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Stock Liquidity and Price Crash Risk: Evidence from a Kernel Matching Approach

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We present firm-level evidence that a company's stock liquidity entails a hidden cost and thus heightens its future crash risk. We employ a difference-in-differences (DID) propensity score matching method in a non-experimental setting to substantiate this causal effect of liquidity on crash risk. Following the recent literature that attributes this risk to the sudden release of bad information, we subsequently identify the negative impact of liquidity on the revelation of firm-level information as a potential viable channel through which liquidity increases the likelihood of stock price crashes. This paper provides a thorough analysis of this causal effect using a nonparametric method.

Key Words: Stock liquidity; Crash risk; Kernel matching; Difference-in-differences (DID); Managerial myopia.
JEL Classification Numbers: G12, G14, G34.

1. INTRODUCTION

Recent financial crises and a few high-profile corporate debacles have renewed the academic interest in the causes of extreme downside movements in stock prices. In this paper, we investigate the causal link between stock liquidity and price crashes. Given that liquidity plays a crucial role in the equity markets and can be effectively influenced by both policymakers and individual firms, it is of considerable importance to empirically explore whether and how liquidity alters a firm's future crash risk.

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As the lifeblood of financial markets,[1] a high degree of liquidity is generally acknowledged to be a desirable feature in the equity markets. For instance, liquidity can reduce a firm's cost of equity (e.g., Diamond and Verrecchia (1991) and Butler et al., (2005)), increase the informativeness of stock prices (e.g., Subrahmanyam and Titman (2001) and Khanna and Sonti (2004)) and promote firm value (Fang, Noe and Tice (2009)).

Despite these benefits of liquidity that have been reported by previous research, there are also specific reasons to suspect that high liquidity can negatively impact the equity market by spurring future crashes. Specifically, an increase in stock liquidity may cause managers to deliberately reduce their disclosure of negative firm-level information. The inevitable lumpy revelation of such information may then lead to stock price crashes. This effect can occur through two channels. First, high liquidity increases the likelihood of a hostile takeover by allowing a large outside trader to buy large stakes in a company at a lower cost[2] (e.g., Kyle and Vila (1991)). This takeover pressure can also exacerbate managerial myopia (Stein (1988)), which then encourages earnings management (Comment and Schwert (1995)) and further aggravates the temporary withholding of bad information.

The matter is further worsened by the fact that highly liquid stocks generally have higher shareholder turnover, a higher speculative price component, and are stocks held by smaller shareholders (Maug (1998), Mei, Scheinkman and Xiong (2009) and Norli, Ostergaard and Schindele (2014)). The dilution of ownership reduces the cost for exits (Bhide (1993)), discourages internal monitoring, and consequently impairs corporate governance (Jensen and Meckling (1976)). In the same vein, Kahn and Winton (1998) suggest that higher liquidity can be associated with decreased monitoring and hinders value-enhancing interventions. Liu, Liu and Qiu (2013) suggest that managers tend to withhold private information when in the presence of potential future fund flows.

Second, liquidity may affect crash risk negatively by directly impinging executive compensation. Consistent with other theoretical and empirical work (e.g., Holmstrom and Tirole (1993), Fang, Noe and Tice (2009)), Jayaraman and Milbourn (2011) report that high stock liquidity is associated with a high proportion of equity-based compensation and greater pay-for-performance sensitivity (PPS). As PPS becomes ever more reliant on stock prices relative to other performance metrics, such as earnings, managers

[1]Fernandez (1999), page 1. Fernandez, F. A. (1999), Liquidity risk. SIA Working Paper.

[2]Hostile takeover becomes more likely, given high liquidity, because hostile outside traders can increase their stakes while going unnoticed by the incumbent management under the camouflage offered by heightened noise trading. Thus traders with enough block shares may eventually attempt a profitable takeover.

will have greater incentives to conceal bad information in order to stabilize and promote stock prices[3]. Benmelech, Kandel and Veronesi (2010), along with Kim, Li and Zhang (2011b), provide further evidence that executives' (particularly, CFO's) equity-based incentives induce the stockpiling of bad news and thus increase the risk of future crashes. Consequently, a positive relationship between high liquidity and greater crash risk is implied.

Although we suggest here a number of ways in which liquidity can heighten crash risk, the signs of this liquidity impact on crash risk can also be reversed. Maug (1998) suggests that even though high liquidity facilitates exits and reduces large shareholders' incentives to monitor managers' performance, that liquidity also allows investors to make less costly purchases of larger blocks of stocks. Based on this latter possibility, Maug (1998) finds that liquidity has a positive impact on monitoring by making corporate governance more effective, a circumstance that is also consistent with the theoretical work of Kahn and Winton (1998). Further still, Admati and Pfleiderer (2009), Edmans (2009), and Edmans and Manso (2010) show that blockholders can exert governance and induce higher managerial effort using the threat of disciplinary trading. Therefore, to the extent that high liquidity facilitates the formation of block holdings and strengthens the monitoring of those holdings, it can limit the ability of managers to withhold bad information over an extended period and consequently reduce the risk of crashes.

In addition, Holmstrom and Tirole (1993) and Chordia et al. (2008) have shown that high stock liquidity increases the marginal value of information and thus motivates market participants to acquire and impound more information in the stock price, a factor that may also limit a manager's ability to hoard information. Further, Fang, Huang and Karpoff (2016) find that lifting short selling constraints, which likely increases liquidity, has a positive effect on the reinforcing of monitoring activities. This theoretical ambiguity, an empirical scarcity, and seemingly contradictory findings reflect the lack of any fully comprehensive examination of this issue. The goal of our study is to fill this important research gap.

We posit that stock liquidity plays an important role in determining the probability of future stock price crashes by affecting the revelation of firm-specific information. First, we utilize a multivariate regression model to show that stocks with higher liquidity do experience a greater crash risk. After controlling for a firm's past crashes, industry and year fixed effects and other relevant firm-specific characteristics, we find that stock illiquidity (measured by Amihud (2002) illiquidity ratio and the relative spread) neg-

[3]These incentives are further strengthened during those periods when higher stock liquidity is associated with higher stock price volatility. For example, in times of expansionary monetary policy that increases stock market liquidity, stock price volatility will also increase as a result (Zhang, Zhang and Breece (2011)).

atively relates to future crash risks (when measured by negative conditional future return skewness, down-to-up volatility, and the likelihood of future extreme downside return movements). This knowledge indicates that high liquidity (a small illiquidity measure) is positively associated with crashes. Further still, we investigate the link between the changes in liquidity and lead changes in a firm's crash risk. The results strongly suggest that an increase in stock liquidity (a decrease in the illiquidity measure) raises the likelihood of future crashes.

Secondly, we focus on further substantiating the causal effect of liquidity on crash risk. To achieve this end, we employ the difference-in-differences (DID) propensity score matching method (Dehejia and Wahba (2002)) that has been already widely applied in the finance literature (e.g., Fang, Noe and Tice (2009) and Fang, Tian and Tice (2014)) to establish causality in non-experimental settings. We use two natural experiments as exogenous "treatments" to provide the identification of DID matching estimation, namely, the decimalization in 2001 and the tick size reduction in 1997. To ensure the validity of these matching procedures, we conduct a number of balancing tests to rule out the possibility that the differences in crash risk after the treatment are driven by the pre-treatment differences of certain firm-specific characteristics. Our results provide confirmatory evidence for the positive causal effect of stock liquidity on future crashes.

Third, we explore the potential channels of this liquidity effect in heightening crash risk. The literature has suggested a few mechanisms by which liquidity may exacerbate managerial myopia and compel managers to chase short-term profits at the cost of long-term performance. Our evidence indicates that the adverse effect of liquidity may partly stem from firm-specific information hoarding, as evidenced by reduced price synchronicity. This channel is of particular importance in our context, as the recent literature (e.g., An and Zhang (2013)) suggests that price crashes are due to accumulated negative, firm-specific information that is suddenly released to the market.

The significance of the present study we believe is twofold. First, to the best of our knowledge, it is a precise study intended to establish a causal link between stock liquidity and future crash risk in a nonparametric setting. Beyond the documented strong evidence that stock liquidity is an important determinant of average returns,[4] we show that liquidity is also a key determinant of extreme downside risk.

Compared to the contemporaneous research by Chang, Chen and Zolotoy (2017) on the impact of stock liquidity on stock crash risk, our research

[4]See, among others, Amihud and Mendelson (1986 and 1989), Brennan and Subrahmanyam (1996), Eleswarapu (1997), Brennan, Chordia and Subrahmanyam (1998), Chordia, Roll and Subrahmanyam(2001), Amihud (2002), Chordia, Huh, and Subrahmanyam (2009).

has the following advantages: First, we use a difference-in-differences (DID) nonparametric propensity score matching (PSM) method instead of OLS and probit regressions, thereby allowing us to relax the assumptions of linearity in the parameters and independence of the error terms, together with other assumptions. Two of the challenges for determining the impact of stock liquidity on price crash risk are the issues of omitted variables and simultaneous causality. Error terms in such OLS regression may include unobservable variables that affect the dependent variables, thereby rendering the error terms correlated with each other and affecting the unbiasedness of the parameter.

We use the PSM method to alleviate these concerns. Further still, our kernel matching provides improvement over the one-to-one matching used by Chang, Chen and Zolotoy (2017). More specifically, one-to-one matched pairs have the potential to be vastly disparate in terms of those firm fundamental variables that are not included in the matching criteria while being comparable in terms of the included variables. Meanwhile, kernel matching uses a weighted average of the control group firms to construct one matched firm for each treated firm, thereby yielding lower variance and a higher similarity in firm fundamentals between the treated and the control firms. This kernel matching method yields a more thorough comparison opportunity. Second, we identify an additional channel through which heightened stock liquidity increases crash risk. Specifically, increased stock liquidity increases firm exposure to a hostile takeover, resulting in more severe managerial myopia and earnings management that eventually can lead to stock price crashes.

We also contribute to the growing strand of literature that underlines the potential adverse consequences of high stock liquidity on corporate operations. For instance, Porter (1992) and Bhide (1993) suggest there is a potential link between stock liquidity and long-term underinvestment. Stiglitz (1985 and 1993) argue that high liquidity that leads to quick information revelation through price changes may indeed reduce incentives for expending private resources to obtain information. More recently, an important study by Fang, Tian and Tice (2014) documents that an increase in stock liquidity causes a reduction in future corporate innovations. In this paper, we explore an additional hidden cost of liquidity, which is to cause an increase in future price crashes.

The rest of the paper proceeds as follows. Section II describes the data and presents summary statistics. Section III presents the empirical results on the effect of stock liquidity on firm-level crash risk. In Section IV, we add to the literature by exploring additional channels of the identified liquidity effect. Section V concludes the paper.

2. DATA AND VARIABLE CONSTRUCTION

In this section, we describe the variable construction of proxies of crash risk, stock liquidity and other control variables. The summary statistics on the key variables are also discussed.

2.1. Measuring Firm-level Crash Risk

Following the methodology of previous researchers (Chen, Hong and Stein (2001), Hutton, Marcus and Tehranian (2009) and Kim, Li and Zhang (2011a) and (2011b)) and using firm-specific weekly returns, firm-specific crash risk is measured using three proxies: (1) the negative conditional skewness of future returns, NCSKEW ; (2) the down-to-up volatility, DUVOL ; and (3) CRASH , the likelihood of the occurrence of future extreme downside return movements.

For each firm i during each fiscal year t, we first estimate firm-specific weekly residual returns from the expanded market model in the following equation (1):

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau-2} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \varepsilon_{i,\tau}, \tag{1}$$

where $r_{i,\tau}$ is the return on stock i in week τ and $r_{m,\tau}$ is the return on the CRSP value-weighted market index in week τ. The lead and lag terms for the market return are included to account for nonsynchronous trading (Dimson (1979)). The weekly returns are used to avoid the concern caused by thinly traded stocks. To exclude those firms that went public, were delisted, or experienced trading halts, we drop any firm that was traded for less than 26 weeks over a fiscal year. A similar practice was adopted by Morck, Yeung and Yu (2000) and An and Zhang (2013). The firm-specific weekly return (denoted as $W_{i,\tau}$) is defined as the natural logarithm of one plus the residuals from equation (1).

Return asymmetry is generally gauged by negative skewness. Our first measure of crash risk is $NCSKEW$, the negative conditional skewness of future returns. As in the related literature, we define NCSKEW as the standardized negative value of the third central moment of firm-specific weekly return, scaled by its sample variance raised to the power of 3/2. More specifically, the $NCSKEW$ of stock i in its fiscal year t is calculated as

$$NCSKEW_{i,t} = -n(n-1)^{3/2} \sum_{\tau \in t} W_{i,\tau}^3 / \left[(n-1)(n-2) \left(\sum W_{i,\tau}^2 \right)^{3/2} \right], \tag{2}$$

where n is the number of weekly observation in year t. We follow the literature by employing the negative value of the skewness to ease the interpretation, so that a larger value for $NCSKEW$ indicates more negatively skewed returns, and thus greater crash risk.

To construct the second crash risk proxy $DUVOL$, for each stock i over fiscal year t, we first group firm-specific weekly returns into "up" weeks, in which the returns are greater than the stock's annual average return, and "down" weeks, in which the returns are below the average. Then, $DUVOL$ is calculated as the logarithm for the ratio of the standard deviation of firm-specific weekly returns in the "down" weeks to that of the "up" weeks. A large value for $DUVOL$ suggests that the stock has large downside price deviations, i.e., great crash risk.

The third measure of crash risk is a dummy variable that takes the value of 1 if a firm experiences one or more crash weeks in a fiscal year and 0 otherwise. Consistent with the literature on crash risk, the crash weeks of a firm are defined as those weeks during which the firm-specific return is more than 3.2 standard deviations below the average firm-specific weekly returns over the entire fiscal year. As an intuitive and rather crude indicator of crashes, this measure is robust enough to potential measurement error. Together, these three proxies can provide a robust and broad assessment of crash likelihood.

2.2. Measuring Stock Liquidity

The available theoretical literature on liquidity is rich, and there are many empirical measures used to quantify liquidity. We construct alternative stock liquidity and crash risk measures to ensure the robustness of our analysis. Our choices of liquidity measures were chosen to favor greater data availability and the capability to capture liquidity behavior at a relatively low frequency so as to match that of the crash risk measures. We, therefore, employ common measures that can be calculated using daily data. As in Amihud (2002) and Fang, Tian and Tice (2014), this paper utilizes two widely-used proxies for stock liquidity: (1) the Amihud (2002) illiquidity ratio ($ILIQ$) and (2) the relative spread (RS). Specifically, the annual Amihud measure is calculated as follows:

$$Amihud_{i,t} = \frac{1}{n}\sum_{s=1}^{n_{i,t}} \frac{|R_{i,s}|}{Vol_{i,s}}, \tag{3}$$

where $n_{i,t}$ is the number of trading days within year t for security i, $R_{i,s}$ is the absolute return on day s, and $Vol_{i,s}$ is the trading volume (in units of currency) on that same day. Amihud captures how much the price moves for each volume unit of trades. It is standard practice to multiply the above estimate by 10^6 for practical purposes. As in the work of Fang, Tian and Tice (2014), we require a stock to be listed at the end of fiscal year t so as to have at least 200 daily observations of returns and trading volume during the same fiscal year in the CRSP and to have a price of $5 or more at the end of that fiscal year. Due to the non-normality of the Amihud (2012) measure, we use the natural logarithm of the Amihud (2012) measure (denoted as $ILIQ$) in all our regression analyses. The second proxy, RS, is the logarithm of the relative quoted spread standardized by the mid-point of the prevailing bid-ask quote calculated for the same sample. Goyenko and Ukhov (2009) and Goyenko, Holden and Trzcinka (2009) also demonstrate that these liquidity proxies are capable of capturing the spread cost and price impact estimated using intra-day data. Also, note that these two liquidity measures employed in our study measure the degree of illiquidity, with a higher value indicating lower market liquidity and greater transaction costs.

2.3. Other Control Variables

To examine the impact of liquidity on crash risk, we include a wide range of control variables that prior studies have indicated are related to a firm's stock price crash risk. For instance, we control for past return performance by including the mean (RET), standard deviation ($SIGMA$) and skewness ($NCSKEW$) of firm-specific weekly returns for the previous fiscal year. Furthermore, we control for $DTURN$, which is the de-trended turnover, calculated as the difference in average monthly turnover between two consecutive fiscal years. $DTURN$ as suggested by Chen, Hong and Stein (2001) to capture the degree of divergence of opinion among investors. Other standard control variables include firm size ($SIZE$), market-to-book ratio (MB), financial leverage (LEV) and return-on-assets (ROA). Moreover, we also construct and control for accrual management ($ABACC$) following Hutton, Marcus and Tehranian (2009), who have documented that a firm's earnings management increases its likelihood of crashes. Overall, our variable construction and inclusion of control variables is broadly consistent with the existing literature. All continuous variables are also winsorized at the 1% and 99% levels to reduce the influence of outliers.

2.4. Descriptive Statistics and the Correlation Matrix

Table 1 presents the descriptive statistics of the crash proxies, illiquidity measures, and other control variables. Focusing on the crash proxies, we see that, on average, firm-specific returns are negatively skewed ($NCSKEW > 0$) with comparable downside and upside return volatility as suggested by the close-to-zero mean of DUVOL. Additionally, 19.8% of the firms have at least one crash week during a fiscal year.

Table 2 reports the correlation matrix for our key variables of interest. Not surprisingly, the two measures of crash magnitude ($NCSKEW$ and $DUVOL$) are highly correlated with a correlation coefficient of 0.95. Also, both measures positively correlate with the crash dummy ($CRASH$).

TABLE 1.

Descriptive Statistics of the Firm Characteristics

Variable	N	Mean	Std. dev.	Skewness	Kurtosis	P25	P50	P75
$NCSKEW$	44543	0.186	0.807	0.939	8.421	−0.254	0.121	0.530
$DUVOL$	44543	−0.002	0.196	−1.704	596.3	−0.027	0.002	0.034
$CRASH$	44543	0.198	0.399	1.513	3.288	0	0	1
$ILIQ$	44543	−4.718	2.710	0.181	2.539	−6.705	−4.889	−2.822
RS	44543	−5.233	1.464	−0.274	2.072	−6.510	−4.965	−4.017
$DTURN$	44543	0.002	0.196	−1.704	596.3	−0.027	0.002	0.034
$SIGMA$	44543	0.061	0.031	1.683	8.850	0.040	0.054	0.075
RET	44543	0.003	0.009	0.373	7.196	−0.001	0.003	0.008
ROA	44543	0.028	0.163	−9.770	222.8	0.014	0.046	0.084
$SIZE$	44543	6.588	1.759	0.361	3.045	5.340	6.482	7.708
MB	44543	1.542	1.863	7.978	165.3	0.585	1.032	1.834
LEV	44543	0.211	0.204	1.936	16.65	0.028	0.182	0.331
$ABACC$	44543	0.075	0.108	10.52	298.8	0.019	0.046	0.095

This table summarizes the statistics for the firm characteristics of the sample. $NCSKEW$ is the negative conditional skewness of future returns, defined as the standardized negative value of the third central moment of firm-specific weekly return scaled by its sample variance and raised to the power of 3/2. $DUVOL$ is calculated as the logarithm for the ratio of the standard deviation of firm-specific weekly returns in "down" weeks to that of the "up" weeks. CRASH is a dummy variable that takes the value of 1 if a firm experiences one or more crash weeks in a fiscal year and 0 otherwise. $ILIQ$ denotes our main illiquidity measure, the natural logarithm of the Amihud (2002) illiquidity ratio as defined in equation (3) and multiplied by 10^6. RS is the logarithm of the relative quoted spread standardized by the midpoint of the prevailing bid-ask quote calculated for the same sample. DTURN is the de-trended turnover calculated as the difference in average monthly turnover between two consecutive fiscal years. RET and $SIGMA$ are the mean and the standard deviation of firm-specific weekly returns in the previous fiscal year, respectively. ROA, $SIZE$, MB and LEV are standard control variables of return-on-assets, firm size, market-to-book ratio, and financial leverage, respectively. $ABACC$ is the measure of accrual management as constructed in Hutton, Marcus, and Tehranian (2009). All continuous variables are winsorized at 1% and 99% levels to reduce the influence of outliers.

The two illiquidity measures ($ILIQ$ and RS) are positively associated with a correlation coefficient of 74.5%. We have also determined that the two illiquidity measures are negatively associated with crash proxies ($NCSKEW$, $DUVOL$ and $CRASH$), which suggests that higher liquidity (i.e., lower $ILIQ$ and RS) is associated with greater crash likelihood. Finally, the proxies of investor heterogeneity ($DTURN$) and return volatility ($SIGMA$) are positively correlated with crash proxies, a finding that is consistent with Chen, Hong and Stein (2001).

TABLE 2.

Correlation Matrix of Key Variables

Variable	$NCSKEW$	$DUVOL$	$CRASH$	$ILIQ$	RS	$DTURN$	$SIGMA$	RET	ROA	$SIZE$	MB	LEV	$ABACC$
$NCSKEW$	1												
$DUVOL$	0.950	1											
$CRASH$	0.563	0.512	1										
$ILIQ$	−0.076	−0.110	−0.021	1									
RS	−0.036	−0.069	−0.008	0.745	1								
$DTURN$	0.021	0.018	0.065	−0.020	−0.010	1							
$SIGMA$	0.182	0.120	0.195	0.186	0.164	0.017	1						
RET	−0.267	−0.277	−0.249	0.027	0.011	0.020	0.009	1					
ROA	−0.047	−0.029	−0.044	−0.117	−0.081	0.034	−0.282	0.160	1				
$SIZE$	−0.007	0.030	−0.049	−0.910	−0.596	0.031	−0.291	0.120	0.165	1			
MB	−0.029	−0.039	−0.046	−0.102	−0.057	0.009	0.179	0.335	−0.029	0.128	1		
LEV	−0.011	−0.006	0.010	−0.075	0.010	0.024	−0.089	−0.073	−0.091	0.099	−0.264	1	
$ABACC$	0.022	0.008	0.017	0.072	0.061	0.007	0.252	0.039	−0.269	−0.097	0.133	−0.039	1

Table 2 reports the correlation matrix of the key variables of interest. $NCSKEW$ is the negative conditional skewness of future returns, defined as the standardized negative value of the third central moment of firm-specific weekly return scaled by its sample variance and raised to the power of 3/2. $DUVOL$ is calculated as the logarithm of the ratio of the standard deviation of firm-specific weekly returns in "down" weeks to that of the "up" weeks. $CRASH$ is a dummy variable that takes the value of 1 if a firm experiences one or more crash weeks in a fiscal year and 0 otherwise. $ILIQ$ is our main illiquidity measure, the natural logarithm of the Amihud (2002) illiquidity ratio defined in equation (3) and multiplied by 10^6. RS is the logarithm of the relative quoted spread standardized by the mid-point of the prevailing bid-ask quote as calculated for the same sample. $DTURN$ is the de-trended turnover calculated as the difference in average monthly turnover between two consecutive fiscal years. RET and $SIGMA$ are the mean and standard deviation of firm-specific weekly returns in the previous fiscal year, respectively. ROA, $SIZE$, MB and LEV are standard control variables for return-on-assets, firm size, market-to-book ratio, and financial leverage, respectively. $ABACC$ is the measure of accrual management as constructed in Hutton, Marcus and Tehranian (2009). All continuous variables are winsorized at the 1% and 99% levels to reduce the influence of outliers.

3. EMPIRICAL RESULTS

Herein, we first employ the widely-used regression framework to examine the role of liquidity in determining crash risk. Then we identify the causal effect of changes in liquidity on crashes using the difference-in-differences (DID) propensity score matching approach that was developed by Dehejia and Wahba (2002) and gradually gained popularity in corporate finance research (e.g., Fang, Noe and Tice (2009) and Fang, Tian and Tice (2014)).

3.1. Regression Analysis

3.1.1. Baseline Results

Our baseline econometric model is in line with the literature (e.g., Fang, Tian and Tice (2014)) and can be specified as follows:

$$Crashproxy_{=}\alpha_0 + \alpha_1 ILIQ_{t-1} + X'_{t-1}\beta + \gamma_1\eta_t + \gamma_2\eta_{IND} + \varepsilon_t, \quad (4)$$

where the firm subscript i is suppressed. The dependent variable is one of two continuous variables $NCSKEW$ or $DUVOL$, or the dummy variable $CRASH$ that indicates the occurrence of one of more crash weeks in year t. $ILIQ$ refers to our main illiquidity measure, the Amihud (2002) illiquidity ratio as defined in equation (3). Further, X_{t-1} is a vector of several other lagged firm-level control variables suggested by related literature, including $DTURN_{t-1}$, $NCSKEW_{t-1}$, $SIGMA_{t-1}$, RET_{t-1}, $DTURN_{t-1}$, ROA_{t-1}, $SIZE_{t-1}$, MB_{t-1}, LEV_{t-1} and $ABACC_{t-1}$. Finally, η_t and η_{IND} capture the year and industry effects, respectively, and ε_t is the error term.

Table 3 reports the estimation results for equation (4). The robust standard errors are consistent with potential heteroscedasticity and with the correlation within firms (clustered by firms). As shown in Column 1, the coefficient of $ILIQ_{t-1}$ is negative and significant at a 1% level (-0.049 with $t = -11.86$). This result indicates that decreases in stock liquidity (i.e., increases in $ILIQ$) reduce future crash risk. In other words, an improvement in liquidity (decrease in $ILIQ$) can aggravate the risk of price crashes. This finding is consistent with our hypothesis that states that high liquidity provides managers with incentives to conceal bad firm-specific information for an extended period, consequently increasing crash likelihood in the near future. In Column 2, which displays the second proxy of crash risk DUVOL, we find that the coefficient of $ILIQ_{t-1}$ remains negative and highly significant with (-0.020 with $t = -11.0$). This result provides further confirmatory evidence of our previous finding that high liquidity increases crash risk.

Column 3 presents the logistic estimates for equation (4), wherein the dependent variable $CRASH$ takes the value of 1 if a firm experiences one or more crash weeks in a fiscal year and 0 otherwise. Similarly, the coefficient of $ILIQ$ is negative and highly significant (-0.075 with $t = -9.07$). This result indicates that stock liquidity is a key determinant of the probability of crash occurrences during a fiscal year.

In terms of economic significance, Column 1 indicates that, ceteris paribus, moving from the third quartile of $ILIQ$ (an improvement in stock liquidity) to the first quartile more than doubles a firm's future average crash risk (as measured by $NCSKEW$).[5] In terms of the occurrence of crashes, Column 3 suggests that, ceteris paribus, when moving from the third quartile of ILIQ to the first quartile, on average, raises the propensity of future

[5]The impact of $ILIQ$ is obtained by multiplying its estimated coefficient (-0.049) with the difference between the 1st and 3rd quartiles of $ILIQ(= -2.822 + 6.705)$ presented in Table 1. The shift in $ILIQ$ would increase a firm's average NCSKEW by 0.19, which is greater than the sample average of $NCSKEW$ (0.186).

TABLE 3.

OLS Regression Analysis: Levels Results

Variable	(1) $NCSKEW$	(2) $DUVOL$	(3) $CRASH$	(4) $NCSKEW$	(5) $DUVOL$	(6) $CRASH$
$ILIQ_{t-1}$	-0.049^{***}	-0.020^{***}	-0.075^{***}			
	(-11.86)	(-10.99)	(-9.07)			
RS_{t-1}				-4.377^{***}	-1.879^{***}	-5.833^{***}
				(-11.39)	(-10.55)	(-7.37)
$DTURN_{t-1}$	0.019	0.004	-0.044	0.017	0.002	-0.044
	(0.91)	(0.38)	(-1.25)	(0.77)	(0.21)	(-1.20)
$NCSKEW_{t-1}$	0.041^{***}	0.020^{***}	0.012	0.040^{***}	0.020^{***}	0.014
	(6.95)	(8.01)	(1.23)	(6.62)	(7.57)	(1.42)
$SIGMA_{t-1}$	0.883^{***}	0.052	-4.690^{***}	1.520^{***}	0.317^{***}	-3.991^{***}
	(4.48)	(0.62)	(-13.09)	(8.20)	(3.91)	(-11.13)
RET_{t-1}	8.522^{***}	4.317^{***}	12.85^{***}	7.154^{***}	3.780^{***}	10.49^{***}
	(16.28)	(18.92)	(12.99)	(13.55)	(16.51)	(10.74)
ROA_{t-1}	0.109^{***}	0.066^{***}	0.056	0.111^{***}	0.066^{***}	0.044
	(3.46)	(4.96)	(1.04)	(3.35)	(4.70)	(0.77)
$SIZE_{t-1}$	-0.031^{***}	-0.006^{**}	-0.112^{***}	0.021^{***}	0.014^{***}	-0.029^{***}
	(-4.69)	(-2.25)	(-8.81)	(6.72)	(9.98)	(-5.05)
MB_{t-1}	0.012^{***}	0.004^{***}	0.022^{***}	0.011^{***}	0.004^{***}	0.020^{***}
	(4.79)	(4.26)	(5.27)	(4.02)	(3.37)	(4.56)
LEV_{t-1}	-0.008	-0.008	0.088^{**}	0.008	-0.000	0.108^{***}
	(-0.35)	(-0.77)	(2.26)	(0.34)	(-0.02)	(2.68)
$ABACC_{t-1}$	0.106^{***}	0.041^{**}	0.226^{***}	0.107^{***}	0.043^{**}	0.204^{***}
	(2.70)	(2.45)	(4.06)	(2.73)	(2.53)	(3.61)
Constant	-0.157	-0.129	0.015	-1.050^{***}	-0.476^{***}	-0.208
	(-0.00)	(-0.00)	(0.10)	(-26.51)	(-26.71)	(-1.50)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44543	44543	44543	44543	44543	44543
Pseudo R^2			0.038			0.0373
Adj. R^2	0.042	0.047		0.042	0.047	

This table reports the coefficient estimates for the following equation: : $Crashproxy_t = \alpha_0 + \alpha_1 ILIQ_{t-1} + X'_{t-1}\beta + \gamma_1\eta_t + \gamma_2\eta_{IND} + \varepsilon_t$, where the firm subscript i is suppressed. The dependent variable is one of two continuous variables $NCSKEW$ or $DUVOL$, or the dummy variable $CRASH$ that indicates the occurrence one of more crash weeks in year t. $ILIQ$ denotes our main illiquidity measure, the Amihud (2002) illiquidity ratio as defined in equation (3). X_{t-1} is a vector of other lagged firm-level control variables as suggested in the related literature, including $DTURN_{t-1}$, $NCSKEW_{t-1}$, $SIGMA_{t-1}$, RET_{t-1}, $DTURN_{t-1}$, ROA_{t-1}, $SIZE_{t-1}$, MB_{t-1}, LEV_{t-1}, and $ABACC_{t-1}$. η_t and η_{IND} capture capture the time and industry effects. ε_t is the error term. The regressors also include industry dummies that are constructed based on two-digit SIC codes and year dummies. The t (or z for the probit model) statistics (corrected for heteroscedasticity and firm-level clustering) are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

crashes by 5.97%.[6] Given that the sample average probability of having at least one crash week during a fiscal year is 19.8%, the effects of $ILIQ$ on $CRASH$ are substantial. Overall, these results demonstrate that both the magnitude and the occurrence of a firm's stock price crashes are sensitive to the stock liquidity of that firm.

The effects of other control variables on crash risk are also plausible. For instance, we find that the coefficient of $NCSKEW_{t-1}$ is positive and highly significant, which indicates the persistence of crash risk and is consistent with the findings of Kim et al. (2011a and 2011b). Also, as argued by Chen, Hong and Stein (2001), the past return (RET_{t-1}) has a positive impact on future crash risk. Further, we find that firms with opaque financial reports (proxied by $ABCCA_{t-1}$) are more prone to stock price crashes.

As a robustness check, in Table 3 (Columns 4-6), liquidity is measured by the relative spread (RS). Here, our previous finding of a positive (negative) relationship between liquidity (illiquidity) and future crashes is fully retained. In particular, the coefficient of $ILIQ$ remains negative and significant at a 1% level across the different measures of crash risk.

3.1.2. Regressions on Changes

In this section, we further investigate the association between the changes in liquidity and lead changes in a firm's crash risk. If managers respond to an improvement in liquidity by hoarding more bad news, we expect to observe a negative relationship between current changes in $ILIQ$ and future changes in that firm's crash risk. This test also provides an alternative way to examine the impact of liquidity on crashes. Table 4 presents the results of this test. After using different measures of illiquidity and crash likelihood, we consistently find that changes in illiquidity have a negative and significant effect on the changes in future crash risk. This result substantiates our previous finding that high liquidity causes future crashes. In addition, it helps to alleviate concerns about endogeneity or prior period information shocks related to the levels results in Table 3. Furthermore, we conduct the tests using firm-level fixed effects regression and a Fama-MacBeth regression, which produces essentially similar results to previous tests.

[6]The marginal effect of a logit model with respect to a particular regressor, x_i is calculated as $\Lambda(X'\beta)[1 - \Lambda(X'\beta)]\beta_i$, where $\Lambda(\cdot)$ is the logistic cumulative distribution function. We report the average of the individual marginal effects, which is asymptotically equivalent to the marginal effect evaluated at the sample means and is favored in small or moderate-sized samples (Greene (2008)).

TABLE 4.

OLS Regression Analysis: Lead Changes

Variable	(1) $\Delta NCSKEW$	(2) $\Delta DUVOL$	(3) $\Delta NCSKEW$	(4) $\Delta DUVOL$
$\Delta ILIQ_{t-1}$	-0.032^{***}	-0.012^{***}		
	(-3.65)	(-3.15)		
ΔRS_{t-1}			-2.421^{***}	-1.120^{***}
			(-3.22)	(-3.20)
$\Delta DTURN_{t-1}$	0.081^{***}	0.025^{**}	0.078^{***}	0.022^{**}
	(3.52)	(2.42)	(3.21)	(2.11)
$\Delta NCSKEW_{t-1}$	-0.496^{***}	-0.210^{***}	-0.496^{***}	-0.211^{***}
	(-104.84)	(-92.97)	(-101.8)	(-90.11)
$\Delta SIGMA_{t-1}$	0.740^{***}	0.707^{***}	0.659^{**}	0.739^{***}
	(3.03)	(6.25)	(2.48)	(6.18)
ΔRET_{t-1}	-10.77^{***}	-3.842^{***}	-12.60^{***}	-4.478^{***}
	(-14.83)	(-12.00)	(-18.43)	(-15.21)
ΔROA_{t-1}	-0.044	-0.021	-0.016	-0.008
	(-0.97)	(-1.09)	(-0.33)	(-0.40)
$\Delta SIZE_{t-1}$	0.590^{***}	0.272^{***}	0.646^{***}	0.293^{***}
	(26.30)	(28.38)	(32.08)	(35.15)
ΔMB_{t-1}	0.007^{*}	0.002	0.006	0.001
	(1.81)	(1.01)	(1.35)	(0.51)
ΔLEV_{t-1}	0.213^{***}	0.067^{***}	0.228^{***}	0.075^{***}
	(3.58)	(2.60)	(3.67)	(2.80)
$\Delta ABACC_{t-1}$	-0.034	-0.016	-0.039	-0.015
	(-0.75)	(-0.89)	(-0.83)	(-0.79)
Constant	0.829^{***}	0.376^{***}	-0.073	-0.032
	(13.97)	(13.70)	(-0.00)	(-0.00)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	37785	37785	37785	37785
Adj. R^2	0.281	0.268	0.283	0.270

This table reports the OLS estimates obtained by regressing the lead changes of a firm's crash risk on its changes in liquidity and those of the other variables included in Table 3. The regressors also include industry dummies' constructed based on two-digit SIC codes and the year dummies. The t statistics (corrected for heteroscedasticity and firm-level clustering) are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In summary, we show that both the level of stock liquidity and its increases contribute to future crashes. This relationship remains robust when using alternative measures of liquidity and crash risk as well as after controlling for lagged moments of a firm's return distribution and other factors that have been identified by previous research to affect crash risk.

3.2. A Difference-in-Differences (DID) Matching Approach

In this paper, we focus on identifying the causal effect of a change in a firm's equity liquidity on its crash risk. Thus, the potential endogeneity between liquidity and crashes is an important issue that needs to be carefully addressed. First, there may be a potential causal link from crashes to stock liquidity, as the expected crashes may reduce demand for the firm's stock, thus affecting liquidity. Secondly, stock liquidity and price crashes may be simultaneously driven by certain firm-level unobservable variables. For instance, Bhide (1993), Kahn and Winton (1998) and An and Zhang (2013) suggest that committed stockholders may reduce agency costs by actively monitoring managers; however, this active monitoring may also reduce stock liquidity by increasing informational asymmetries and at the same time deter bad information hoarding. Although the inclusion of a broad set of firm characteristics and industry/time fixed effects may alleviate such concern in a multivariate regression setting, controlling for all potential variables is difficult if not impossible. Thus, these two potential problems (simultaneous causality and omitted variables) may result in a correlation between the liquidity proxy and regression residuals and cause spurious inferences regarding the effects of liquidity.

3.2.1. The DID Matching Framework

This paper employs the nonparametric difference-in-differences propensity score matching approach (Dehejia and Wahba (2002)) to identify the causal effect of liquidity on crash risk. We also carefully explore the appropriateness of the matching procedures by using a number of balancing tests. DID methods have been commonly used to study the effects of numerous policy and structural changes (See, for instance, Besley and Burgess (2003), Smith and Todd (2005), Galiani et al. (2005), and Girma and Görg (2007)). Also, following the example of Fang, Tian and Tice (2014), we take advantage of the exogenous shocks that greatly improve market liquidity, namely, 1) the decimalization of minimum tick size implemented around 2001 and 2) the shift in minimum tick for quotes from \$1/8th to \$1/16th in 1997. These two regulation changes have dramatically increased stock liquidity since their implementation.

The estimation framework can be described as follows: Let $G \in \{0, 1\}$ be a group indicator of whether the firm stock liquidity is exposed to the "treatment", i.e., as affected by the policy change in the minimum tick size. G takes the value of 1 for the treatment group and 0 for the control group. Define $t = 0$ as a pre-treatment (pre-decimalization) period and $t = 1$ as the post-treatment (post-decimalization) period. Denote $Crash^1_{i,t=1}$ as firm i's crash risk after decimalization and $Crash^0_{i,t=1}$ as that firm's crash likelihood if it had not been affected by decimalization. The causal effect of liquidity change on this firm's crash risk is defined as $Crash^1_{i,t=1} - Crash^0_{i,t=1}$, wherein the value of $Crash^1_{i,1}$ can be directly measured; $Crash^0_{i,1}$ is unobservable, given that firm i has been affected by the treatment. Therefore, the fundamental identification problem is that for any particular firm i and time i, we cannot observe both potential outcomes $Crash^1_{i,t}$ and $Crash^0_{i,t}$; therefore, we cannot directly compute the individual treatment effect.

As in Heckman et al., (1997) and Dehejia and Wahba (2002), the average effect of decimalization on the treated firms is

$$\begin{aligned} & \mathbb{E}(Crash^1_{i,t=1} - Crash^0_{i,t=1} | G_i = 1) \\ = \ & \mathbb{E}(Crash^1_{i,t=1} | G_i = 1) - \mathbb{E}(Crash^0_{i,t=1} | G_i = 1), \end{aligned} \tag{5}$$

where the first term is the average crash risk of the treatment firms after decimalization. This causal inference relies on the construction of the counterfactual for the second term, which is the average crash risk that the treated group would have been exposed to had their liquidity not been affected by the decimalization. $\mathbb{E}(Crash^0_{i,t=1}|G_i = 1)$ is estimated by the average crash risk of the firms in the control groups, the liquidity of which remains unaffected by the policy shift, i.e., $(Crash^0_{i,t=1}|G_i = 0)$.

Closely following Fang, Tian and Tice (2014), the treatment group and the control group are identified based on the changes of our primary illiquidity measure from the pre-decimalization year $(d-1)$ to the post-decimalization year $(d+1)$, wherein d is a firm's fiscal year in which the decimalization occurred. Specifically, we sort firms into terciles based on $\Delta ILIQ_{d-1tod+1}$.[7] The top tercile forms the treatment group and consists of firms that experienced the largest drop in $ILIQ$. The third tercile, in which the firm's liquidity was least affected by the decimalization, serves as the control group.

Next, the propensity score matching (PSM) by Rosenbaum and Rubin (1983) provides a useful tool for matching individual firms within the treat-

[7]We focus on the change in liquidity one year before and after the implementation of the policy change to avoid the problem where using several years of serially-correlated data for DID may result in inconsistent standard errors (Bertrand, Duflo and Mullainathan (2004)).

ment group to a set of firms in the control group that are otherwise similar. This matching is conducted on the basis of a propensity score, which facilitates the comparison of firms across a high-dimensional set of pre-treatment characteristics. To estimate this propensity score, we first estimate a probit model for the pooled sample of the treatment and the control groups. The dependent variable is an indicator that takes the value of 1 if a firm belongs to the treatment group and 0 otherwise. For firm i, its probability (i.e., propensity score) of experiencing sizable drops in $ILIQ$ is thus

$$p_i = Pr(G_i = 1|Z) = \Phi(Z'_{d-1}\hat{\theta}), \tag{6}$$

where Φ is the cdf of the standard normal distribution, and $\hat{\theta}$ is the estimated coefficients from the probit model. The control variables Z include the pre-decimalization values of all regressors in our baseline regressions, X_{d-1}. We further control for the institutional holding (IH_{d-1}), which has been suggested as an important determinant of stock liquidity (e.g., Tinic (1972) and Hamilton (1978)).

In the context of our paper, the general form of the treatment effect estimated by PSM is

$$\frac{1}{N}\sum_{i\in\{G_i=1\}}\left(Crash_i - \sum_{j\in\{G_j=0\}}\omega(p_i,p_j)Crash_j\right), \tag{7}$$

where $\omega(\cdot)$ assigns the weights for the comparison firm j when constructing the counterfactual term for firm i in the treatment group.[8] The idea behind such kernel-weighted matching is to compare firm i in the treatment group to the entire control group and weight the firms in the control group by how similar they are to firm i. In our analysis, we employ the most commonly used Gaussian kernel function as the weighting scheme. Specifically,

$$\omega(p_i,p_j) \equiv \frac{\phi\left[\frac{p_i-p_j}{h}\right]}{\sum_{k\in\{G_k=0\}}\phi\left[\frac{p_i-p_k}{h}\right]}, \tag{8}$$

where $\phi(\cdot)$ is the PDF of the standard normal distribution and h is the bandwidth parameter.[9] A small h sharpens the kernel ω and causes most of the weights to be assigned to a few of the most similar (defined by the difference in propensity scores from firm i) firms in the control group.

[8]For more about kernel-based matching, see Heckman, Ichimura and Todd (1997 and 1998).

[9]For the nearest-neighbor matching, $\omega(p_i,p_j) = \min_{k\in\{G_k=0\}}\{|p_i - p_k|\}$.

Subsequently, the DID matching estimator is defined as follows:[10]

$$DID = \frac{1}{N} \sum_{i \in \{G_i=1\}} \left(\Delta Crash_i - \sum_{j \in \{G_j=0\}} \omega(p_i, p_j) \Delta Crash_j \right), \quad (9)$$

where $\Delta Crash$ is the difference in the crash risk proxy before and after decimalization. Intuitively, if high liquidity leads to greater crash risk, we would expect the first term on the right- hand side of equation (9) (the average induced change of crash risk in the treatment group) to be greater than that for the second term (the weighted average liquidity of firms in the control group, for which liquidity is the least affected by decimalization). Therefore, a positive and statistically significant DID estimator establishes a firm-level causal link from stock liquidity to future crash risk.

3.2.2. Balancing Tests of the Matching Procedures

The key assumption of the DID matching technique is that the PSM yields a valid and robust estimate if the pre-decimalization variables are "balanced" between the treatment and the control groups, so we can isolate the effect of decimalization and attribute any change in crash risk proxies to the decimalization variable. In other words, conditional on the propensity score, the potential outcomes $Crash^1_{i,t=1}$ and $Crash^0_{i,t=1}$ should be independent of decimalization; thus, the DID estimator is 0 in the absence of the treatment. Lack of balance indicates a potential mis-specification of the propensity score estimation and casts doubt on the DID estimator, as the inbalance might be partly driven by the pre-treatment differences of certain firm-specific characteristics.

Thus concretely, before decimalization, if there is a considerable difference in firm size between the treatment and the control groups, one might suspect that any subsequently observed differences in crash risk between the two groups could be attributed to the intrinsic difference in firm size. Hence, as Rosenbaum and Rubin (1993) and Dehejia and Wahba (2002) highlight, it is important to ensure that the various aspects of the firm characteristics are balanced before the treatment. This process will produce a study regime that resembles a randomized experiment in terms of

[10] Conceptually, DID is defined as $\mathbb{E}(Crash^1_{i,t=1} - Crash^0_{i,t=1} | G_i = 1) - \mathbb{E}(Crash^1_{i,t=1} - Crash^0_{i,t=1} | G_i = 0)$. To avoid matching a firm in the treatment group with firms in the control group that are all distant in terms of their propensity score, we discard the observations for which the minimum difference in propensity scores between the treatment and control groups is greater than the sample median. Alternatively, one may specify a tolerance limit for the matching procedure.

the observed covariates. We perform a number of balancing tests proposed by recent studies (Dehejia (2005) and Smith and Todd (2005)) to validate the matching procedures. The basic idea of these tests is to check whether firms with the same propensity score have the same mean of observable covariates independently of their treatment status.

We first check the balance between the treatment and the control group for each of the variables in Z (as in equation (6)) using the standardized difference proposed by Rosenbaum and Rubin (1985). For instance, the standardized difference of the pre-treatment $ILIQ_{d-1}$ is calculated as

$$SDiff(\%) = \frac{\frac{1}{N}\sum_{i\in\{G_i=1\}}(\Delta ILIQ_i - \sum_{j\in\{G_j=0\}}\omega(p_i,p_j)\Delta ILIQ_j)}{\sqrt{\frac{Var_{i\in\{G_i=1\}}(ILIQ_i)+Var_{j\in\{G_i=0\}}(ILIQ_j)}{2}}}\times 100, \tag{10}$$

where the numerator is the difference in means between the treatment group ($G = 1$) and the matched control group ($G = 0$); and the denominator is the square root of the average sample variances. A large value of SDiff suggests the existence of great discrepancy in the covariate between the treatment and the control group before decimalization, which might contribute to the post-decimalization difference in crash risk between the two groups. Therefore, a small value of $SDiff$ is desired for valid matching. In the absence of a formal criterion, Rosenbaum and Rubin (1985) suggest that a standardized difference that is greater than 20 should be considered "large" and raise concerns.

The second balancing check is the conventional paired t-test conducted for each covariate that is used to estimate the propensity score. After properly matching every firm in the treatment group with the firms in the control group, no significant difference is observed for each variable. Notably, prior to decimalization, the treatment and control firms have similar levels of liquidity ($ILIQ_{d-1}$) and also crash risk ($NCSKEW_{d-1}$).

So far, the testing for balance has been conducted for each of the covariates individually. However, we now use a joint test for the equality of means for all the covariates in the treatment and the control group. This test is known Hotelling's T-squared test (an F-test), and it can be used either for testing the entire sample or for testing separate segments of the sample partitioned by propensity score estimates. Similar to Grima and Görg (2007), this test is implemented for the sub-samples as divided by the propensity score median and the full sample.

Table 5, Panel A reports the summary of the standardized difference and the paired t-test for each of the covariates. We find that, after kernel matching, the treatment and the control group have very similar firm-specific characteristics in all respects. In particular, the two groups have similar means (Columns 1 and 2) and the standardized differences are all less than 10, suggesting that the matching procedures are successful. The paired t-test (Column 4) also fails to reject the null hypothesis indicating that there is no difference in each covariate between the two groups. The results for the Hotelling's T-squared test shown in Panel B further confirm the validity of our matching procedures, since the joint hypothesis stating that the differences between all covariates are 0 cannot be rejected at a conventional significance level. To conclude, the three balancing tests consistently indicate that the PSM procedure was properly executed in our study. Consequently, the DID estimator is an unbiased and reliable assessment of the impact of liquidity change on future crashes.

3.2.3. The DID Matching Estimates of the 2001 Decimalization

Having validated the accomplishment of proper matching, we report the DID estimates in Table 5, Panel C. Columns 1 and 2 show the average changes for each of the three crash risk proxies ($NCSKEW$, $DUVOL$ and $CRASH$) caused by 2001 decimalization for the treatment and the control group, respectively. Columns 3 and 4 present the DID estimates defined in equation (10) and the two-tailed t-test statistics for the null hypothesis that the DID estimates are zero. All of the DID estimates are significant at a conventional level. More specifically, these results indicate that, compared to firms in the control group, the $NCSKEW$ of the treated firms increased by 0.122 (or roughly 66% of the sample mean) after the exogenous shock in liquidity enhancement. We also have observed a dramatic jump in $DUVOL$, which suggests that the stock price experiences more large downside deviations. Further, the DID estimate of the indicator variable $CRASH$ shows that the treatment firms are 8.2% more likely to experience one or more crash weeks after decimalization than their counterparties will in the control group. Taken together, we find strong evidence that higher stock liquidity causes greater crash risk.

3.2.4. Further Evidence from the 1997 Tick Size Reduction

Similar to the 2001 change to decimal pricing, the 1997 decision to slash the tick size in half, from one-eighth of a dollar to one-sixteenth of a dollar, decreased transactions costs and increased liquidity (see, for example, Ronen and Weaver (2001) and Ricker (1998)). We thus utilize this exogenous shock in liquidity to examine the robustness of our findings.

TABLE 5.

DID Matching Estimates of 2001 Decimalization

Panel A. Balancing tests for kernel matching				
Variable	Treatment	Control	% Bias	T-stat (p-value)
$ILIQ_{d-1}$	−2.749	−2.659	−4.950	−1.083 (0.28)
$DTURN_{d-1}$	−0.006	−0.002	−2.596	−0.438 (0.66)
$NCSKEW_{d-1}$	0.164	0.124	5.048	0.813 (0.42)
$SIGMA_{d-1}$	0.084	0.081	6.725	1.224 (0.22)
RET_{d-1}	0.005	0.004	8.851	1.414 (0.16)
ROA_{d-1}	0.023	0.020	1.670	0.178 (0.86)
$SIZE_{d-1}$	5.558	5.485	5.898	1.054 (0.29)
MB_{d-1}	1.564	1.522	1.579	0.355 (0.72)
LEV_{d-1}	0.226	0.232	−2.573	−0.479 (0.63)
$ABACC_{d-1}$	0.122	0.119	1.431	0.194 (0.85)
IH_{d-1}	1.266	1.283	−1.533	−0.269 (0.79)
Panel B. Hotelling's T-squared test by propensity score				
Variable	T-squared stat	F-test stat	P-value	
1st half	17.24	1.465	0.151	
2nd half	17.23	1.464	0.151	
All	24.40	2.146	0.017	
Panel C. Difference-in-differences (DID) test				
Variable	Mean treatment effect (post minus pre)	Mean control effect (post minus pre)	Mean DID estimator (treatment minus control)	T-stat for the DID estimator
$NCSKEW$	0.247	0.124	0.122^{**}	2.050 (0.04)
$DUVOL$	0.144	0.076	0.068^{**}	2.508 (0.01)
$CRASH$	0.117	0.035	0.082^{**}	2.485 (0.01)

Table 5 presents test results for the exogenous shock of the 2001 decimalization. Panel A presents the mean, the standardized difference, and the paired t-test for each covariate in the treatment group and also the control group. The standardized difference is calculated using equation (10). Observations where the minimum difference of the propensity scores between the treatment and control groups is greater than the sample median are discarded. Panel B presents the results for Hotelling's T-Squared test based on the propensity score using two sub-samples and then the full sample. The subsamples are divided by the propensity score median. Panel C presents the result of our main DID test. Columns 1 and 2 show the average changes in the crash risk proxies caused by the 2001 decimalization of the treatment group and the control group, respectively. Columns 3 and 4 present the DID estimates and the two-tailed t-test results for the null hypothesis in that the DID estimates are zero.

As described in the previous sections, we identify the treatment and the control groups, performed a careful matching procedure and calculated the DID estimates for the 1997 liquidity shock. Table 6, Panels A and B report the balancing test results, and Panel C presents the DID estimates. As shown in Panel A, for each control variable that is used to calculate

TABLE 6.

DID Matching Estimates of 1997 Tick Size Reduction

Panel A. Balancing tests for kernel matching				
Variable	Treatment	Control	% Bias	T-stat (p-value)
$ILIQ_{d-1}$	−1.969	−1.832	9.349	−1.528 (0.13)
$DTURN_{d-1}$	−0.010	−0.024	9.734	1.270 (0.21)
$NCSKEW_{d-1}$	−0.001	0.059	8.181	−0.913 (0.36)
$SIGMA_{d-1}$	0.062	0.062	1.509	−0.208 (0.84)
RET_{d-1}	0.006	0.005	9.998	1.350 (0.18)
ROA_{d-1}	0.036	0.028	6.403	0.830 (0.41)
$SIZE_{d-1}$	5.106	4.983	11.42	1.516 (0.13)
MB_{d-1}	1.744	1.540	11.62	1.543 (0.12)
LEV_{d-1}	0.185	0.182	1.513	0.202 (0.840)
$ABACC_{d-1}$	0.093	0.090	3.287	0.436 (0.66)
IH_{d-1}	1.132	1.074	6.354	0.866 (0.39)
Panel B. Hotelling's T-squared test by propensity score				
	T-squared stat	F-test stat	P-value	
1st half	14.32	1.116	0.365	
2nd half	14.86	1.130	0.359	
All	12.06	1.013	0.439	
Panel C. Difference-in-differences (DID) test				
Variable	Mean treatment effect (post minus pre)	Mean control effect (post minus pre)	Mean DID estimator (treatment minus control)	T-stat for DID estimator
$NCSKEW$	0.265	0.059	0.206***	2.410 (0.02)
$DUVOL$	0.135	0.016	0.118***	3.190 (0.00)
$CRASH$	0.122	0.124	−0.002	−0.056 (0.95)

Table 6 presents test results for the exogenous shock of the 1997 regime shift (tick size reduction). Panel A presents the mean, the standardized difference, and the paired t test for each covariate in the treatment group and the control group. The standardized difference is calculated using equation (10). Observations where the minimum difference of the propensity scores between the treatment and control groups was greater than the sample median are discarded. Panel B presents the results for Hotelling's T-Squared test by propensity score, using two subsamples and then the full sample. The subsamples are divided by the propensity score median. Panel C presents the results of our main *DID* test. Columns 1 and 2 show the average changes in the crash risk proxies caused by the 1997 regime shift for the treatment group and the control group, respectively. Columns 3 and 4 present the *DID* estimates and the two-tailed t-test results for the null hypothesis that the *DID* estimates are zero.

the propensity score, the standardized difference is well below 20 and the null hypothesis of equal means in the treatment and control groups cannot be rejected at a 10% significance level. The Hotelling's T-squared test statistics reported in Panel B corroborates the success of our matching procedure since, for both the subsamples and the full sample, the joint hypothesis stating that the differences between all covariates are zero cannot be rejected at any conventional significance level.

Table 6, Panel C presents the DID estimates for the shock. Consistent with the results of the 2001 decimalization, we find that the treated firms experienced sizable jumps in their crash risk ($NCSKEW$ and $DUVOL$) compared with the control firms, and the DID estimates are significant at a 1% level. The estimate in $CRASH$ is less pronounced, which might be attributed to the observation by Fang, Tian and Tice (2014) that the 2001 decimalization introduced a greater liquidity boost than the 1997 tick change. Nevertheless, these results further substantiate the causal effect of stock liquidity on future crash risk.

4. POTENTIAL CHANNELS FOR THE LIQUIDITY EFFECT ON CRASH RISK

A few underlying economic channels have been suggested by recent studies, whereby high liquidity can pressure managers for short-term performance as well as provide strong incentives to conceal bad information that eventually causes future crashes. Particularly, the model by Jin and Myers (2006) suggests that when accumulated negative firm-specific information reaches a tipping point wherein managers cannot or will not conceal anymore, the sudden release of large amounts of negative information can cause stock price crashes. To the extent that high liquidity motivates the stockpiling of bad news, we hypothesize that liquidity deters full revelation of firm-specific information and subsequently causes crashes. Similar to the efforts of Hutton, Marcus and Tehranian (2009) and An and Zhang (2013), we measure the amount of firm-specific information disclosure by the R^2 of the expanded market model shown in equation (1). Higher return R^2 indicates greater price synchronicity and lower firm-specific return variations, as less firm-level information is incorporated into the stock prices (Roll (1988) and Morck, Yeung and Yu (2000)).

To examine the causal effect of liquidity on firm-level information disclosure, we employ the same DID matching estimation procedure introduced here in the previous section. First, using the matching sample for the 2001 decimalization (described in Section 3.2.2 and 3.2.3), we begin the balancing test to examine whether there is a significant difference in R^2 between the treatment firms and the matched control firms before decimalization. Table 7, Panel A1 shows that prior to decimalization, firms in the treatment and control groups have a similar average R^2. The standardized difference in R^2 is 7.6, which is less than 20, the threshold that raises concerns for unbalanced matching. Moreover, the t-test statistic for the equal means of R^2 yields an insignificant result, suggesting there is no significant difference in the information revelation between the two groups of firms before decimalization. Panel A2 presents the DID estimate. We also find that for the treatment group the liquidity shock reduces firm-level information release, as evidenced by a 7.2% increase in R^2. Compared to the matched control firms, the average R^2 of treatment firms is 1.5% higher (with a p-value of 8%), a result that is economically significant given that the sample average R^2 is 6.45%.

TABLE 7.

Effect of Liquidity on Firm-level Information Disclosure

Panel A: 2001 decimalization				
Panel A1				
	Treatment	Control	% Bias	T-stat (p-value)
R^2	0.157	0.165	7.600	−0.983 (0.33)
Panel A2				
	Mean treatment effect (post minus pre)	Mean control effect (post minus pre)	Mean DID estimator (treatment minus control)	T-stat for the DID estimator
R^2	0.072	0.057	0.015*	1.757 (0.08)
Panel B: 1997 tick size reduction				
Panel B1				
	Treatment	Control	% Bias	T-stat (p-value)
R^2	0.135	0.129	7.495	0.948 (0.34)
Panel B2				
	Mean treatment effect (post minus pre)	Mean control effect (post minus pre)	Mean DID estimator (treatment minus control)	T-stat for DID estimator
R^2	0.091	0.070	0.021**	2.044 (0.04)

Table 7 presents the difference in R^2 between the treatment and control groups before and after the liquidity interventions in 1997 and 2001, in order to isolate the effect of liquidity changes. Panel A1 compares the average R^2s of the control and treatment groups and tests the statistical significance of the difference between the two groups before the decimalization. Panel A2 reports the R^2s of the difference in means before and after the decimalization, and tests the statistical significance of the isolated effect of decimalization. Panels B1 and B2 repeats the same procedures for the tick size reduction in 1997 to provide further evidence of its causal effect.

Secondly, we replicate our analysis with R^2 using the matched samples constructed for the 1997 tick reduction (see Section 3.2.4). Consistently, we observe no significant difference in R^2 before the tick shift (shown in Panel B1). However, Panel B2 does show that, on average, firms in the treatment group greatly reduced information release, as confirmed by a 2.1% (with a p-value of 4.2%) larger increase in average R^2 values compared to the same changes in the control group. The results shown in Table 7 thus provide strong support for our hypothesis, namely, that high liquidity increases crash risk by reducing firm-specific information disclosure (i.e., by increasing R^2).

Our study, while among the first to identify the causal inference between liquidity and crash risk, also identifies firm-level information disclosure as an additional potential mechanism that might contribute to the adverse effects of stock liquidity on managerial myopia, producing both bad information hoarding and future price crashes. A number of other mechanisms that may explain the positive effect of liquidity on crashes are suggested in the recent literature, including equity-based managerial incentives (Fang, Noe and Tice (2009), Benmelech, Kandel and Veronesi (2010) and Kim, Li and Zhang (2011b)), increased exposure to hostile takeover, and the higher presence of non-dedicated institutional investors (Fang, Tian and Tice (2014)). Nonetheless, the channel of firm-level information disclosure identified by our study here is of great importance, as the recent literature does suggest that price crashes are due to the sudden release of accumulated negative, firm-specific information into the market.

5. CONCLUSION

This study investigates the impact of high stock liquidity on firm-level future crash risk and provides strong evidence of a causal link by using several econometric tests. In a multivariate regression setting, we find a robust and economically significant positive link from high liquidity to crash risk. To substantiate this causal effect, we conduct a difference-in-differences propensity score matching analysis to evaluate the causal effect of the 1997 and 2001 liquidity interventions on those firms' future crash risk. We find compelling evidence that liquidity hike leads to an increase in both the magnitude and the likelihood of future crashes. We subsequently identify the impact of liquidity on firm-level information revelation as a potential channel of the liquidity effect on crashes. We also provide a comprehensive analysis of the impact of stock liquidity on firm-level future stock price crashes. Our study further highlights the usefulness of nonparametric matching methods for finance and accounting research.

The benefits of increasing liquidity have been widely promoted by both the regulatory entities and researchers. On the one hand, there has been a series of regulatory changes in the equity market designed to improve liquidity and reduce transaction costs by tightening bid-ask spreads. On the other hand, other researchers (e.g., Amihud and Mendelson (1991) and Dass et al. (2011)) argue that companies can benefit by undertaking steps to increase their stock liquidity. Our study, however, highlights the potential cost of high liquidity for escalating stock price crash risk. So far, the dark side of liquidity enhancement has also raised concerns in the literature. Notably, Fang, Tian and Tice (2014) have documented that high liquidity impedes firm innovations, while Porter (1992) and Bhide (1993) show that liquidity leads to firms' long-term underinvestment. We join these research studies and further accentuate the potential adverse effects of liquidity promotion on managerial incentives and firm operations.

Further research could conduct empirical tests on the effect of hostile takeover pressure on crash risk. Moreover, scholars can extend the literature on the dark side of liquidity enhancement by exploring other channels through which higher liquidity can impede market efficiency and firm operations.

REFERENCES

Admati, A. R. and P. Pfleiderer, 2009. The "Wall Street Walk" and Shareholder Activism: Exit as a Form of Voice. *The Review of Financial Studies* **22(7)**, 2645-2685.

Amihud, Y. and H. Mendelson, 1986. Asset Pricing and the Bid-ask Spread. *Journal of Financial Economics* **17**, 223-249.

Amihud, Y. and H. Mendelson, 1989. The Effects of Beta, Bid-ask Spread, Residual Risk and Size on Stock Returns. *Journal of Finance* **44**, 479-486.

Amihud, Y. and H. Mendelson, 1991. Liquidity, Asset Prices and Financial Policy. *Financial Analysts Journal* **47(6)**, 56-66.

Amihud, Y., 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets* **5**, 31-56.

An, H. and T. Zhang, 2013. Stock Price Synchronicity, Crash Risk, and Institutional Investors. *Journal of Corporate Finance* **21**, 1-15.

Benmelech, E., E. Kandel, and P. Veronesi, 2010. Stock-based Compensation and CEO (Dis)Incentives. *The Quarterly Journal of Economics* **125(4)**, 1769-1820.

Besley, T. and R. Burgess, 2003. Halving Global Poverty. *The Journal of Economic Perspectives* **17(3)**, 3-22.

Bhide, A., 1993. The Hidden Costs of Stock Market Liquidity. *Journal of Financial Economics* **34**, 31-51.

Brennan, M. J. and A. Subrahmanyam, 1996. Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics* **41**, 441-464.

Brennan, M. J., T. Chordia, and A. Subrahmanyam, 1998. Alternative Factor Specifications, Security Characteristics, and the Cross-section of Expected Stock Returns. *Journal of Financial Economics* **49**, 345-373.

Butler, A. W., G. Grullon, and J. P. Weston, 2005. Stock Market Liquidity and the Cost of Issuing Equity. *Journal of Financial and Quantitative Analysis* **40(2)**, 331-348.

Chang, X., Y. Chen, and L. Zolotoy, 2017. Stock Liquidity and Stock Price Crash Risk. *Journal of Financial and Quantitative Analysis* 1-33.

Chen, J., H. Hong, and J. C. Stein, 2001. Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices. *Journal of Financial Economics* **61(3)**, 345-381.

Chordia, T., H. Sahn-Wook, and A. Subrahmanyam, 2009. Theory-Based Illiquidity and Asset Pricing. *Review of Financial Studies* **22**, 3629-3668.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001. Market Liquidity and Trading Activity. *The Journal of Finance* **56(2)**, 501-530.

Comment, R. and G. W. Schwert, 1995. Poison or Placebo? Evidence on the Deterrence and Wealth Effects of Modern Antitakeover Measures. *Journal of Financial Economics* **39(1)**, 3-43.

Dass, N., V. Nanda, and C. Xiao, 2011. Do Firms Choose Their Stock Liquidity? A Study of Innovative Firms and Their Stock Liquidity, Working Paper, Georgia Institute of Technology.

Dehejia, R., 2005. Practical Propensity Score Matching: A Reply to Smith and Todd. *Journal of Econometrics* **125(1)**, 355-364.

Dehejia, R. and S. Wahba, 1999. Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American Statistical Association* **94**, 1053-1062.

Dehejia, R. and S. Wahba, 2002. Propensity Score Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics* **84(1)**, 151-161.

Diamond, D. W. and R. E. Verrecchia, 1991. Disclosure, Liquidity, and The Cost of Capital. *The Journal of Finance* **46(4)**, 1325-1359.

Dimson, E., 1979. Risk Measurement When Shares Are Subject to Infrequent Trading. *Journal of Financial Economics* **7(2)**, 197-226.

Edmans, A., 2009. Blockholder Trading, Market Efficiency, and Managerial Myopia. *The Journal of Finance* **64(6)**, 2481-2513.

Edmans, A. and G. Manso, 2010. Governance Through Trading and Intervention: A Theory of Multiple Blockholders. *The Review of Financial Studies* **24(7)**, 2395-2428.

Eleswarapu, V. R., 1997. Cost of Transacting and Expected Returns in the NASDAQ Market. *Journal of Finance* **52**, 2113-2127.

Fang, V.W., A. H. Huang, and J. M. Karpoff, 2016. Short Selling and Earnings Management: A Controlled Experiment. *The Journal of Finance* **71(3)**, 1251-1294.

Fang, V.W., T. H. Noe, and S. Tice, 2009. Stock Market Liquidity and Firm Value. *Journal of Financial Economics* **94(1)**, 150-169.

Fang, V.W., X. Tian, and S. Tice, 2014. Does Stock Liquidity Enhance or Impede Firm Innovation? *The Journal of Finance* **69(5)**, 2085-2125.

Galiani, S., P. Gertler, and E. Schargrodsky, 2005. Water for Life: The Impact of the Privatization of Water Services on Child Mortality. *Journal of Political Economy* **113(1)**, 83-120.

Girma, S. and H. Görg, 2007. Evaluating the Foreign Ownership Wage Premium Using a Difference-in-Differences Matching Approach. *Journal of International Economics* **72(1)**, 97-112.

Goyenko, R.Y.,C. W. Holden, and C. A. Trzcinka, 2009. Do Liquidity Measures Measure Liquidity? *Journal of Financial Economics* **92(2)**, 153-181.

Goyenko, R.Y. and A. D. Ukhov, 2009. Stock and Bond Market Liquidity: A Long-Run Empirical Analysis. *Journal of Financial and Quantitative Analysis* **44(1)**, 189-212.

Hamilton, J. L., 1978. Marketplace Organization and Marketability: Nasdaq, the Stock Exchange and the National Market System. *The Journal of Finance* **33(2)**, 487-503.

Heckman, J. J., H. Ichimura, and P. E. Todd, 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program. *Review of Economic Studies* **64**, 605-654.

Heckman, J. J., H. Ichimura, and P. E. Todd, 1998. Matching as an Econometric Evaluation Estimator. *Review of Economic Studies* **65**, 261-294.

Holmström, B. and J. Tirole, 1993. Market Liquidity and Performance Monitoring. *Journal of Political Economy* **101(4)**, 678-709.

Hutton, A.P., A. J. Marcus, and H. Tehranian, 2009. Opaque Financial Reports, R2, and Crash Risk. *Journal of Financial Economics* **94(1)**, 67-86.

Jayaraman, S. and T. T. Milbourn, 2011. The Role of Stock Liquidity in Executive Compensation. *The Accounting Review* **87(2)**, 537-563.

Jensen, M.C. and W. H. Meckling, 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* **3(4)**, 305-360.

Jin, L. and S. C. Myers, 2006. R2 Around the World: New Theory and New Tests. *Journal of Financial Economics* **79(2)**, 257-292.

Kahn, C. and A. Winton, 1998. Ownership Structure, Speculation, and Shareholder Intervention. *The Journal of Finance* **53(1)**, 99-129.

Khanna, N. and R. Sonti, 2004. Value Creating Stock Manipulation: Feedback Effect of Stock Prices on Firm Value. *Journal of Financial Markets* **7(3)**, 237-270.

Kim, J.B., Y. Li, and L. Zhang, 2011. Corporate Tax Avoidance and Stock Price Crash Risk: Firm-level Analysis. *Journal of Financial Economics* **100(3)**, 639-662.

Kim, J.B., Y. Li, and L. Zhang, 2011. CFOs Versus CEOs: Equity Incentives and Crashes. *Journal of Financial Economics* **101(3)**, 713-730.

Kyle, A.S. and J. L. Vila, 1991. Noise Trading and Takeovers. *The RAND Journal of Economics* **22(1)**, 54-71.

Liu, X., Z. Liu, and Z. Qiu, 2013. Stock Market Manipulation in the Presence of Fund Flows. *Annals of Economics and Finance* **14(2)**, 483-491.

Maug, E., 1998. Large Shareholders as Monitors: Is There a Trade-off Between Liquidity and Control? *The Journal of Finance* **53(1)**, 65-98.

Mei, J.,J. A. Scheinkman, and W. Xiong, 2009. Speculative Trading and Stock Prices: Evidence from Chinese AB Share Premia. *Annals of Economics and Finance* **10(2)**, 225-255.

Morck, R., B. Yeung, and W. Yu, 2000. The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements? *Journal of Financial Economics* **58(1)**, 215-260.

Norli, Ø., C. Ostergaard, and I. Schindele, 2014. Liquidity and Shareholder Activism. *The Review of Financial Studies* **28(2)**, 486-520.

Porter, M., 1992. Capital Disadvantage: America's Failing Capital Investment System. *Harvard Business Review* **70(5)**, 65-82.

Ricker, Jeffrey P., 1998. Breaking the Eighth: Sixteenths on the New York Stock Exchange, Working Paper.

Roll, R., 1988. The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture of Distributions Hypothesis. *The Journal of Finance* **43(3)**, 541-566.

Ronen, T. and D. G. Weaver, 2001, "Teenies" Anyone? *Journal of Financial Markets* **4(3)**, 231-260.

Rosenbaum, P. R. and D. B. Rubin, 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* **70(1)**, 41-55.

Rosenbaum, P. R. and D. B. Rubin, 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician* **39(1)**, 33-38.

Smith, J. A. and P. E. Todd, 2005. Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators? *Journal of Econometrics* **125(1)**, 305-353.

Stein, J. C., 1988. Takeover Threats and Managerial Myopia. *Journal of Political Economy* **96(1)**, 61-80.

Stiglitz, J. E., 1985. Credit Markets and the Control of Capital. *Journal of Money, Credit and Banking* **17(2)**, 133-52.

Stiglitz, J. E., 1993. The Role of the State in Financial Markets. *The World Bank Economic Review* **7(suppl_1)**, 19-52.

Stuart, E. A.,H. A. Huskamp, K. Duckworth, J. Simmons, Z. Song, M. E. Chernew, and C. L. Barry, 2014. Using Propensity Scores in Difference-in-Differences Models to Estimate the Effects of a Policy Change. *Health Services and Outcomes Research Methodology* **14(4)**, 166-182.

Subrahmanyam, A. and S. Titman, 2001. Feedback from Stock Prices to Cash Flows. *The Journal of Finance* **56(6)**, 2389-2413.

Tinic, S. M., 1972. The Economics of Liquidity Services. *The Quarterly Journal of Economics* **86(1)**, 79-93.

Zhang, C. S., D. Y. Zhang, and J. Breece, 2011. Financial Crisis, Monetary Policy, and Stock Market Volatility in China. *Annals of Economics and Finance* **12(2)**, 371-388.