional ownership data is from Thomson-Reuters Institutional (13F) Holdings database available at WRDS. Blockholder ownership (BLOCK) is calculated by aggregating institutional blockholders ownership in percent which is above 5% of total common shares outstanding at the end of year. The number of blockholders

[10] For Zeros, the result is not consistent with Kelly and Ljungqvist (2012) due to two reasons. The first reason is that our Zeros measure exclude missing return days but Kelly and Ljungqvist (2012) include both missing and zero return days. The second reason is that Kelly and Ljungqvist (2012) use a shorter window in their analysis while we use longer window (one year) in our test.

[11] The results for the two variance ratios are consistent with Kelly and Ljungqvist (2008). Kelly and Ljungqvist (2008) do not use Corr as their informational efficiency measure. Our analysis shows that the DID estimator for Corr is not significant.

(NBLOCK) is the number of block owners who hold at least 5% of total common shares outstanding at the end of year.

Similar to the methodology we employ in Part 5.1.1, we first examine the effect of stock liquidity on the blockholder ownership (BLOCK) and the number of blockholders (NBLOCK) based on the matched sample constructed in Part 4.2.2. We subtract the changes of blockholder measure of the control firms from the changes of blockholder measure of the treatment firms to obtain the difference-in-difference estimators[12] and then do t-tests to examine whether there is significant difference between the changes of blockholder measure (ΔBLOCK and ΔNBLOCK) of the treatment firms and that of the control firms. The difference-in-difference estimators and the corresponding t-statistics presented in Panel A Table X indicate that the treatment firms that have higher increase in liquidity show a significantly larger increase of 0.0173 and 0.2364 in BLOCK and NBLOCK respectively than the control firms.

Then we run the following regression on the matched sample constructed to test whether the increase in blockholder measure surrounding the decimalization can lead to the decrease in EDF:

[12] To save space, we do not show the diagnostic tests of the parallel trends assumption. The results of the tests suggest that the assumption is not violated.

$$\Delta EDF_{i,t-1 \text{ to } t+1}$$
$$= \alpha_0 + \alpha_1 \Delta Blockholder_{i,t-1 \text{ to } t+1} + \alpha_2 \Delta Ln(E)_{i,t-1 \text{ to } t+1}$$
$$+ \alpha_3 \Delta Ln(F)_{i,t-1 \text{ to } t+1} + \alpha_4 \Delta(\frac{1}{\sigma_E})_{i,t-1 \text{ to } t+1} + \alpha_5 \Delta EXRET_{i,t-1 \text{ to } t+1}$$
$$+ \alpha_6 \Delta NITA_{i,t-1 \text{ to } t+1} + error_{i,t-1 \text{ to } t+1}$$

The negative and significant coefficients for both ΔBLOCK and ΔNBLOCK in Panel B Table X suggest that the increase in blockholder ownership and the number of blockholders surrounding the decimalization can lead to drops in EDF. Thus we conclude that the exogenous rise in stock liquidity can increase both the blockholder ownership and the number of blockholders. The improved power of governance through both monitoring and disciplinary trading by more blockholders can reduce firms' default probability.

[Insert Table X here]

6. Extension

In previous sections, we have find evidence that stock liquidity is a significant factor in predicting firm default risk. To test whether there is a spillover effect from stock liquidity to corporate bond market, we employ the yield spread linear regression in Chen, Lesmond, and Wei (2007) and Bharath and Shumway (2008) and add stock liquidity measure as follows:

$$\begin{aligned}\text{Yield Spread}_{it} = {} & \alpha_0 + \alpha_1\text{Liquidity}_{it} + \alpha_2\sigma_{E_{it}} + \alpha_3\text{Maturity}_{it} + \alpha_4\ln(\text{amount})_{it} \\ & + \alpha_5\text{T90RET}_t + \alpha_6\text{Coupon}_{it} + \alpha_7\text{Coverage Dummy}_{1_{it}} \\ & + \alpha_8\text{Coverage Dummy}_{2_{it}} + \alpha_9\text{Coverage Dummy}_{3_{it}} + \alpha_{10}\text{OISA}_{it} \\ & + \alpha_{11}\text{LDTA}_{it} + \alpha_{12}\text{TDMC}_{it} + \alpha_{13}\text{Rating}_{it};\end{aligned}$$

where yield spread is the difference between the corporate bond yield and the yield of a benchmark treasury; liquidity is stock liquidity measure; σ_E is stock volatility; maturity is corporate bond's time-to-maturity; amount is bond's trading amount; T90RET is the 3-month T-bill rate; coupon is referred to corporate bond's coupon rate; coverage stands for the pre-tax interest coverage, defined as the ratio of [operating income after depreciation+interest expense (Compustat quarterly data #22)] to interest expense, specifically, if coverage<5, coverage dummy1=1, if 5=<coverage<10, then coverage dummy2=1, if 10<=coverage, then coverage dummy3=1; OISA is the operating income to sales; LDTA is long-term debt to asset; TDMC is total debt to capitalization; Rating is corporate bond issuers' credit ratings.

Our sample period in this section is from 2004 to 2010. The data related to corporate bonds and treasuries are from the following sources:

1. Corporate bond yields and bond characteristics from the Trade Reporting and Compliance Engine Database (TRACE);

2. Credit ratings from Standard &Poor's Issuer rating file;

3. Treasury data from CRSP U.S. treasury dataset.

For TRACE bond trading records, we first apply an error filter introduced by Dick-Nielsen (2009) to delete true duplicates, reversals, and same-day corrections. Then we calculate daily bond yield, which is the volume-weighted mean of yields for each bond during a trading day. We also calculate daily trading amount by cumulating trading volume for each trade over a trading day for a particular bond. After obtaining bond daily yields and trading amounts, we merge them with bond characteristics (i.e. coupon rate, maturity date and grade) obtained from TRACE master file. We then eliminate high-yield bond (Grade ='H'). The corporate bond yield spread is the difference between the bond yield and the yield of a benchmark U.S. treasury. The treasury data come from CRSP U.S. treasury dataset. For each corporate bond, the benchmark treasury is the one with the same remaining time to maturity and the closest maturity date as those of the corporate bond. After obtaining the daily yield spread, we calculate the annual yield spread by averaging the daily yield spread over one calendar year. The annual amount is also computed by averaging daily trading amount over one year. The bond issuers' credit ratings are from Standard &Poor's Issuer monthly rating file available in Compustat. We use the domestic long-term issuer credit rating and assign integer numbers to the ratings, i.e. AAA=1, AA+, AA, AA-=2, A+, A, A-=3, BBB+, BBB, BBB-=4, BB+, BB, BB-=5, B+, B, B-=6, CCC+,

CCC, CCC-=7.

Panel A Table XI reports the summary statistics for the variables used in bond yield spread regressions. Panel B of Table XI displays the results of OLS regression with corporate bond yield spread as dependent variable.

[Insert Table XI here]

The coefficients for Relative Effective Spread, Relative Quoted Spread, Amihud measure, and Zeros are all positive and significant, suggesting that corporate bond yield spreads are higher when the firm's stock is less liquid.

7. Conclusion

In this paper, we investigate the effects of stock liquidity on firm's bankruptcy risk and the mechanism through which stock liquidity affects firm's bankruptcy risk. Using the Cox proportional hazard model and EDF regression in which we add liquidity measures, we find a significant negative relationship between stock liquidity and firm's bankruptcy risk. Using the decimalization event as an exogenous shock to stock liquidity, we employ the difference-in-difference analysis to test the causal effect of stock liquidity on firm default risk and show that stock liquidity has a negative causal effect on firm default risk.

We then examine how stock liquidity affects firm's default risk. First, we show that the increase in stock liquidity surrounding the decimalization improves price informational efficiency, managers then tend to make more informative investing decisions which leads to lower bankruptcy risk. We also use brokerage terminations as natural experiment which decreases price efficiency of affected stocks and find that the affected firms have higher default risk. Thus we conclude that higher stock liquidity reduces firm’s bankruptcy risk through higher price informational efficiency. Second, we find evidence that the exogenous increase in stock liquidity facilitates blockholders to exert governance through both monitoring and disciplinary trading, leading to lower default risk.

Finally, we find evidence that stock liquidity can reduce corporate bond yield spread.

Table I Variable Definitions and Summary Statistics

Panel A reports variable definitions for the variables used in this paper. Panel B reports summary statistics for the sample firm-year observations.

The sample contains 47,169 firm-year observations between 1993 and 2007 (the sample period for DD and EDF is1994-2008). The sample used for regressions has a smaller number of observations due to data availability.

Panel A Variable Definitions

Variable	Definition
RESPR	Annual relative effective spread. Relative effective spread is twice the difference between the execution price and the midpoint of the prevailing best bid-ask quote divided by the midpoint of the prevailing best bid-ask quote. Measured over one year.
RQSPR	Annual relative quoted spread. Relative quoted spread is the prevailing best bid-ask spread divided by the midpoint of the prevailing best bid-ask quote. Measured over one year;
Amihud	Annual Amihud Measure. Annual average of the daily ratio of absolute value of stock return divided by dollar trading volume;
Zeros	Proportion of days with zero returns. Measured over one year;
DD	Distance-to-Default;
EDF	Expected Default Frequency;
E	Market value of equity (in millions of dollars) calculated as the product of the number of shares outstanding and stock price at the end of year;
F	Face value of debt computed as the sum of debt in current liabilities (Compustat quarterly data #45) and one-half of long-term debt (Compustat quarterly data #51);
EXRET	Excess return. Firm's annual return, calculated from monthly stock returns over the previous year, minus the market's return over the same period;
σ_E	Annualized stock return volatility computed as the standard deviation of stock monthly returns over the prior year;
NITA	The ratio of net income (Compustat quarterly data #69) to total asset (Compustat quarterly data #44);
Corr	The absolute value of the correlation between contemporaneous weekly stock returns and the one week lagged weekly stock returns;
|VRx-1|	The absolute value of the variance ratio minus one. The variance ratio, VRx, is calculated by dividing variance of x weeks compound returns by x times the variance of weekly returns;
BLOCK	Aggregate institutional blockholders ownership in percent which is above 5% of total common shares outstanding at the end of year;

NBLOCK	The number of block owners who hold at least 5% of total common shares outstanding at the end of year.

Panel B Summary Statistics

Variable	N	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	Std Dev	Skewness
RESPR	47169	1.4424	0.0441	0.3748	0.9701	2.1752	5.3433	1.3416	1.1168
RQSPR	47169	8.4470	0.0000	1.9920	5.9524	12.6984	35.7724	8.0324	1.2803
Amihud	47169	0.4406	0.0001	0.0029	0.0224	0.1910	8.6982	1.2883	4.5871
Zeros	47169	1.2343	0.0327	0.2707	0.7464	1.7263	7.8108	1.3806	2.1216
DD	42446	7.3500	-1.3805	3.1348	5.9853	10.0157	30.2891	5.9810	1.3841
EDF	42446	0.0500	0.0000	6.50E-24	1.08E-09	0.0009	1.0000	0.1605	4.1343
E	45631	2387.98	22.22	138.14	401.77	1376.86	52133.45	6931.83	5.3975
F	45278	354.69	0.00	1.11	28.76	197.25	6718.00	999.49	4.5572
EXRET	47169	0.0491	-0.9913	-0.3783	-0.0705	0.2608	3.6337	0.7236	2.2386
σ_E	47169	0.5475	0.1168	0.2974	0.4500	0.6882	2.0837	0.3626	1.7817
NITA	45667	-0.0095	-0.3596	-0.0119	0.0084	0.0210	0.0909	0.0667	-2.8377
Corr	47169	0.1231	0.0020	0.0488	0.1043	0.1785	0.3992	0.0920	0.8618
|VR3-1|	47169	0.2365	0.0036	0.0957	0.2029	0.3434	0.7648	0.1746	0.8411
|VR4-1|	47169	0.2915	0.0050	0.1198	0.2534	0.4221	0.9430	0.2116	0.8237
BLOCK	47169	0.1488	0.0000	0.0000	0.1209	0.2329	1.9348	0.1429	1.1319
NBLOCK	47169	1.7173	0	0	1	3	11	1.5536	0.8707

Table II Univariate Analysis

This table reports the distribution of EDF across ten groups of stocks which are formed on the basis of illiquidity measures. In year t, stocks are assigned into five groups based on their liquidity which is measured in year t-1, most liquid stocks (with lowest illiquidity measure) are assigned into the first group and least liquid stocks (with highest illiquidity measure) are assigned into the fifth group. For each group, we compute the average of EDF every year. After getting the yearly averages of EDF, we calculate the time-series mean of these averages of EDF for each group. We use four illiquidity measures, RESPR, RQSPR, Amihud, and Zeros, to form stock groups. The sample period is from 1993 to 2007. See Table I Panel A for definitions of all the variables. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Rank for Illiquidity Measures	EDF mean			
	(1) RESPR	(2) RQSPR	(3) Amihud	(4) Zeros
1	0.0063	0.0054	0.0087	0.0107
2	0.0202	0.0184	0.0211	0.0186
3	0.0364	0.0348	0.0377	0.0339
4	0.0563	0.0567	0.0578	0.0585
5	0.1048	0.1094	0.0971	0.0976
Rank 5-Rank 1	0.0986***	0.1040***	0.0884***	0.0869***
T-Test (t value)	5.89	6.32	5.77	5.97

Table III Cox Proportional Hazard Model Likelihood Estimates

This table contains likelihood estimates for the Cox proportional hazard model with the time-to-default as dependent variable. There are totally 38,129 firm-year observations between 1993 and 2007. The number of bankruptcies is 482. Column (1) presents the estimated results of the model without liquidity measure. Column (2) to (4) reports the results of hazard model with Relative Effective Spread, Relative Quoted Spread, Amihud, and Zeros as liquidity measures respectively. Other control variables are Ln(E), Ln(F), $1/\sigma_E$, EXRET, and NITA. We also add industry and year dummies. See Table I Panel A for definitions of all the variables. Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Column Liquidity	(1) No	(2) RESPR	(3) RQSPR	(4) Amihud	(5) Zeros
Liquidity		0.1957***	0.3456***	0.0878***	0.0411***
		(0.0247)	(0.0410)	(0.0267)	(0.0071)
Ln(E)	-0.4055***	-0.3092***	-0.1998***	-0.3655***	-0.3053***
	(0.0468)	(0.0482)	(0.0514)	(0.0476)	(0.0505)
Ln(F)	0.3647***	0.3720***	0.3969***	0.3721***	0.3585***
	(0.0309)	(0.0312)	(0.0322)	(0.0311)	(0.0309)
$1/\sigma_E$	-0.7967***	-0.7446***	-0.7008***	-0.7923***	-0.8068***
	(0.1018)	(0.0969)	(0.0947)	(0.1006)	(0.1004)
EXRET	-2.6420***	-2.5719***	-2.5229***	-2.6438***	-2.6136***
	(0.2438)	(0.2399)	(0.2344)	(0.2419)	(0.2404)
NITA	-3.2494***	-3.3420***	-3.2942***	-3.3372***	-3.3434***
	(0.5489)	(0.5502)	(0.5503)	(0.5481)	(0.5475)
#obs	38129	38129	38129	38129	38129
#bankruptcies	482	482	482	482	482
Sample probability of bankruptcy	1.26%	1.26%	1.26%	1.26%	1.26%
Stock liquidity marginal effect	N/A	0.25%	0.44%	0.11%	0.05%
Industry Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes

Likelihood Ratio	3137.87	3178.99	3206.70	3146.72	3167.41
-2 Log L	6335.92	6294.79	6267.08	6327.06	6306.37
-2Log L Difference	0	41.12	68.83	8.86	29.55

Table IV Regressions with Two-Dimension Clustered Errors and with EDF as Dependent Variable

This table presents regression results with standard errors clustered by both firm and year. There are totally 36,967 firm-year observations between 1993 and 2007. The number of clusters is 36,967. The dependent variable is expected default probability (EDF). Column (1) presents the results of the regression without liquidity measure. Column (2) to (4) reports the results of regressions with Relative Effective Spread, Relative Quoted Spread, Amihud, and Zeros as liquidity measures respectively. Other control variables are Ln(E), Ln(F), $1/\sigma_E$, EXRET, and NITA. See Table I Panel A for definitions of all the variables. Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Column	(1)	(2)	(3)	(4)	(5)
Liquidity	No	RESPR	RQSPR	Amihud	Zeros
Intercept	0.2031***	0.1313***	0.0373	0.1620***	0.1765***
	(0.0334)	(0.0266)	(0.0262)	(0.0293)	(0.0296)
Liquidity		0.0203***	0.0362***	0.0215***	0.0012
		(0.0057)	(0.0072)	(0.0037)	(0.0008)
Ln(E)	-0.0274***	-0.0204***	-0.0101***	-0.0223***	-0.0239***
	(0.0046)	(0.0034)	(0.0032)	(0.0041)	(0.0038)
Ln(F)	0.0208***	0.0207***	0.0212***	0.0210***	0.0202***
	(0.0030)	(0.0030)	(0.0031)	(0.0031)	(0.0030)
$1/\sigma_E$	-0.0219***	-0.0202***	-0.0189***	-0.0216***	-0.0229***
	(0.0045)	(0.0043)	(0.0039)	(0.0043)	(0.0048)
EXRET	-0.0113***	-0.0117***	-0.0116***	-0.0132**	-0.0108***
	(0.0057)	(0.0057)	(0.0059)	(0.0051)	(0.0058)
NITA	-0.2097***	-0.1800***	-0.1447***	-0.1943***	-0.2080***
	(0.0491)	(0.0525)	(0.0465)	(0.0466)	(0.0498)
#obs	36967	36967	36967	36967	36967
R-square	0.1347	0.1555	0.1716	0.1543	0.1371

Table V Regressions with Fixed Effects and with EDF as Dependent Variable

This table presents regression results with year dummies and with standard errors clustered by firm. There are totally 36,967 firm-year observations between 1993 and 2007. The dependent variable is expected default probability (EDF). Column (1) presents the results of the regression without liquidity measure. Column (2) to (4) reports the results of regressions with Relative Effective Spread, Relative Quoted Spread, Amihud, and Zeros as liquidity measures respectively. Other control variables are Ln(E), Ln(F), $1/\sigma_E$, EXRET, and NITA. See Table I Panel A for definitions of all the variables. Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Column	(1)	(2)	(3)	(4)	(5)
Liquidity	No	RESPR	RQSPR	Amihud	Zeros
Intercept	0.2203***	0.1625***	0.0568***	0.1834***	0.1490***
	(0.0068)	(0.0069)	(0.0080)	(0.0067)	(0.0073)
Liquidity		0.0206***	0.0419***	0.0199***	0.0044***
		(0.0013)	(0.0017)	(0.0015)	(0.0003)
Ln(E)	-0.0282***	-0.0213***	-0.0090***	-0.0234***	-0.0168***
	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0011)
Ln(F)	0.0204***	0.0206***	0.0214***	0.0206***	0.0190***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
$1/\sigma_E$	-0.0190***	-0.0182***	-0.0167***	-0.0190***	-0.0220***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
EXRET	-0.0168***	-0.0166***	-0.0177***	-0.0179***	-0.0167***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
NITA	-0.1863***	-0.1565***	-0.1022***	-0.1755***	-0.1610***
	(0.0196)	(0.0194)	(0.0195)	(0.0196)	(0.0193)
#obs	36967	36967	36967	36967	36967
#clusters	6287	6287	6287	6287	6287
Year Dummies	Yes	Yes	Yes	Yes	Yes
R-square	0.1592	0.1794	0.2040	0.1756	0.1760

Table VI OLS Regression Surrounding the Decimalization

This table presents OLS regression results with ΔEDF as dependent variable. Δ presents the change of variables from 2000 (prior to decimalization) to 2002 (after decimalization). Column (1) presents the results of the regression without the change of liquidity measure. Column (2) to (4) reports the results of regressions with ΔRESPR, ΔRQSPR, ΔAmihud, and ΔZeros as the change of liquidity measures respectively. Other control variables are ΔLn(E), ΔLn(F), $\Delta(1/\sigma_E)$, ΔEXRET, and ΔNITA. See Table I Panel A for definitions of all the variables. Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Column	(1)	(2)	(3)	(4)	(5)
ΔLiquidity	No	ΔRESPR	ΔRQSPR	ΔAmihud	ΔZeros
Intercept	0.0100**	0.0037	0.0253***	0.0005	0.0634***
	(0.0043)	(0.0044)	(0.0041)	(0.0044)	(0.0055)
ΔLiquidity		0.0124***	0.0650***	0.0179***	0.0100***
		(0.0020)	(0.0038)	(0.0023)	(0.0007)
ΔLn(E)	-0.0526***	-0.0517***	-0.0150**	-0.0490***	-0.0144***
	(0.0072)	(0.0071)	(0.0071)	(0.0071)	(0.0073)
ΔLn(F)	0.0003	-0.0003	-0.0009	0.0001	-0.0015
	(0.0039)	(0.0038)	(0.0036)	(0.0038)	(0.0037)
$\Delta(1/\sigma_E)$	-0.0132***	-0.0121***	-0.0117***	-0.0118***	-0.0218***
	(0.0035)	(0.0035)	(0.0033)	(0.0035)	(0.0034)
ΔEXRET	-0.0176***	-0.0167***	-0.0270***	-0.0215***	-0.0218***
	(0.0047)	(0.0047)	(0.0045)	(0.0047)	(0.0045)
ΔNITA	-0.0068	0.0100	0.0607	-0.0130	0.0455
	(0.0718)	(0.0713)	(0.0676)	(0.0708)	(0.0687)
#obs	2161	2161	2161	2161	2161
R-square	0.0560	0.0726	0.1679	0.0828	0.1387
Adj. R-square	0.0538	0.0701	0.1656	0.0802	0.1363

Table VII Difference-in-Difference Analysis

This table presents the results of the difference-in-difference analysis surrounding the decimalization year.

Panel A Column (1) reports the results of the probit model based on the pre-matched firms in the treatment and the control groups. The dependent variable of the probit model equals one if the firm belongs to the treatment group and zero if the firm comes from the control group. The independent variables of the probit model are the control variables we used in the Hazard model and EDF regression measured in the pre-decimalization year. Panel A Column (2) report the results of the same probit model but based on the post-matched firms in the treatment and the control groups. See Table I Panel A for definitions of all the variables. Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel B reports the statistical distributions of the propensity scores of the treatment and control groups and their differences.

Panel C reports variables means for both treatment and control group, the differences in means of each variable, and the corresponding t-statistics in the pre-decimalization year.

Panel D reports the DID estimator and the t-statistics.

Panel A Probit Regressions with Pre-matched and Post-matched samples in Pre-decimalization Year

Probit Regressions		
Dependent Variable: DDl=1 if in treatment group; 0 in control group		
Parameter	(1) Pre-match	(2) Post-match
Intercept	-1.8150***	0.2096
	(0.4536)	(0.3845)
RESPR	0.8171***	-0.0122
	(0.0857)	(0.0568)
Ln(E)	0.0610	-0.0333
	(0.0622)	(0.0551)
Ln(F)	0.0206	-0.0287
	(0.0256)	(0.0248)
$1/\sigma_E$	0.1565***	0.0550
	(0.0607)	(0.0586)
EXRET	0.5671***	-0.0422
	(0.0800)	(0.0620)
NITA	4.3544***	0.2483
	(0.9767)	(0.9503)
#obs	1557	1506
Likelihood Ratio	258.2146	4.7151
-2 Log L	1900.168	2083.044

Panel B Propensity Scores Distribution

Propensity Scores	N	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	Std Dev
Treatment	753	0.5664	0.0658	0.4288	0.5441	0.7040	0.9831	0.1865

Control	753	0.5663	0.0615	0.4293	0.5448	0.7029	0.9834	0.1864
Difference		0.0001	0.0043	-0.0005	-0.0007	0.0012	-0.0003	0.0001

Panel C Differences in Variables in Pre-decimalization Year

Variable	Treatment	Control	Difference	t Value	Pr > |t|
EDF	0.0680	0.0751	-0.0071	-0.78	0.4329
RESPR	1.6648	1.6221	0.0427	0.68	0.4966
Ln(E)	5.5833	5.6885	-0.1052	-1.51	0.1322
Ln(F)	3.0167	3.2088	-0.1921	-1.47	0.1404
$1/\sigma_E$	1.8279	1.7926	0.0353	0.71	0.4785
EXRET	0.2384	0.2888	-0.0504	-1.07	0.2835
NITA	-0.0041	-0.0040	-0.0001	-0.05	0.9631

Panel D Difference-in-Difference Estimator

Variable: ΔEDF				
DID Estimator	Mean	Std Dev	t Value	Pr > |t|
Treat-Control	-0.0944	0.3513	-6.76	<.0001

Table VIII Difference-in-Difference Tests for Informational Efficiency Channel around Decimalization

Panel A presents the results of the difference-in-difference test on how exogenous changes in RESPR surrounding the decimalization year affect the informational efficiency of stock price. Corr is the absolute value of the correlation between contemporaneous weekly stock returns and the one week lagged weekly stock returns. VR3 (VR4) is calculated by dividing variance of 3 (4) weeks compound returns by three (four) times the variance of weekly returns and |VR3-1| (|VR4-1|) is the absolute value of the variance ratio minus one. The difference-in-difference estimators are computed by subtracting the ΔCorr (Δ|VR3-1| or Δ|VR4-1|) of the control firms from those of the treatment firms. The DID test is based on the matched sample constructed in section 3.4.

Panel B reports OLS regression results with ΔEDF as dependent variable based on the matched sample constructed in section 3.4. Δ presents the change of variables from 2000 (prior to decimalization) to 2002 (after decimalization). Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Difference-in-Difference Estimator

Variable	DID Estimator	Mean	Std Dev	t Value	Pr > |t|
ΔCorr	Treat-Control	-0.0286	0.2001	-3.9	0.0001
Δ|VR3-1|	Treat-Control	-0.0293	0.3693	-2.17	0.0304
Δ|VR4-1|	Treat-Control	-0.0337	0.4716	-1.95	0.0516

Panel B OLS Regression Surrounding the Decimalization

Depedent variable	ΔEDF		
ΔPrice efficiency	(1) ΔCorr	(2) Δ|VR3-1|	(3) Δ|VR4-1|
Intercept	0.0912***	0.0885***	0.0888***
	(0.0076)	(0.0076)	(0.0076)
ΔPrice efficiency	0.2039***	0.0692***	0.0503**
	(0.0506)	(0.0265)	(0.0206)

ΔLn(E)	-0.1066***	-0.1094***	-0.1076***
	(0.0130)	(0.0130)	(0.0131)
ΔLn(F)	0.0076	0.0065	0.0065
	(0.0061)	(0.0062)	(0.0062)
$\Delta(1/\sigma_E)$	-0.0303***	-0.0257***	-0.0261***
	(0.0066)	(0.0065)	(0.0065)
ΔEXRET	-0.0146*	-0.0157*	-0.0150*
	(0.0081)	(0.0081)	(0.0081)
ΔNITA	0.1323	0.1400	0.1213
	(0.1256)	(0.1261)	(0.1262)
#obs	1272	1272	1272
R-square	0.0970	0.0904	0.0898
Adj. R-square	0.0928	0.0861	0.0854

Table IX Difference-in-Difference Tests for Informational Efficiency Channel around Brokerage Terminations

This table presents the Difference-in-Difference results based on the matched sample constructed in section 6.1.2. Δ presents the change of variables from pre-event to post-event. The second and third columns show the mean of changes in each variable for treatment and control firms respectively. The difference-in-difference estimators are computed by subtracting the ΔEDF, ΔAmihud, ΔRESPR, ΔRQSPR, ΔZeros, ΔCorr, Δ|VR3-1|, and Δ|VR4-1| of the control firms from those of the treatment firms. The last two columns show the t-Value and p-Value for the DID estimators. See Table I Panel A for definitions of all the variables.

Variables	Treatment Mean	Control Mean	DID Estimator	t Value	Pr > |t|
ΔEDF	0.0277	0.0154	0.0124	2.06	0.0399
ΔAmihud	0.2071	-0.1076	0.3146	5.18	<.0001
ΔRESPR	0.0697	0.0114	0.0584	2.00	0.0457
ΔRQSPR	-0.0674	-0.1204	0.0530	2.24	0.0250
ΔZeros	-1.7926	-1.3865	-0.4061	-2.52	0.0117
ΔCorr	0.0092	0.0036	0.0056	1.13	0.2581
Δ|VR3-1|	0.0345	0.0038	0.0307	3.14	0.0017
Δ|VR4-1|	0.0207	-0.0101	0.0308	2.65	0.0080

Table X Stock Liquidity and Corporate Governance

Panel A presents the results of the difference-in-difference test on how exogenous changes in RESPR surrounding the decimalization year affect the blockholder ownership and the number of blockholders. Blockholder ownership (BLOCK) is calculated by aggregating institutional blockholders ownership in percent which is above 5% of total common shares outstanding at the end of year. The number of blockholders (NBLOCK) is the number of block owners who hold at least 5% of total common shares outstanding at the end of year. The DID test is based on the matched sample constructed in section 3.4.

Panel B reports OLS regression results with ΔEDF as dependent variable based on the matched sample constructed in section 3.4. Δ presents the change of variables from 2000 (prior to decimalization) to 2002 (after decimalization). Standard errors are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Difference-in-Difference Estimator

Variable	DID Estimator	Mean	Std Dev	t Value	Pr > |t|
ΔBLOCK	Treat-Control	0.0173	0.1579	3.01	0.0027
ΔNBLOCK	Treat-Control	0.2364	1.8821	3.45	0.0006

Panel B OLS Regression Surrounding the Decimalization

Dependent Variable	ΔEDF	
ΔBlockholder	(1) ΔBLOCK	(2) ΔNBLOCK
Intercept	0.0769***	0.0769***
	(0.0073)	(0.0073)
ΔBlockholder	-0.1963***	-0.0114**
	(0.0612)	(0.0052)
ΔLn(E)	-0.0659***	-0.0635***
	(0.0134)	(0.0134)
ΔLn(F)	0.0203***	0.0202***

	(0.0070)	(0.0070)
$\Delta(1/\sigma_E)$	-0.0274***	-0.0274***
	(0.0065)	(0.0065)
ΔEXRET	0.0441***	0.0439***
	(0.0071)	(0.0071)
ΔNITA	0.0492	0.0566
	(0.1461)	(0.1465)
#obs	1300	1300
R-square	0.0742	0.0703
Adj. R-square	0.0699	0.0659

Table XI Stock Liquidity and Corporate Bond Yield Spread

The sample contains 15,408firm-year observations between 2004 and 2010.Maturity is the bond's remaining time to maturity in years; Amount is the amount outstanding; T90RET is the 3-month T-bill rate; Coupon is the coupon rate; Coverage, the pre-tax interest coverage, is defined as the ratio of [operating income after depreciation+interest expense (Compustat quarterly data #22)] to interest expense; OISA is the ratio of operating income (Compustat quarterly data #21)to sales (Compustat quarterly data #2); LDTA is the ratio of long-term debt to total asset; TDMC is the ratio of total debt to asset, where total debt is the sum of debt in current liabilities (Compustat quarterly data #45) and long-term debt (Compustat quarterly data #51).

Panel A reports the summary statistics of the variables used in corporate bond yield spread regressions for the sample firm-year observations.

Panle B reports OLS regression results with industry and year fixed effects. Column (2) to (4) reports the results with Relative Effective Spread, Relative Quoted Spread, Amihud, and Zeros as liquidity measures respectively. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Summary Statistics

Variable	N	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	Std Dev	Skewness
Yield Spread	15408	0.0190	0.0045	0.0110	0.0161	0.0237	0.0682	0.0114	1.7082
σ_E	15408	0.2693	0.0867	0.1401	0.2106	0.3170	1.1193	0.1835	2.1545
Maturity	15408	13.6444	2	7	11	20	30	8.0255	0.5760
Amount	15408	164814	1181	5913	67547	209974	1450520	256833	2.7450
T90RET	15408	0.0204	0.0013	0.0022	0.0204	0.0308	0.0509	0.0193	0.5040
Coupon	15408	0.0590	0.0000	0.0510	0.0575	0.0670	0.1240	0.0138	-0.0888
Rating	15253	2.9962	1	2	3	4	7	1.1744	-0.2674
Coverage	15320	7.0905	-0.3005	2.9177	4.3103	7.3272	57.7065	8.2445	3.7053
OISA	15371	0.2301	0.0167	0.1470	0.2417	0.2992	0.6873	0.1135	1.0147
LDTA	15388	0.3040	0.0584	0.2229	0.3051	0.3784	0.5416	0.1111	-0.0081
TDMC	15386	0.3937	0.0735	0.2567	0.3596	0.5502	0.6565	0.1710	0.1810
Amihud	15408	0.0002	5.89E-06	1.60E-05	0.0001	0.0002	0.0026	0.0004	3.9059
Zeros	15408	1.1363	0.0000	0.3968	0.7937	1.5873	3.9683	0.9955	1.2217

RESPR	15408	0.0760	0.0207	0.0304	0.0393	0.0593	1.4742	0.1672	6.9103
RQSPR	15408	0.0584	0.0226	0.0376	0.0472	0.0692	0.2431	0.0354	2.7483
EDF	15398	0.0389	0	1.66E-31	7.25E-17	3.55E-06	0.9984	0.1475	3.8430

Panel B OLS regressions with corporate bond yield spread as dependent variable (2004-2010)

Dependent Variable	Yield Spread				
Column	(1)	(2)	(3)	(4)	(5)
Liquidity	No	RESPR	RQSPR	Amihud	Zeros
Intercept	-0.0131***	-0.013***	-0.0128***	-0.0131***	-0.0132***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Liquidity		0.0008*	0.0288***	0.6504***	0.0002**
		(0.0004)	(0.0026)	(0.1974)	(0.0001)
σ_E	0.0076***	0.0075***	0.0057***	0.0075***	0.0076***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Maturity	-2.4E-05**	-2.4E-05**	-2.4E-05***	-2.4E-05**	-2.4E-05**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln(amount)	-0.0007***	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
T90RET	11.2772***	11.1784***	11.2878***	11.2627***	11.3186***
	(0.2221)	(0.2286)	(0.2212)	(0.2221)	(0.2227)
Coupon	0.0618***	0.0618***	0.0597***	0.0618***	0.0619***
	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0055)
OISA	0.0019**	0.002**	0.0028***	0.0022***	0.002***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
LDTA	-0.019***	-0.0188***	-0.018***	-0.019***	-0.0189***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
TDMC	0.0276***	0.0274***	0.0244***	0.0274***	0.027***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Coverage1	0.001**	0.001***	0.0013***	0.001***	0.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Coverage2	-0.0011***	-0.0011***	-0.0008**	-0.0011***	-0.0011***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Coverage3	-0.002***	-0.002***	-0.0019***	-0.002***	-0.002***

	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Rating	0.0042***	0.0042***	0.0039***	0.0042***	0.0042***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Industry Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
# Obs	15221	15221	15221	15221	15221
R-Square	0.5188	0.5189	0.5227	0.5191	0.5189

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