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How Does Stock Liquidity Affect Default Risk?

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Abstract

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Firms with greater liquidity experience decreased default risk through firm policy decisions. Specifically, empirical evidence in this paper suggests that bankruptcy risk is mitigated for liquid firms due to less risky investment choices of research and development expenditures and conservative tax avoidance activities. I identify these channels by exploiting exogenous liquidity provisions through decimalization event and S&P index additions. Results from both event studies provide support for the firm policy channels, and are robust to other possible explanations and endogeneity.

Keyword : Liquidity, Default Risk, Credit Risk, Innovation, Tax Avoidance
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Chapter 1. Introduction

This paper investigates channels of firm policy decisions through which liquidity mitigates default risk. Stock liquidity enables stocks to be traded at a lower cost with less frictions, and is often employed as a mechanism to enhance firm value (Fang et al, 2009). Moreover, bankruptcy of a firm being one of the most critical events of the market as a whole, the need to understand its determinants and implied mechanisms is well recognized in the literature. However, the channels connecting the two measures are yet to be fully comprehended, and I intend to contribute to understanding the intricate relationship.

Brogaard, Li and Xia (2017) is the first to identify channels between stock liquidity and default risk. Motivated by previous literature discussing stock liquidity, they have pointed to corporate governance and price efficiency channels of stock liquidity decreasing credit risk. Stock liquidity could alleviate credit risk by incentivizing entrance of blockholders and hence enhancing corporate governance (Edmans, 2009). Moreover, higher informational efficiency provided by increased stock liquidity enables managers to make better investment and capital allocation decisions (Holstrom and Tirole, 1993; Subrahmanyam and Titman, 2001) and thus increase firm value (Chen et al., 2007, Fang et al., 2009). Empirical analysis using various measures of illiquidity suggests that higher stock liquidity decreases default risk of firms. We use an expanded data of US equity market and document negative relationship between liquidity and default risk. Both univariate analysis of sorting stocks based on their liquidity levels and multivariate analysis controlling other determinants of default risk confirm the negative relationship discovered in Brogaard et al. (2017).

This paper is inspired by Brogaard et al. (2017) and proposes two novel channels of internal policy decisions for how stock liquidity could affect default risk. The first channel is risky investment choice; risky investment means R&D channel of investment choice is associated with firms allocating less research and development expenditures, leading to decreased default risk. Greater stock liquidity could induce less innovation due to outside threats; firms with higher liquidity experience higher takeover pressures because large amount of stock trading provides enough camouflage to enable a large outsider to profit by acquiring a significant stake without being noticed (Kyle and Vila, 1991). Resulting takeover pressures induce managers to sacrifice long-term performance of innovation for current profits to keep the stock from becoming undervalued (Fang et al., 2014). Hence, decreased cash flow uncertainty from less innovation investments mitigates riskiness of firms (Shi, 2003).

The second channel that I study describes a mechanism where stock liquidity decreases risky choices of tax avoidance. Chatterjee et al. (2021) recently pointed out that higher stock liquidity relaxes financial constraints by allowing easier and cheaper stock financing. More financially constrained firms are more incentivized to use saved cash from tax avoidance, and they engage in aggressive tax avoidance decisions. (Chen et al., 2012; Law and Mills, 2015). Hasan et al. (2014) provide a partial link to the channel by showing that firm credit risk is mitigated by conservative tax policy decisions through decreased uncertainty of tax evasion behavior.

Empirical analysis in this paper uses data between 1993 and 2021 in the U.S. stock market and simultaneously discovers that less risky policy choices of decreased R&D expenditure and tax avoidance are significant channels of liquidity mitigating default risk. Treatment firms that experience largest liquidity provisions show significant decrease in both R&D expenditures by 1.6% and tax avoidance activities by 6.4%, compared to control firms. Furthermore, these firms also experience a large drop in default probabilities by 18.11%. Main results from regression analysis reveal that changes in the two channels after liquidity shock are associated with decreases in expected default frequency (EDF) by 8.95% and 7.76% each.

I recognize the possibility of existence of other channels, and reduce this concern by controlling for other possible mechanisms. Brogaard et al. (2017) have provided empirical evidence supporting the corporate governance and price efficiency channels of stock liquidity affecting default risk. They employ two measures each for the two channels; blockholder ownership percentage and number of blockholders to proxy for the first channel, and correlation between weekly stock returns and price delay measure for the second. I include similar measures in the main results to proxy and control for the suggested channels of Brogaard et al. (2017). When the policy decision channels are incorporated to a horse race regression, the governance and price efficiency mechanisms lose their significance, and the newly proposed channels show dominant explanatory power.

I address an endogeneity concern of this paper's empirical analysis that liquidity provisions of treatment firms compared to control firms should be exogenous in nature by the use of two separate event studies. Such crucial concern is associated with an issue that treatment firms could have been endogenously selected into greatest liquidity provisions due to their specific characteristics. The first event study applies the decimalization event as popularly used in previous literature and also applied by Brogaard et al. (2017). Decimalization event refers to the regulation change of Securities and Exchange Commission requiring securities to be traded and quoted in pennies instead of one sixteenth of a dollar as before. This paper provides evidence that treatment firms experience exogenous liquidity provisions surrounding the event compared to control firms, and show significant changes in default risk through altered R&D expenditures and tax avoidance activities.

The second event study that employs S&P 500 index additions reduces the possibility of temporal effects associated with the decimalization event and displays robustness of the proposed channels. The decimalization event is concurrent with the burst of the dot-com bubble and associated economic shocks, and identification strategies using the event could present biased evidence (Fang et al., 2014; Li and Xia, 2021). The separate event study using S&P index addition relaxes the concern of specific yearly interruptions, as the additions are carried out every year based on public information changes on firm fundamentals. Both event studies unanimously provide supporting evidence for the robustness of less risky firm policy channels.

The contribution of this paper to existing literature is twofold; the first being the investigation of novel mechanisms through which liquidity affects firm credit risk. Brogaard et al (2017) have suggested channels of governance and price efficiency. Nadarajah et al. (2021) document stock liquidity mitigating default risk in international markets using a sample of 46 countries, and investigate the same channels proposed by Brogaard et al. (2017). Similarly, Ali et al. (2018) studied relationships between corporate governance and default risk through enhanced stock liquidity in Australian firms. This paper differs from the papers discussed above in that it proposes new channels of changes in internal firm policies. Furthermore, empirical evidence suggests that they are dominant over previously studied channels.

The second contribution to literature is the usage of S&P index addition in testing the robustness of channels between stock liquidity and credit risk. Fang et al. (2009) use the decimalization event as an exogenous liquidity shock, as in Brogaard et al; they show that stock liquidity improves firm value proxied by Tobin's Q. Fang et al. (2014) also employ the decimalization event in identifying effects of stock liquidity in firm innovation levels. However, the decimalization coincides with the burst of the dot-com bubble and other regulations including the Regulation FD and the Sarbanes-Oxley Act (SOX), hence presenting the possible interventions of temporal effects (Fang et al., 2014; Li and Xia, 2021). This paper differs from those of Brogaard et al. (2017), Fang et al (2009), and Fang et al. (2014) in that it applies the S&P index addition to test the soundness of empirical results from the first event study using the decimalization regulation.

This paper also shows contrast with papers by Brisker et al. (2013) and Hedge and Mcdermott (2003) in that while both applied S&P 500 index additions in identifying exogenous liquidity provisions, these papers do not specifically investigate impacts in default risk. The results from the two event studies in this paper coincide with each other, providing evidence that the newly proposed channels are plausible explanations of liquidity affecting default risk. Hence, this paper adds to the literature linking liquidity and firm risk by providing unanimous evidence on new channels with two separate event studies.

The rest of the paper is organized as follows. Section 2 describes the data and details of variable construction. Section 3 presents empirical relationship and evaluates causality based on the first event study, decimalization, and explores the possible channels. Section 4 presents evidence of causality based on the second event study, S&P 500 index addition, and confirms robustness of channels. Section 5 concludes.

Chapter 2. Data and Variable Construction

The data encompasses U.S. common and non-financial stocks between 1990 and 2021 attained from the Center for Research in Security Prices (CRSP) stock file and financial data of firms from Compustat Quarterly Files. We exclude financial firms with standard industrial classification codes between 6000 and 6999, and use publicly traded stocks with share codes of 10 and 11. To ensure that we have sufficient number of observations in calculating daily illiquidity measures, we exclude firm-year observations with less than two hundred active trading days at each year. The final sample contains 71543 firm-year observations. The details of each variable constructions are illustrated in Table 1.

We construct three measures of stock liquidity using Bid-ask spread, Amihud (2002) illiquidity ratio, and Zeros defined by Lesmond et al. (1999). Our main illiquidity measure of bid-ask spread is calculated as difference between ask and bid prices divided by the mean value of the two prices. We exclude observations with larger spreads than half of quote midpoint, and observations having zero values for both ask and bid prices. We multiply the value by a hundred so that the bid-ask spread variable is expressed in percentages.

The second liquidity measure is Amihud (2002) illiquidity ratio, defined as the absolute value of daily stock return divided by daily dollar trading volume, multiplied by one million. The intuition behind the liquidity measure is that compared to the amount of trading volume, liquid stocks would experience smaller changes in stock prices than illiquid stocks. The third illiquidity measure of Zeros is constructed by following Lesmond et al. (1999), where the variable is measured as

Table 1: Variable Definitions

	Definition
Panel A: Liquidity Measures	
Bid-ask Spread	Difference of bid and ask prices divided by the mean of bid and ask prices.
Amihud Illiquidity Ratio	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.
Panel B: Default Probability Measures	
DD	Distance-to-default, calculated by following Merton(1974) and Bharath and Shumway (2008)
EDF	Expected Default Frequency, calculated as $N(-DD)$, where $N(.)$ is the cumulative standard normal distribution function.
Panel C: Control Variables	
Equity	Market value of equity as the product of the number of shares outstanding and stock price
Debt	Face value of debt as the sum of debt in current liabilities and one-half of long-term debt
Excess Return	Annual excess return as difference between stock return and CRSP value-weighted return
Stock Volatility	Annualize stock return volatility from standard deviation of monthly returns
Income/Assets	Ratio of total net income to total asset
Tobin's Q	Market value of assets over book value of assets
Panel D: Channels	
Innovation	Ratio of R&D expenditure divided by total assets
Tax Avoidance	Negative value of cash effective tax rate, calculated by cash tax paid to pretax income
Cash Holdings	Cash ratio; ratio of cash and short-term investment over total book assets
Executive Delta	Pay-for-performance sensitivity calculated as a dollar change in wealth associated with a one percent change in the firm's stock price (Coles et al., 2006; Core and Guay, 2002)
Dividend Payout	Ratio of cash dividend paid to total income
Correlation	Absolute value of the correlation between contemporaneous weekly stock returns and the one-week lagged weekly stock returns (Brogaard et al., 2017)

the proportion of days in a year with zero returns, multiplied by one hundred. Illiquid stocks are more likely to have zero returns due to large trading costs and low trading activity; hence, higher Zeros value expresses higher illiquidity.

Default risk is measured by expected default frequency (EDF) as in Bharath and Shumway (2008), which is motivated by the Merton (1974) structural distance-to-default model. A naïve default probability measure suggested by Bharath and Shumway (2008) retains the structural form of Merton model and yet is known to show similar performance as the original model. We follow Bharath and Shumway (2008) to compute EDF as follows:

$$\mathrm{DD}_{\mathrm{i,t}} = \frac{\log\left(\frac{\mathrm{Equity}_{\mathrm{i,t}}+\mathrm{Debt}_{\mathrm{i,t}}}{Debt_{i,t}}\right)+\left(r_{i,t-1}-\frac{\sigma^2_{Vi,t}}{2}\right)\times T_{i,t}}{\sigma_{Vi,t}\times\sqrt{T_{i,t}}} \ , \tag{1}$$

,

$$\boldsymbol{\sigma}_{\mathbf{Vi,t}} = \frac{\boldsymbol{Equity_{i,t}}}{\boldsymbol{Equity_{i,t}+Debt_{i,t}}} \times \boldsymbol{\sigma_{Ei,t}} + \frac{\boldsymbol{Debt_{i,t}}}{\boldsymbol{Equity_{i,t}+Debt_{i,t}}} \times (\mathbf{0.05} + \mathbf{0.25} \times \boldsymbol{\sigma_{Ei,t}}) \tag{2}$$

and

$$\mathrm{EDF}_{\mathrm{i,t}} = N(-DD_{i,t}) \tag{3}$$

where $Equity_{i,t}$ is the 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 the year; $Debt_{i,t}$ is the face value of debt computed as the sum of debt in current liabilities and half of long-term debt at the end of each year. Each firm's past annual return, $r_{i,t-1}$, is calculated from monthly stock returns over the previous year; the stock return volatility for firm i during year t is estimated using the monthly stock return from the previous year. Standard deviation of stocks, $\sigma_{\mathrm{Vi,t}}$, is calculated from the stock return variance approximating the volatility of firm assets, $\sigma_{Ei,t}$. The time used in the equation is set to one year. We construct yearly distance-to-default of all sample firms as of the last day of each year, and EDF is computed through applying is the cumulative standard normal distribution function to the distance-to-default measure.

This paper applies the control variables suggested by Bharath and Shumway (2008) and employed by Brogaard et al. (2017). Possible determinants of default risk defined as following are included for main analysis in following sections. Ln(Equity) is the natural log of market value of equity at the end of the year. Ln(Debt) is the natural log of face value of debt. $1/\sigma_{\mathrm{E}}$ is the inverse of the annualized stock return volatility. Excess Return is the difference between the stock's annual return and the CRSP value-weighted return. Income/Assets is the ratio of net income to total asset, and Tobins' Q is computed as market value of assets over book value of assets.

Table 2 reports the summary statistics including the mean, minimum, median, maximum, and standard deviation of each variables winsorized at the 1st and 99th percentiles for the whole sample period between 1991 and 2021. Illiquidity measures of Bid-ask Spread, Amihud and Zeros have each have mean value of 1.96%, 1.25%, and 8.85% with a reasonable degree of variations.

Table 2: Summary statistics.

The table reports summary statistics for the sample firm-year observations, as the variables are defined in Table 1. The table contains 71,543 firm-year observations for the sample period between 1991 and 2021. The descriptive statistics are the number of observations, mean, minimum, maximum, and standard deviation of the key variables.

Variable	N	Mean	Minimum	Maximum	Std. Dev.
Amihud	71,543	1.2568	0.0000	29.7392	4.2573
Bid-ask Spread	71,543	1.9619	0.0162	12.4871	2.5732
Zeros	71,543	8.8546	0	37.5510	9.7118
Distance-to-Default	71,543	7.9496	-2.3204	26.9112	5.4643
EDF	71,543	0.0443	0	1	0.1712
Equity	71,543	3689.72	3.6295	65991.02	10261.63
Debt	71,543	820.67	0.0005	15380.50	2349.23
Excess Return	71,543	0.0360	-1.0088	3.3114	0.6541
Return Volatility	71,543	0.3592	0.1721	0.7665	0.1118
Income/Asset	71,543	-0.0179	-0.5859	0.1257	0.0958
Tobin's Q	71,543	1.9724	0.6181	11.5410	1.5696
R&D	71,543	0.0430	0	0.9750	0.1159
Tax Avoidance	71,543	-0.2111	-1.6120	1.9482	0.3862
Executive Delta	71,543	1.9803	0.5549	8.1463	2.0582
Cash Holdings	71,543	0.1476	0.0002	0.9334	0.1905
Dividend Payout	71,543	0.1789	0	2.7673	0.4033
Correlation	71,543	0.1278	0.0022	0.6046	0.0953

Chapter 3. Empirical Tests and Results of Decimalization

3.1. Panel Analysis

Before turning to causal interpretations, we examine the general relationship between liquidity and default risk. Empirical findings using univariate analysis suggest that increased liquidity decreases default risk, confirming the findings of Brogaard et al. (2017). We begin by comparing distributions of expected default frequencies across groups sorted based on all three illiquidity measures and conclude that the negative relationship holds. Note that while Brogaard et al. (2017) use the effective spread as their main illiquidity measure, we use bid-ask spread along with Amihud and Zeros measures and show similar robustness.

We first form portfolios by sorting stocks based on their liquidity ratios and confirm that the default probabilities decrease monotonically with stock liquidity across all liquidity measures. In each year t, stocks are assigned into one of five groups based on their liquidity measures. We compute the portfolio EDF in year t + 1 by taking the average of the EDF across all stocks in the portfolio. Results in Panel A of Table 3 suggests that EDF declines monotonically with stock liquidity. Firms in more liquid portfolios have lower expected default frequency than for firms in portfolios of lower liquidity. The results hold for all three measures of liquidity and are economically large. The 5-1 measure row reports the average EDF difference between the least liquid and most liquid portfolios, and shows highly significant statistical values.

Other possible determinants of default risk are not controlled in the univariate analysis; thus, we turn to multivariate regressions. The negative relationship between liquidity and default risk remains robust even when considering various factors. To control for the direct determinants of default risk, we follow Bharath and Shumway (2008) to include five control variables: Ln(Equity), Ln(Debt), $1/\sigma_{\mathrm{E}}$, Excess Return, and Income/Asset. Multivariate analysis also suggests that liquidity and default risk have negative relationship even when possible determinants of default risk are controlled as in equation below:

$$\mathrm{EDF_{i,t}} = \alpha + \beta Liquidity_{i,t} + \gamma_1 Ln(Equity)_{i,t} + \gamma_2 Ln(Debt)_{i,t} + \frac{\gamma_3 1}{\sigma_{E,i,t}} + \gamma_4 ExcessReturn_{i,t} + \frac{\gamma_5 Income}{Assets}_{i,t} + \theta' Firm + \varphi' Year + Error_{i,t} \tag{4}$$

The results from the multivariate regression analysis support the previous univariate results. The negative relation between liquidity and default risk persists even after controlling for firm characteristics known to be associated with default risk. The coefficients in Panel B of Table 3 presents that a 1% increase for each of the illiquidity measures is associated with 0.68%, 0.34% and 0.04% increase in expected default frequency. The coefficients can be interpreted as following: a one standard deviation increase in Bid-ask Spread is associated with a 1.74% (0.0068 × 2.5732) increase in default risk.

Table 3: Relationship between liquidity measures and expected default frequency (EDF)

Panel A in the table reports the distribution of EDF across five groups of stocks sorted on three illiquidity measures. Stocks are sorted into one of the five groups based on their liquidity measure for each year. Group 1 consists of stocks with highest liquidity, and group 5 consists of stocks with lowest liquidity. 5-1 column represents difference between the two groups.

Panel B in the table reports ordinary least squares coefficients of regressions of default probabilities on liquidity and other control variables. Numbers reported in parentheses are standard errors for the statistics. *, **, and *** indicate statistical significance level at the 10%, 5%, and 1% level for the t-statistics.

Panel A

	EDF					
Liquidity measures	1	2	3	4	5	5-1
Bid-ask Spread	0.0099	0.0337	0.0376	0.0439	0.0965	0.0865***
Amihud	0.0094	0.0210	0.0354	0.0565	0.0994	0.0900***
Zeros	0.0170	0.0297	0.0540	0.0510	0.0696	0.0526***

Panel B

	Dependent Variable: EDF			
Variable	(1)	(2)	(3)	(4)
Bid-ask Spread		0.0068*** (0.0003)		
Amihud			0.0034*** (0.0001)	
Zeros				0.0004*** (0.0000)
Ln(Equity)	-0.0446*** (0.0004)	-0.0400*** (0.0004)	-0.0413*** (0.0004)	-0.0456*** (0.0004)
Ln(Debt)	0.0334*** (0.0003)	0.0330*** (0.0003)	0.0330*** (0.0003)	0.0334*** (0.0001)
$1/\sigma_E$	-0.0188*** (0.0001)	-0.0185*** (0.0001)	-0.0189*** (0.0001)	-0.0183*** (0.0001)
Excess Return	0.0047*** (0.0009)	0.0045*** (0.0009)	0.0031*** (0.0009)	0.0045*** (0.0009)
Income/Assets	-0.0601*** (0.0068)	-0.0463*** (0.0068)	-0.0525*** (0.0068)	-0.0609*** (0.0068)
Intercept	-1.4429*** (0.1527)	-2.8748*** (0.1699)	-1.5335*** (0.1524)	-0.8441*** (0.1964)
Firm and Year fixed effects	Yes	Yes	Yes	Yes
Number of Obs.	71543	71543	71543	71543
Adjusted R^2	0.2109	0.2154	0.2167	0.2112

3.2. Exogeneity

The causality between stock liquidity and default risk remains unresolved through panel analysis in the previous section. Copeland and Galai (1983) suggests evidence of causal relationship between liquidity and default risk, but in the opposite direction. Default risk could be a determinant of illiquidity, as market makers demand higher premiums for highly distressed firms by quoting wider spreads. Therefore, the identification strategy for causality in this section employs an exogenous shock of liquidity to ensure that liquidity provision in fact causes significant changes in default probabilities.

Endogeneity concern of stock liquidity provision is addressed through the first event study of decimalization event as an exogenous positive shock. Decimalization is popularly used in literature concerning effects of liquidity (Fang et al., 2009; Edmans et al., 2013; Kang and Kim, 2013). Decimalization refers to a Securities and Exchange Commission regulation reform in 2001, where all price quotes for stocks were changed from one-sixteenth of a dollar to a penny, making spreads between quotes smaller. Improved stock liquidity from decimalization is highly unlikely to be endogenous as the event was not driven by firm-specific characteristics; rather, the regulation was carried out by SEC to support the market with less trading frictions.

Following Fang et al. (2014) and Brogaard et al. (2017), we first construct sample firms using propensity score matching before implementing DID analysis. Sample firms are ranked based on their liquidity changes from the year prior to and after the decimalization event, and separated into terciles. Firms in the first tercile are used as a treatment group, which have experienced the highest exogenous liquidity provision. Conversely, firms in the third tercile are designated as a control group. We then estimate a probit model where the dependent variable is a dummy variable set to one for the treatment group, and zero for the control group. The estimated probit model includes liquidity measures and firm-specific control variables used in the previous analyses. The predicted probabilities estimated from the model are used to construct propensity scores for each firm. Firms in the treatment group are matched with firms in the control group based on their propensity scores. Firms without matches are excluded from the sample, and we are left with 788 treatment-control matches.

We perform further analysis to confirm that the treatment and control groups have similar characteristics before performing DID regressions. We estimate the probit model using the both whole sample and matched sample, and the results are documented in table 5. The first column describes regression coefficients for the probit model using the whole sample before the matching procedure. All variables including the illiquidity measure and the firm characteristic variables are significant factors in probability of a firm being included in the treatment. However, after matching the groups based on their propensity scores, all variables lose significance. The interpretation is that after propensity score matching, no observable different characteristics exist between the treatment and control groups in the pre-decimalization year. The magnitude of the coefficient estimates in the post-match analysis are smaller, and no longer statistically significant, compared with that of the coefficients in the pre-match analysis, suggesting a weaker relation between firm characteristic differentials of the treatment and control groups.

Using the samples from propensity score matching procedure, we perform difference-in-differences analysis to investigate whether changes in liquidity caused

Table 4: Difference-in-differences analysis

The table reports a difference-in-differences analysis of stock liquidity on default probabilities. Column 1 of Panel A presents coefficients for the probit regression with a dependent variable of a dummy variable that equals one (zero) if the firm is in the treatment (control) group. The variables used in the regression are measured in the pre-decimalization year. Column 2 of Panel A presents coefficients for the identical probit regression in Column 1, but using the sample after propensity score matching. After omitting firm samples without propensity score matches, 786 firms are used for the regression in Column 2.

Panel B of the table reports coefficients for the difference-in-differences regression with dependent variable as expected default frequency. Treatment variable represents a dummy variable that equals one (zero) for firms with highest (lowest) liquidity provision after the decimalization event. After variable equals one for the post-decimalization year, 2002, and equals zero for the pre-decimalization year, 2000. Treatment*After is the interaction term for the two variables.

Panel A: Probit regressions with pre- and post-matched samples

Variable	Pre-match (1)	Post-match (2)
Bid-ask Spread	0.4475***	0.0302
	(0.0320)	(0.0201)
Ln(Equity)	0.0428	-0.0511
	(0.0346)	(0.0347)
Ln(Debt)	0.0666***	0.0266
	(0.0212)	(0.0232)
$1/\sigma_E$	0.6502***	0.2198
	(0.0782)	(0.0865)
Excess Return	0.3507***	0.0927
	(0.0676)	(0.0735)
Income/Assets	2.3556***	0.7433
	(0.5071)	(0.5490)
Intercept	-3.3680***	-0.4198
	(0.2783)	(0.2375)
Number of Obs.	1251	786

Table 4: Continued

Panel B: Difference-in-differences regression

Variable	Dependent variable: EDF (1)	(2)
Treatment*After	-0.0928***	-0.0935***
	(0.0217)`	(0.0218)
Treatment	0.0008	0.0012
	(0.0147)	(0.0147)
After	0.1022***	0.1027***
	(0.0156)	(0.0156)
Ln(Equity)	-0.0638***	-0.0634***
	(0.0036)	(0.0036)
Ln(Debt)	0.0545***	0.0544***
	(0.0024)	(0.0024)
$1/\sigma_{\mathrm{E}}$	-0.0263***	-0.0252***
	(0.0090)`	(0.0091)
Excess Return	-0.0071	-0.0073
	(0.0090)	(0.0090)
Income/Assets	-0.2413***	-0.2391***
	(0.0594)	(0.0595)
ΔTobin's Q*After	0.0109**	0.0109**
	(0.0109)	(0.0049)
Intercept	0.2613***	0.2431***
	(0.0254)	(0.0317)
Firm fixed effects	No	Yes
Number of Obs.	1572	1572

significant changes default probabilities around the decimalization event. The DID analysis is implemented using a regression framework as follows:

$$\mathrm{EDF}_{\mathrm{i,t}} = \alpha + \beta_1 Treatment_i * After_t + \beta_2 Treatment_i + \beta_3 After_t + \gamma Controls_{i,t} + Error_{i,t} \quad (5)$$

where Treatment is a dummy variable equal to one (zero) if a stock is part of the treatment (control) group, After is a dummy variable equal to one for 2002 (post-decimalization year) and zero for 2000 (pre-decimalization year), and Treatment ∗After is the interaction between these two variables. Control variables discussed in the previous sections are also applied to ensure other possible determinants of default probabilities are controlled.

Empirical evidence in table 5 of DID regression analysis shows that firms with highest liquidity provision experience a significant reduction in default probabilities. The statistically significant and negative coefficients of −0.0928 for Treatment ∗After indicates that the treatment firms experience a larger drop of 9.28% in EDF after the decimalization compared with the control group. The same analysis is performed in column (2) with industry fixed effects added, and the results remain robust.

3.3. Possible Mechanisms

With causal relationship between liquidity and default risk established, the paper then investigates related channels through which liquidity mitigates risk. After we show that the exogenous liquidity provision causes significant changes in the channels, further analysis investigates whether the changes in these channels are directly transferred to reduction in credit risk.

The first mechanism describes a relationship where greater stock liquidity causes less innovation; firms with higher liquidity experience higher takeover pressures because large amount of stock trading provides enough camouflage to enable a large outsider to profit by acquiring a significant stake without being noticed (Kyle and Vila, 1991). Takeover pressures could induce managers to sacrifice long-term performance of innovation for current profits to keep the stock from becoming undervalued (Fang et al., 2014). Less innovation may lead to lower risk in that R&D outcomes have a high degree of uncertainty (SFAS No.2); an increase in the uncertainty of future cash flows that is attributed to R&D investments increases riskiness of firms. Hence, bondholders demand a higher premium for firms with higher R&D intensity. (Shi, 2003)

Second channel is tax avoidance. Chatterjee et al. (2021) recently pointed out that higher stock liquidity relaxes financial constraints by allowing easier and cheaper stock financing. More financially constrained firms are more incentivized to use saved cash from tax avoidance; they engage in aggressive tax avoidance decisions. (Chen et al., 2012; Law and Mills, 2015). Edwards, Schwab, and Shevlin (2016) find that firms facing increased financial constraints exhibit decreases in cash effective tax rates (ETRs). Tax avoidance behavior is associated with bankruptcy risk of a firm, as it is perceived negatively by debtholders (Hasan et al., 2014) and are thus penalized by rating agencies by lower credit and bond ratings. (Ayers et al., 2010; Dhawan et al., 2020).

The third channel discussed in this paper is cash holdings affected by liquidity. Firms are incentivized to hold more cash to take advantage of undervalued equity when stock liquidity is high. Increased stock liquidity raises a firm’s capacity to benefit from repurchases and, as a consequence, its incentive for holding cash

(Nyborg and Wang, 2021). The precautionary motive says that firms hold cash as a hedge against excessive costs of external capital and financial constraints in the future; larger cash holdings have a positive impact on firm stability (Bates et al., 2009).

The empirical findings of DID analysis suggest that increased liquidity in treatment firms induced significant changes in all channels. Table 6 reports the changes in channels of treatment and control groups for the years before and after the decimalization event. Innovation and tax avoidance show significant reduction compared to the control group, consistent with the hypothesis of Fang et al. (2014) and Chen et al. (2012). Conversely, cash holdings show significant increase in the treatment group relative to the control group, coinciding with the conjectures of Jayaraman and Milbourn (2012) and Nyborg and Wang (2021). We also confirm the findings of the corporate governance and price efficiency channel discussed in Brogaard et al. (2017), buy using the executive delta and dividend payout policy as governance measure and by using the correlation as price efficiency measure. Expected default frequency is also shown to significantly decrease in the treatment group.

Table 5: Possible channels of liquidity affecting default risk

The table reports results for a difference-in-differences test on changes in each measure of channels before and after the decimalization event, for both the treatment and control firms.

	Treatment		Control		DID	t-stat
Variable	Before (2000)	After (2002)	Before (2000)	After (2002)		
Innovation	0.0328	0.0297	0.0560	0.0694	-0.016***	-3.72
Tax Avoidance	-0.2327	-0.2270	-0.2231	-0.1563	-0.0640**	-1.87
Cash Holdings	0.0906	0.1159	0.21521	0.1576	0.0201***	2.47
Executive Delta	1.543	1.7160	1.5435	1.3863	0.3423***	5.28
Dividend Payout	0.1646	0.1652	0.0485	0.0349	0.0601	1.24
Correlation	0.1519	0.1198	0.1306	0.1404	-0.0432***	-4.23
EDF	0.0700	0.0441	0.0628	0.2153	-0.1811***	-7.96

Table 6: Ordinary least squares regression

The table reports regression coefficients of regression with changes in default probabilities as a dependent variable. Δ represents the change of measures from the pre-decimalization year of 2000 to the post-decimalization year of 2002. Column (6) reports results for the horse race regression with all possible channels considered as determinants of expected default frequency.

	Dependent Variable: EDF						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔR&D	0.4846***						0.0895***
	(0.1620)						(0.0297)
ΔTax		0.0527**					0.0776***
Avoidance		(0.0194)					(0.0289)
ΔCash			0.0618				0.0232
Holdings			(0.0884)				(0.0241)
ΔExecutive				0.0155			0.0404
Delta				(0.0110)			(0.0396)
ΔDividend					-0.0214		-0.0279
Payout					(0.0253)		(0.0287)
ΔCorrelation						-0.0112	-0.0057
						(0.0672)	(0.0289)
Intercept	-0.03***	-0.04***	-0.03**	-0.0***	-0.04	-0.0406	0.0264
	(0.0281)	(0.0281)	(0.0286)	(0.0283)	(0.0283)	(0.0283)	(0.0847)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	788	788	788	788	788	788	788
Adj. R^2	0.3490	0.3476	0.3419	0.3432	0.3421	0.3473	0.3536

By regressing the changes of default risk on changes of each channels, robustness of each channels as significant mechanisms is discussed. While changes in all three mechanisms independently hold significant as determinants of default risk, a horse race regression that includes all measures of channels in one regression analysis suggests that innovation and tax avoidance remain robust when controlling for other overlapping effects of channels. Interestingly enough, the corporate governance and price efficiency channel suggested by Brogaard et al. (2017) loses its explanatory power when novel channels of innovation and tax avoidance are considered.

Chapter 4. Empirical Tests and Results of S&P 500 Index Addition

4.1. Exogeneity

Criticisms against decimalization as an exogenous event are addressed with the application of S&P 500 index addition as another liquidity provision event. The decimalization coincides with the passage of several other regulations, including the Regulation Fair Disclosure and the Sarbanes-Oxley Act (SOX), raising the concern that it might capture the effects of other factors or regulatory changes (Li and Xia, 2021). Concerns of the decimalization event overlapping with the dot-com bubble collapse also suggests the need to employ other methodologies in discerning the effects of exogenous liquidity. (Fang et al., 2014)

S&P 500 index additions are exogenous liquidity provisions in that firms do not self-select themselves into the index; index changes are performed based on public information (Becker-Blease and Paul, 2008). Moreover, the goal of the S&P Index is to make the index representative of the U.S. economy, and index itself does not signal additional information about included firm's future cash flows. Hence, additions can be treated as relatively exogenous to the firm (Jayaraman and Milbourn, 2012). Note that the deletions from S&P index are not treated as exogenous negative liquidity shocks, as most deletions from the index are caused by mergers or de-listings. The deleted firms often do not continue to be active, posing a serious survivorship bias if counted as an exogenous negative shock.

Empirical evidence of liquidity provision ex-post of S&P index addition has been documented in multiple papers. Beneish and Whaley (1996) find statistically and economically significant increase in trading volume, trading size, and decrease in bid-ask spread after index addition. Improvement in liquidity when a stock is added to the S&P 500 Index can be due to enhanced informational efficiencies that are derived from the link between index derivatives and underlying stocks. (Shleifer, 1986; Erwin and Miller, 1998). Significant decrease in the direct cost of trading and decline in asymmetric information can be another process behind long-term improvement in liquidity after index addition (Hedge and McDermott, 2003).

We confirm significant reductions in all three illiquidity measures after index additions. There are 2019 index additions between 1990 and 2021, but 375 firms remain in sample after excluding financial and non-publicly traded firms without the default probability observations. Panel A of table 7 shows that all three measures of illiquidity exhibit significant reduction for five years before and after

Table 7: Changes in liquidity measures before and after index additions.

Panel A in the table reports changes in illiquidity measures and default probability of stocks before and after S&P 500 index additions. Panel B reports coefficients for ordinary least square regression with dependent variable of illiquidity measures. All regressions are two-way panel regressions with both firm and year fixed effects.

Panel A

	Bid-ask Spread	Amihud	Zeros	EDF
Pre-Index Addition	1.0136	0.0132	4.6882	0.0226
Post-Index Addition	0.4651	0.0012	3.6568	0.0082
t-statistic	9.70***	5.40***	6.36***	5.52***

Panel B

	Bid-ask Spread	Amihud	Zeros
Post-Index Addition	-1.1239*** (0.0232)	-0.7788*** (0.0348)	-5.1538*** (0.1821)
Price	-2.3966*** (0.0254)	-2.7097*** (0.0277)	-11.198*** (0.0273)
Volume	-0.0000*** (0.0598)	-0.0000*** (0.0531)	-0.0001*** (0.0542)
Return Variance	0.5754*** (0.0428)	0.7746*** (0.0398)	0.7177*** (0.0465)
Firm and Year Fixed Effect	Yes	Yes	Yes
Adjusted R	0.3607	0.0790	0.4876
Number of Obs.	71543	71543	71543

the index additions. A multivariate analysis in Panel B using possible determinants of liquidity as control variables also suggest that firms that have been added to the S&P index experience significant increase in stock liquidity.

4.1. Possible Mechanisms

Robustness of channels of liquidity impacting default risk discussed in the previous sections are tested by treating S&P 500 index addition as another exogenous liquidity shock. Changes in EDF and measures of each channels before and after the index addition is reported in table 8. Firms added to the index experience significant decrease in the default probability, and all channels including the governance and the price efficiency channel of Brogaard et al. (2017) show changes consistent with the hypotheses.

Table 8: Ordinary least squares regression

The table reports coefficients of regression with dependent variable of default risk and possible channels as independent variables. Addition is the dummy variable that equals one if the firm belongs to S&P index addition group, and 1(Channel) is an indicator variable for firms with channel measures above the median value in a given year. Column (7) reports coefficients for the horse race regression with all channels included as determinants of default probabilities.

	Dependent Variable: EDF						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Addition*1(Innovation)	0.0171***						0.0644***
	(0.0207)						(0.0208)
1(Innovation)	-0.0145**						-0.2356***
	(0.0456)						(0.0484)
Addition*1(Tax)		0.0072**					0.0423**
		(0.0220)					(0.2210)
1(Tax Avoidance)		-0.0048					-0.0611
		(0.0324)					(0.0368)
Addition*1(Cash)			0.0003				-0.0259
			(0.0189)				(0.0221)
1(Cash Holdings)			0.0028				0.0512
			(0.0388)				(0.0385)
Addition*1(Delta)				-0.0179***			0.0880*
				(0.0254)			(0.0226)
1(Executive Delta)				-0.0072**			-0.0931**
				(0.000)			(0.000)
Addition*1(Dividend)					-0.0087**		0.0478
					(0.0213)		(0.0226)
1(Dividend Payout)					-0.0156***		-0.1588***
					(0.0438)		(0.0414)
Addition*1(Correlation)						-0.0021	-0.0572
						(0.0437)	(0.0501)
1(Correlation)						0.0064	0.0826**
						(0.0376)	(0.0371)
Addition Dummy	-0.0020	-0.0023	0.0013	-0.0063	-0.0014	0.0026	-0.1328**
	(0.0653)	(0.0623)	(0.0676)	(0.0640)	(0.0550)	(0.0559)	(0.0650)
Intercept	-2.89***	-2.75***	-2.75***	-2.82***	-2.71***	2.88***	-3.33**
	(2.7148)	(3.413)	(3.3846)	(3.2424)	(3.0953)	(3.7125)	(3.7168)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	5763	5763	5763	5763	5763	5763	5763
Adj. R^2	0.1384	0.1370	0.1368	0.1389	0.1395	0.1374	0.1531

By regressing the interactions of index added groups and channel measures, we show the robustness of mechanisms investigated in the previous section. The post addition variable is set to one for period after the index addition, and the channel variable is a indicator function set to one for channel measures above its median value for the given year. The most significant interaction terms of the channels are innovation and tax avoidance, signaling the robustness of effective mechanisms discussed from the first event study.

Chapter 5. Conclusion

This paper discovers novel channels of liquidity mitigating default risk. We provide support that decreased innovation investment and tax avoidance are the two channels of effective mechanisms. A horse race regression between the mechanisms shows that the both channels remain significant even after controlling for other effects of channels.

We extend previous findings by using an expanded set of data and applying another exogenous event of liquidity provision. Brogaard et al. (2017) investigates the relationship by only employing the decimalization event as an exogenous liquidity shock. We address the concerns of decimalization by applying a separate event study of S&P 500 index addition. The new mechanisms between liquidity and default risk remain robust across two independent event studies.

This paper elaborates on the effects of liquidity and determinants of firm defaults. The process of enhanced liquidity mitigating default risk is more complex and exhibits relationships with diverse firm characteristics than discussed by previous literature. This paper provides insights on what sectors managers should anticipate on being affected by stock liquidity and which mechanisms drive default likelihood of the firms.

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초 록

주식 유동성이 파산 위험에 미치는 영향

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본 논문은 주식 유동성의 외생적 충격에 대한 두 가지 사건연구(event study)를 통해 유동성이 파산 위험에 미치는 구체적인 영향을 탐구한다. 다양한 유동성 척도를 사용한 경험적 분석에 따르면 주식 유동성이 높을수록 기업의 채무불이행 위험이 감소하는 것으로 나타났다. 십진화 규제(Decimalization)와 S&P 500 지수의 두 가지 유동성 공급 사건을 활용함으로써 파산 확률에 영향을 미치는 유동성의 내재성 우려를 해결한다. 유동성과 채무불이행 위험 사이의 인과관계가 확립된 후, 본 논문은 유동성이 위험을 완화하는 경로를 조사한다. 혁신, 조세 회피 및 현금 보유의 가능한 메커니즘을 조사한다. 경험적 분석은 혁신 감소와 조세 회피가 유동성이 파산 위험을 감소시키는 중요한 메커니즘임을 시사한다.

주요어 : 주식 유동성, 파산 위험, 채무불이행 위험, 혁신, 조세 회피
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