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Author(s)	Chang, Xin; Chen, Yangyang; Zolotoy, Leon
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Stock Liquidity and Stock Price Crash Risk

Xin Chang, Yangyang Chen, and Leon Zolotoy*

Abstract

We find that stock liquidity increases stock price crash risk. To identify the causal effect, we use the decimalization of stock trading as an exogenous shock to liquidity. This effect is increasing in a firm's ownership by transient investors and nonblockholders. Liquid firms have a higher likelihood of future bad earnings news releases, which are accompanied by greater selling by transient investors, but not blockholders. Our results suggest that liquidity induces managers to withhold bad news, fearing that its disclosure will lead to selling by transient investors. Eventually, accumulated bad news is released all at once, causing a crash.

I. Introduction

Crash risk in security prices has attracted increasing attention in recent years from a broad spectrum of parties, including academics, practitioners, and legislators. Recent high-profile corporate scandals (e.g., WorldCom, Enron, and Xerox) have triggered a rapidly growing stream of research that examines the mechanism of stock price crashes. These studies view the accumulation of bad news ("bad news hoarding") as the key factor in the formation of a stock price crash.[1] Incentives such as compensation contracts and career concerns induce firm management to conceal bad news from the market to preserve inflated share prices

*Chang, x.chang@jbs.cam.ac.uk and changxin@ntu.edu.sg, Cambridge Judge Business School, University of Cambridge, and Nanyang Business School, Nanyang Technological University; Chen (corresponding author), yangyang.chen@polyu.edu.hk, Faculty of Business, Hong Kong Polytechnic University; and Zolotoy, l.zolotoy@mbs.edu, Melbourne Business School, University of Melbourne. We thank Michael Chng, Ning Gong, Jarrad Harford, Elaine Hutson, John Lyon, Mark Maffett, Spencer Martin, Nadia Massoud, participants of the 2014 Auckland Finance Meeting and the 2015 Macquarie Global Quantitative Research Conference, and seminar participants at Deakin University, Monash University, the University of Adelaide, and the University of Melbourne. We are especially grateful to Hendrik Bessembinder (the editor) and two anonymous referees for the insightful comments and suggestions that have significantly improved the paper. We are also grateful to Hans Stoll and Christoph Schenzler of Vanderbilt University for providing the relative effective spread data, Brian Bushee for sharing the institutional investor classification data, and Fotis Grigoris for excellent research assistance.

[1]See, for example, Jin and Myers (2006), Bleck and Liu (2007), Hutton, Marcus, and Tehranian (2009), Benmelech, Kandel, and Veronesi (2010), Kim, Li, and Zhang (2011a), (2011b), and Callen and Fang (2015). We review the relevant literature in greater detail in Section II.A.

(Ball (2009), Kothari, Shu, and Wysocki (2009)). As unfavorable information accumulates and eventually reaches its upper limit, it is revealed at once, leading to large stock price declines.

We examine the relation between stock liquidity and stock price crash risk. Stock liquidity is generally defined as the ability to trade a significant quantity of a company's stock at a low cost in a short time (Holden, Jacobsen, and Subrahmanyam (2014)). Prior research has offered differing views on the impact of stock liquidity on crash risk. Governance theory suggests that higher stock liquidity may result in lower crash risk, because it facilitates monitoring of firm management by blockholders (e.g., Maug (1998), Edmans (2009)). More effective monitoring by blockholders reduces the likelihood of bad news formation due to inefficient investment decisions, thereby leading to lower crash risk. Moreover, higher stock liquidity enhances information production and informed trading (Holmstrom and Tirole (1993), Holden et al. (2014)). As stock prices become more informative about firms' economic fundamentals, managers should be less able to accumulate bad news for a substantial period of time, which, in turn, should lower crash risk.

However, a competing viewpoint is that higher stock liquidity results in higher crash risk. Prior research has advanced two potential mechanisms for this effect. First, short-termism theory suggests that, because of low trading costs, higher liquidity can attract more transient institutional investors with short investment horizons and excessive focus on firms' short-term performance (Porter (1992), Fang, Tian, and Tice (2014)). To avoid the downward stock price pressure exerted by these investors, managers may withhold bad news to inflate short-term earnings. Such an effect will lead to accumulation of bad news over time. Eventually, accumulated bad news is released all at once, triggering "cutting-and-running" selling by transient investors and causing a crash. Second, governance theory suggests that higher stock liquidity can facilitate blockholder exit (e.g., Edmans (2009)) when bad news is made public.[2] Heavy selling pressure from blockholders can magnify market responses to negative information about firms and cause stock prices to plunge.

In sum, prior research has offered competing views as to whether stock liquidity mitigates or exacerbates crash risk. Therefore, it is ultimately an empirical question as to which effect prevails. Using a large sample of U.S. firms for 1993–2010, we find strong support for the latter perspective. We use relative effective spread as our primary measure of stock liquidity (e.g., Fang, Noe, and Tice (2009)), and we capture crash risk using the likelihood of extremely low firm-specific weekly stock returns and negative skewness of stock returns (e.g., Chen, Hong, and Stein (2001), Hutton et al. (2009)). We document that stocks with higher liquidity (i.e., lower relative effective spreads) are more susceptible to crash risk, as reflected in a higher subsequent probability of extremely low

[2]Note that even though liquidity facilitates monitoring of firm management by blockholders, blockholder exit can still occur and result in crashes. Specifically, assume that firm value is determined by managerial efforts and exogenous shocks. Greater liquidity leads to a greater threat of exit and induces managers to exert greater efforts, leading to more efficient investment decisions and a lower likelihood of bad news formation. However, bad news can still happen due to negative shocks (e.g., bad industry conditions). Greater liquidity may facilitate blockholders' exit when bad news comes out if blockholders are more capable than other investors of processing news.

returns and more negatively skewed returns. The effect is economically meaningful: Increasing stock liquidity by 1 standard deviation increases the probability of a future stock price crash by 0.027 and raises negative skewness of stock returns by 0.047. Our results are robust to alternative measures of crash risk and stock liquidity.

We also perform several tests to address endogeneity concerns. Among these tests, we utilize the decimalization of stock trading as a positive exogenous shock to stock liquidity (e.g., Fang et al. (2009)). In 2001, the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotation (NASDAQ) began quoting and trading stocks in decimal increments (as opposed to increments of one-sixteenth of $1). Chordia, Roll, and Subrahmanyam (2008) show that after decimalization, firms experienced a substantial increase in stock liquidity. We document a significant increase in crash risk following the year of decimalization. Additional analysis reveals that the increase in crash risk is more pronounced for low-priced stocks, the liquidity of which is more affected by decimalization (Edmans, Fang, and Zur (2013)). To further ensure that the increase in crash risk is driven by decimalization instead of other confounding events in 2001, we compare the changes in crash risk around 2001 in the United States with those in major non-U.S. markets that did not experience an event comparable to decimalization. We find that the change in crash risk is significantly more positive for the U.S. market. The entirety of these results confirms the causal effect of stock liquidity on crash risk.

Having established the sign of and causality for the stock liquidity–crash risk relation, we further explore its potential mechanisms. As discussed above, such an effect can occur either through the transient investor channel (i.e., high stock liquidity exacerbates short-termism-induced bad news hoarding and subsequent cutting-and-running selling by transient institutional investors when bad news is released) or through the blockholder channel (i.e., with higher stock liquidity, blockholders, as informed investors, can sell their holdings more aggressively upon bad news). Because higher liquidity implies a lower price impact for a given sale volume, both channels implicitly require that in response to bad news releases, the selling pressure from investors (transient investors or blockholders) must be large enough to have a very negative price impact on liquid stocks.

We conduct several tests to assess the relative importance of the two channels in shaping the stock liquidity–crash risk relation. Collectively, the findings offer strong support for the transient investor channel, but not for the blockholder channel. Specifically, we document that the effect of stock liquidity on crash risk is stronger for firms with a higher proportion of transient institutional ownership, but not for those with higher blockholder ownership. Furthermore, we find that crash weeks are characterized by a higher intensity of very bad earnings news releases (e.g., extremely low unexpected earnings and/or negative management earnings guidance) than noncrash weeks and that higher liquidity is positively associated with the intensity of subsequent unexpected very bad earnings news releases. These results are consistent with the transient investor channel, which implies accumulation of bad news over time, until the point when all bad news is released at once and crash occurs. Finally, we examine the level of institutional selling during crash weeks and find it to be higher for firms with higher liquidity. Further analysis reveals that the positive effect of stock liquidity on abnormal institutional selling during crash weeks is stronger for firms with higher transient institutional ownership, but not for those with higher blockholder ownership. This result indicates that the abnormal institutional selling for liquid stocks during crash weeks is driven primarily by the cutting-and-running exit of transient institutions, instead of blockholders' exit. Taken together, our findings imply that stock liquidity increases crash risk not only because high liquidity increases short-termism pressure and induces managers to withhold bad news ex ante, but also because it facilitates the exit of transient institutions, thereby magnifying stock price responses to bad news releases ex post.

Our article contributes to the existing literature in several ways. First, we contribute to the stream of research that examines the determinants of stock price crash risk. There are growing concerns among academics and legislators that stock liquidity can cause instability in the capital markets (e.g., O'Hara (2004)).[3] Our findings provide firm-level evidence that these concerns are valid. In this context, our findings should be relevant for regulators, because stock liquidity can be altered by financial market regulations and securities laws (e.g., O'Hara (2004), Chordia, Roll, and Subrahmanyam (2008)). Furthermore, identifying stock liquidity as an important predictor of extreme return outcomes could be useful in risk management applications that focus on tail events and option pricing (e.g., Berkowitz and O'Brien (2002), Cohen, Cornett, Marcus, and Tehranian (2014)).

Second, our study extends prior research that examines the effect of stock liquidity on managerial short-termism. Studies such as Fang et al. (2014) focus primarily on how liquidity-induced short-term pressures can distort investment decisions. We provide new evidence from the context of bad news hoarding activities. Such activities avert timely disclosure of bad news, and can thus avoid disappointing transient institutional investors in the short run. But they can ultimately result in a "pile up" of bad news, and thus expose firms to higher crash risk in the long run.

Third, our results contribute to the market microstructure literature that examines the links between stock liquidity and stock price declines (e.g., Bernardo and Welch (2003), Brunnermeier and Pedersen (2009)). These studies suggest that substantial declines in stock prices can result in decreasing liquidity. Our findings imply that causality may also run in the opposite direction from stock liquidity to stock price crashes.

The remainder of the article is organized as follows: Section II reviews the relevant literature and develops our empirical predictions. Section III describes our data, variables, and summary statistics. Section IV reports our main findings regarding the effect of stock liquidity on crash risk, and Section V examines its potential mechanisms. Section VI concludes.

[3]Specifically, O'Hara ((2004), p. 1) points out that "there is debate as to whether liquidity fosters or retards financial market stability. This divergence reflects a deeper disagreement as to whether liquidity is best viewed as a virtue or a vice."

II. Related Literature and Empirical Predictions

A. Stock Price Crash Risk: A Brief Review of Prior Research

Corporate managers often possess higher levels of private information about firm operations, asset values, and future prospects than outside investors. As managers' decisions to disclose or conceal their private information are governed by a variety of incentives, their disclosure preferences are not perfectly aligned with those of outside investors (e.g., Healy and Palepu (2001), Kothari et al. (2009)). In particular, managers may tend to strategically withhold or delay the disclosure of bad news, gambling that it will ultimately be offset by subsequent good news. A number of studies suggest this tendency arises from managerial incentives such as career concerns (Kothari et al. (2009)), desire to maintain the esteem of peers (Ball (2009)), and equity-based incentives (Kim et al. (2011b)).[4] The survey evidence in Graham, Harvey, and Rajgopal (2005) also suggests chief financial officers (CFOs) delay bad news disclosure in the hope that firm status will improve before the required release date, which averts the need to disclose unfavorable information to the market.

However, bad news hoarding by firm management engenders crash risk because the amount of bad news a manager is willing or able to withhold is limited (Jin and Myers (2006)). As a sufficiently long run of bad news or bad performance accumulates and reaches a certain tipping point, managerial incentives for withholding bad news collapse and a large amount of negative firm-specific information comes out in one fell swoop, resulting in a crash.

Several theoretical studies link bad news hoarding to crash risk using an agency theory framework. Jin and Myers (2006) argue that when a firm is not completely transparent, its managers can capture a portion of cash flows in ways not perceived by outside investors. To protect their jobs, managers may absorb downside risk and losses caused by temporary firm performance by hiding firm-specific bad news until a crash occurs. Bleck and Liu (2007) argue that managers may prefer to keep bad projects for private benefits. To prevent investors and directors from taking timely abandonment actions, they may hide negative information using historical cost accounting. But the poor performance of bad projects accumulates over time and eventually materializes, leading to crashes. Using a hidden action model, Benmelech et al. (2010) show that stock-based compensation induces managers to conceal bad news about future growth options, which results in inflated stock prices and subsequent crashes.

As these theoretical studies suggest, bad news hoarding and crash risk are driven by conflicts of interest between managers and outside investors, which cause managers to hang on to bad projects or conceal bad performance to benefit themselves at the expense of shareholders. Consistent with these theoretical arguments, recent empirical studies provide strong support for the bad news hoarding theory of crash risk.[5]

[4]For additional analyses of the channels through which equity-based incentives can lead to strategic timing of corporate news releases, see Aboody and Kasznik (2000), Daines, McQueen, and Schonlau (2014), and Edmans, Goncalves-Pinto, Wang, and Groen-Xu (2014).

[5]These studies show that factors such as corporate tax avoidance (Kim et al. (2011a)), chief financial officer's (CFO's) equity incentives (Kim et al. (2011b)), chief executive officer (CEO)

B. Stock Liquidity and Crash Risk

Prior research suggests that stock price crash risk can occur when a large amount of bad news that was previously withheld by firm management is released at once. This implies that stock liquidity can influence crash risk by affecting 1 or more of the following 3 items: the likelihood of bad news formation (i.e., the likelihood that bad news arises because of managerial underperformance or a negative shock), the extent of managerial bad news hoarding (i.e., whether, once bad news arises, it is released or hoarded by managers), and the strength of the market response when bad news is revealed. Prior research on stock liquidity has offered two relevant theories on crash risk: governance theory and short-termism theory. Governance theory predicts that higher stock liquidity encourages investors' information production and informed trading, and enhances large shareholders' (i.e., blockholders') incentives and capability to monitor firms. Short-termism theory predicts that higher stock liquidity attracts transient investors and induces managers to engage in short-termist behavior. In what follows, we develop the predictions of these theories regarding the effects of stock liquidity on the three items associated with crash risk. For convenience, we summarize the predictions in Table 1.

We first discuss the links between stock liquidity and the likelihood of bad news formation. Governance theory suggests that higher stock liquidity enhances blockholders' monitoring of firm management, thus preventing managers from undertaking value-destroying projects. This reduces the likelihood of bad news formation. For example, Kahn and Winton (1998) and Maug (1998) show that stock liquidity encourages large shareholders' intervention through facilitating the accumulation of shares and increasing profits from intervention.[6] A more recent

TABLE 1

Predictions Regarding the Effect of Stock Liquidity on Crash Risk

Stock liquidity can influence crash risk if it affects at least 1 of the following 3 items: the likelihood of bad news formation, the extent of managerial bad news hoarding, and the strength of the market response to bad news releases. Based on prior research on stock liquidity, we consider two relevant theories for the effects of stock liquidity on crash risk: governance theory and short-termism theory. Governance theory predicts that higher stock liquidity encourages investors' information production and informed trading, and enhances blockholders' incentive and capability to monitor firms. Short-termism theory suggests that stock liquidity attracts transient investors and induces managers to engage in short-termist behavior. Table 1 lists the predictions of the two theories regarding the effects of stock liquidity on the 3 crash risk items. "Increase" ("Decrease") indicates that higher stock liquidity increases (decreases) the extent of the crash risk item. "NA" indicates that there is no clear prediction. "Ambiguous" indicates that the net effect of stock liquidity on the crash risk item is unclear because of conflicting predictions. The last column summarizes the net effect of stock liquidity on crash risk for each theory.

Theory	Bad News Formation	Bad News Hoarding	Market Response to Bad News Releases	Net Effect on Crash Risk
Governance theory	Decrease	Decrease	Ambiguous	Ambiguous
Short-termism theory	N/A	Increase	Increase	Increase

overconfidence (Kim, Wang, and Zhang (2016)), opaque financial reports (Hutton et al. (2009)), international financial reporting standards (DeFond, Hung, Li, and Li (2015)), and religiosity (Callen and Fang (2015)) are associated with crash risk in a manner consistent with managers' tendencies to conceal bad news.

[6]Specifically, higher stock liquidity makes blockholders more able to purchase additional shares (before intervention) at a price that does not yet reflect the benefits of intervention. Consequently, higher stock liquidity increases blockholder's profits from intervention and encourages blockholders' intervention.

stream of research emphasizes how stock liquidity can strengthen blockholder governance via exit, namely, selling a firm's stock based on private information (e.g., Edmans (2009), Edmans and Manso (2011)). Because managerial compensation is typically linked to stock prices, ex post, managers suffer from low stock prices caused by informed blockholders selling shares. Therefore, ex ante, the threat of blockholder exit induces managers to act in the best interest of shareholders, deterring managers from engaging in value-destructive behavior (Admati and Pfleiderer (2009)).

Next, we outline potential interplays between stock liquidity and the extent of bad news hoarding by firm management. Governance theory predicts that higher stock liquidity alleviates bad news hoarding. Holmstrom and Tirole (1993) show that the marginal value of information acquisition goes up with stock liquidity because informed investors can profit from private information by trading against liquidity traders. Therefore, higher stock liquidity increases investors' information production, enhances informed trading, and improves the information content of stock prices.[7] In addition, Edmans (2009) argues that higher stock liquidity encourages costly information acquisition and more aggressive trading on private information by blockholders. By making stock prices more informative about firms' economic fundamentals, enhanced information discovery and informed trading can weaken managers' ability to pile up bad news for a substantial period of time.

In contrast, short-termism theory implies that stock liquidity exacerbates bad news hoarding by inducing short-termism pressures. Porter (1992) notes that a large percentage of U.S. institutional investors are transient institutions, chasing short-term price appreciation and exiting in response to low reported earnings. High-liquidity stocks attract transient investors because low trading costs facilitate their entry and exit (e.g., Fang et al. (2014)). Bushee (1998), (2001) shows that transient institutions tend to favor firms with greater expected short-term earnings, pressuring managers into an overly short-term focus. In response, short-term-focused managers may pile up bad news to avert the hit to reported earnings and avoid the negative impact of transient investors' selling pressure on current stock prices. Consistent with this, Matsumoto (2002) documents that firms with higher transient institutional ownership are more likely to manage earnings upward to meet earnings targets or exceed analyst forecasts.

Finally, we explore the impact of stock liquidity on the strength of market responses to bad news. Higher stock liquidity reduces the exit costs for unhappy stockholders (e.g., Bhide (1993)) and thus amplifies market responses to unfavorable information. The short-termism theory of stock liquidity implies that higher stock liquidity should magnify the response of transient institutional investors to bad news releases, inducing a cutting-and-running type of selling that can lead to crashes. However, governance theory's predictions about how liquidity affects market responses to bad news releases are less clear. To the extent that informed investors trade primarily on private rather than public information,

[7]Consistent with this, prior studies document that stock liquidity reduces stock mispricing (Chordia et al. (2008), Boehmer and Kelley (2009)), increases the use of equity-based compensation (Jayaraman and Milbourn (2012)), and reduces reliance on board independence (Ferreira, Ferreira, and Raposo (2011)).

their trading responses to public bad news releases should be weak, as the news is already incorporated in stock prices, especially when the bad news is interpreted unambiguously by investors. Conversely, if information advantage makes blockholders more capable of processing bad news disclosures than other investors, we would expect to observe strong stock selling by blockholders upon bad news releases. Edmans (2009), (2014) shows that stock liquidity facilitates initial block formation and allows blockholders to trade more aggressively based on their information. As a result, blockholders' exit may also amplify the market responses to bad news and cause stock price crashes.[8]

To summarize, there are competing predictions regarding the effect of stock liquidity on crash risk. On the one hand, higher stock liquidity can reduce the likelihood of bad news formation by enhancing blockholder governance through either intervention or the threat of exit. It can also constrain managers' ability to pile up bad news by encouraging information production and improving stock price informativeness. Furthermore, higher stock liquidity can mitigate trading responses of informed investors to bad news releases. These arguments suggest that higher stock liquidity results in lower crash risk. On the other hand, higher stock liquidity can also attract more transient institutional investors whose short-term focus pressures managers to pile up bad news, and facilitate cutting-and-running selling by transient investors when accumulated bad news is, eventually, released all at once. Further, it can magnify the market responses to bad news releases by facilitating blockholders' exit upon bad news. These arguments predict that higher stock liquidity results in higher crash risk. Therefore, it is not clear a priori which effect will prevail, and there is a need for empirical evidence to inform theory.

III. Variables and Data

A. Sample Selection

We obtain our data from multiple sources. Data for constructing the stock liquidity measure come from the Trade and Quote (TAQ) database. Stock prices and returns come from the Center for Research in Security Prices (CRSP). We obtain firm financial information from the merged Compustat/CRSP database, institutional holdings data from Thomson Reuters Institutional Holdings (13f), institutional investor classification data from Brian Bushee's Web site,[9] and earnings forecasts and guidance data from the Institutional Brokers' Estimate System (IBES).

Following Kim et al. (2011a), we exclude observations with negative book value of equity, year-end stock prices less than \$1, or fewer than 26 weeks of stock return data. We further exclude observations with insufficient information for constructing the crash risk measures and those with missing values for stock liquidity or control variables. Following common practice, we winsorize all

[8]It is plausible that if blockholders' exit is sufficiently strong, it may outweigh the negative effect of stock liquidity on bad news formation through the threat of exit, thereby turning the relation between stock liquidity and crash risk into a positive one.

[9]http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

variables (except the crash dummy) in regression analyses at both the 1st and 99th percentiles to mitigate the effect of outliers. Our final sample consists of 58,533 firm-year observations for 9,285 U.S. firms for 1993–2010.

B. Crash Risk Measures

To construct our crash risk measures, we build on Jin and Myers (2006) who define a stock price crash as a remote, negative outlier in a firm's residual stock return. Accordingly, we compute residual stock returns and measure crash risk using two common metrics: the crash dummy and negative skewness. Specifically, we first calculate firm-specific weekly returns from the following expanded index model regression for each firm-year (Hutton et al. (2009)):

$$(1) \qquad r_{i,t} = \beta_0 + \beta_1 r_{\mathrm{MKT},t-1} + \beta_2 r_{\mathrm{IND},t-1} + \beta_3 r_{\mathrm{MKT},t} + \beta_4 r_{\mathrm{IND},t} + \beta_5 r_{\mathrm{MKT},t+1} + \beta_6 r_{\mathrm{IND},t+1} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return on stock i in week t, r_{MKT_t} is the return on the CRSP value-weighted market index, r_{IND_t} is the return on Fama and French's (1993) value-weighted industry index, and $\varepsilon_{i,t}$ is the error term. We include the lead and lag market and industry index returns to account for nonsynchronous trading (Dimson (1979)). Following prior research (e.g., Chen et al. (2001), Hutton et al. (2009)), we estimate the firm-specific weekly return, $W_{i,t}$, as the natural log of 1 plus the regression residual (i.e., $W_{i,t} = \ln(1+\varepsilon_{i,t})$). We obtain similar (untabulated; available from the authors) results by estimating crash risk measures using raw residual returns.

The first measure, crash dummy (CRASH), equals 1 if a firm experiences 1 or more crash weeks over the fiscal year, and 0 otherwise. Following Hutton et al. (2009), we define crash weeks as those when a firm experiences firm-specific weekly returns that are 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year. The number 3.09 is chosen to generate a 0.1% frequency in the normal distribution. In Section IV.C, we experiment with alternative definitions of crash weeks and obtain similar results.

We compute our second measure, negative skewness (NSKEW), by following Chen et al. (2001) and Kim et al. (2011a), (2011b). NSKEW for each firm-year is the ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by -1, as shown below:

$$(2) \qquad \mathrm{NSKEW}_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{3/2}}.$$

A higher value of NSKEW implies a more left-skewed return distribution and thus a more "crash-prone" stock.

C. Stock Liquidity Measure

Our primary measure of stock liquidity, the relative effective spread, is generally considered to be among the best liquidity measures (e.g., Fang et al. (2009), Fang et al. (2014)). It is constructed using high-frequency trading data and is often used as the benchmark for liquidity measures constructed using low-frequency data (e.g., Hasbrouck (2009), Goyenko, Holden, and Trzcinka (2009)). It is the ratio of the absolute value of the difference between the trade price and the midpoint of the bid–ask quote over the trade price. The data are from Vanderbilt University's Financial Markets Research Center, which computes daily relative effective spread for a given stock as the trade-weighted average of the relative effective spreads of all trades for a given stock during the day, as per TAQ. To obtain the annual relative effective spread, we take the arithmetic mean of the daily spreads over the firm's fiscal year. Because a higher relative effective spread indicates lower stock liquidity, we define stock liquidity (LIQ) as the annual relative effective spread multiplied by −1. For ease of interpretation, we multiply stock liquidity by 100. The robustness tests described in Section IV.C show that our findings are robust to alternative liquidity measures.

D. Control Variables

Our selection of control variables follows the prior literature. We use stock return volatility (SIGMA), past stock returns (RET), and past stock turnover (DTURN), because Chen et al. (2001) show that these variables are positively associated with crash risk. We control for firm size (SIZE) using market capitalization, and growth opportunities using the market-to-book ratio (MB) because Chen et al. and Hutton et al. (2009) find that these two variables are positively correlated with crash risk. We further control for leverage (LEV) and return on assets (ROA) because Hutton et al. document their negative correlations with crash risk. We include discretionary accruals (ACCM) as Hutton et al. show that firms with higher levels of ACCM are more prone to crashes.[10] Finally, we control for lagged NSKEW, as Chen et al. find that stock return skewness is persistent over time. Detailed definitions of these variables are in the Appendix.

E. Descriptive Statistics

Table 2 reports the number of observations by year, as well as the mean values of crash dummy, negative skewness, stock liquidity, and firm-specific stock returns on crash weeks for each year. The mean crash dummy (the proportion of firms experiencing at least 1 crash over the year) is higher during the 2000s than in the 1990s, possibly because of the dot-com bubble burst and the recession of 2008–2009. A similar trend is observed for mean negative skewness. Mean stock liquidity increases from −1.21 in 1993 to −0.345 in 2010, suggesting a substantial improvement in market liquidity over our sample period. The mean firm-specific weekly stock return on crash weeks is −24.7%. Furthermore, (untabulated) results show that 95% of firms in our sample that experienced stock price crashes have firm-specific returns lower than or equal to −7.8% during crash weeks. These observations suggest that our crash risk definition captures substantially negative events for firms' stock prices.

[10]Based on these results, Hutton et al. (2009) conclude that opacity of firm's financial statements allows managers to obscure negative information about underlying fundamentals. However, because a financial statement's bottom line is only one of many ways to convey information (Lambert (2010)), managers may use a variety of methods other than managing firm's earnings to withhold bad news from investors (Kim et al. (2011b)).

TABLE 2
Distribution by Year for Key Variables

Table 2 presents the sample distribution by year and mean values of the crash risk measures, stock liquidity, and firm-specific stock returns on crash weeks for each year. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is the ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by −1. Firm-specific stock returns on crash weeks are the raw residual weekly returns calculated using equation (1). All variables are winsorized at both the 1st and 99th percentiles.

Year	No. of Obs.	CRASH	NSKEW	LIQ	Residual Return on Crash Weeks
1993	2,531	0.148	−0.060	−1.210	−0.220
1994	2,755	0.148	−0.055	−1.209	−0.219
1995	2,961	0.142	−0.089	−1.125	−0.216
1996	3,202	0.147	−0.083	−1.093	−0.242
1997	3,308	0.161	−0.069	−0.936	−0.262
1998	3,423	0.180	0.000	−0.874	−0.282
1999	3,359	0.153	−0.075	−0.842	−0.306
2000	3,330	0.185	0.052	−0.859	−0.352
2001	3,182	0.184	0.080	−0.647	−0.297
2002	3,149	0.229	0.170	−0.567	−0.293
2003	3,247	0.180	−0.033	−0.423	−0.213
2004	3,359	0.207	0.003	−0.358	−0.206
2005	3,225	0.228	0.018	−0.302	−0.189
2006	3,658	0.220	−0.003	−0.275	−0.184
2007	3,605	0.213	0.031	−0.263	−0.204
2008	3,513	0.260	0.213	−0.487	−0.298
2009	3,325	0.193	0.015	−0.490	−0.256
2010	3,401	0.181	−0.022	−0.345	−0.184
Total	58,533	0.188	0.008	−0.664	−0.247

Table 3 presents the summary statistics and the Pearson correlation matrix of variables. Panel A shows that, on average, 18.8% of firm-years in our sample experience 1 or more crash weeks during the fiscal year. This and other summary statistics are generally in line with those reported in prior research (e.g., Hutton et al. (2009), Kim et al. (2011a), (2011b)). Panel B shows that the two crash risk measures are significantly correlated. Moreover, both crash dummy and negative skewness are positively correlated with stock liquidity.

IV. Stock Liquidity and Crash Risk: Main Results

A. Univariate Analysis

We begin by plotting crash dummy and negative skewness against stock liquidity. First, we divide the entire sample into deciles by 1-year lagged stock liquidity. We then calculate the mean values of the two crash risk measures for each liquidity decile. Finally, we plot the mean values against deciles from lowest to highest. Graph A of Figure 1 shows an increasing trend in the crash dummy as liquidity increases. We observe a similar trend for negative skewness. For both measures, the difference between the mean values of crash risk for firms in the 1st versus 10th deciles of stock liquidity is statistically significant (smallest t-statistic $= 13.898$).

Because stock liquidity in our sample is significantly correlated with firm size, we repeat our analysis using residual stock liquidity deciles to ensure that

TABLE 3

Summary Statistics and Correlation Matrix

Table 3 presents the summary statistics and correlation matrix. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. Other variable definitions are in the Appendix. * and *** indicate statistical significance at the 10% and 1% levels, respectively.

Panel A. Summary Statistics

			Percentiles				
Variable	Mean	Std. Dev.	5th	25th	50th	75th	95th
CRASH	0.188	0.391	0.000	0.000	0.000	0.000	1.000
NSKEW	0.008	0.762	−1.140	−0.417	−0.028	0.372	1.310
LIQ	−0.664	0.826	−2.360	−0.907	−0.332	−0.112	−0.037
SIGMA	0.057	0.031	0.020	0.034	0.050	0.072	0.117
RET	−0.206	0.250	−0.671	−0.255	−0.123	−0.057	−0.019
DTURN	0.006	0.103	−0.129	−0.021	0.001	0.028	0.154
SIZE	6.066	2.040	2.961	4.554	5.949	7.400	9.713
MB	2.801	4.478	0.476	1.178	1.898	3.250	8.561
LEV	0.174	0.190	0.000	0.005	0.120	0.280	0.537
ROA	0.011	0.184	−0.307	−0.003	0.038	0.086	0.198
ACCM	0.358	0.346	0.043	0.135	0.259	0.463	0.787

Panel B. Correlation Matrix

	CRASH	NSKEW	LIQ	SIGMA	RET	DTURN	SIZE	MB	LEV	ROA	ACCM
CRASH	1.000										
NSKEW	0.622***	1.000									
LIQ	0.066***	0.099***	1.000								
SIGMA	0.102***	0.059***	−0.339***	1.000							
RET	−0.076***	−0.023***	0.284***	−0.950***	1.000						
DTURN	0.030***	0.023***	0.046***	0.138***	−0.163***	1.000					
SIZE	0.017***	0.083***	0.560***	−0.468***	0.376***	0.034***	1.000				
MB	−0.032***	−0.032***	0.086***	0.043***	−0.053***	0.061***	−0.058***	1.000			
LEV	−0.007*	0.001	0.066***	−0.056***	0.047***	0.014***	0.239***	−0.085***	1.000		
ROA	−0.013***	−0.005	0.134***	−0.375***	0.377***	0.039***	0.219***	−0.032***	−0.057***	1.000	
ACCM	0.019***	0.015***	−0.001	0.263***	−0.239***	0.001	−0.188***	0.090***	−0.024***	−0.191***	1.000

the pattern in Graph A of Figure 1 is not driven by the high correlation between stock liquidity and firm size. Residual stock liquidity is the regression residual of stock liquidity against firm size (SIZE). Graph B shows that both crash risk measures increase monotonically with residual stock liquidity. The difference between the mean values of crash risk for firms in the 1st versus 10th deciles is statistically significant (smallest t-statistic = 10.662). Collectively, these findings provide preliminary evidence for the positive relation between stock liquidity and crash risk. Although interesting, these unconditional relations require more refined multivariate tests, which we turn to next.

B. Regression Analysis

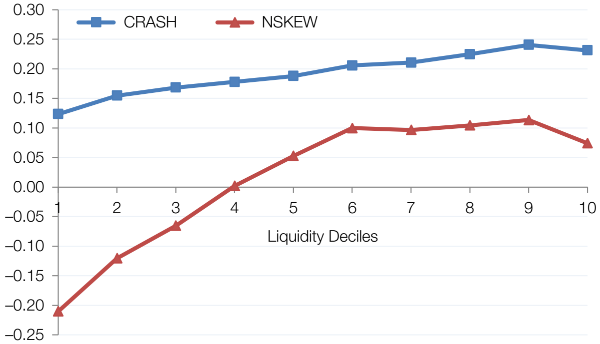
In this section, we perform regression analyses to examine the relation between stock liquidity and crash risk. The regression specifications are as follows:

FIGURE 1

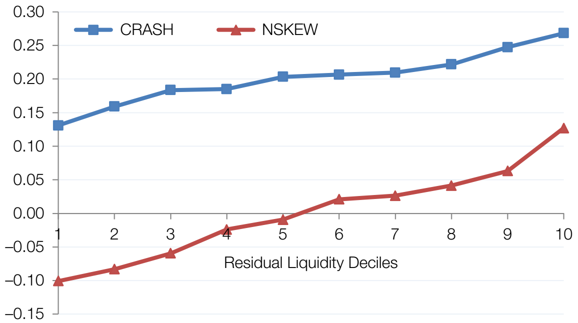
Plot of Crash Risk Measures for Stock Liquidity Deciles

Figure 1 presents the mean values of crash risk measures for raw and residual stock liquidity deciles (from lowest to highest). Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. Residual stock liquidity is the residual from regressing stock liquidity against firm size (SIZE). The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is the ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by −1.

Graph A. Stock Liquidity Deciles



Graph B. Residual Stock Liquidity Deciles



$$\begin{aligned}
\text{(3a)}\quad \text{CRASH}_{i,t} = {} & \beta_0 + \beta_1\text{LIQ}_{i,t-1} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} \\
& + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} \\
& + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} \\
& + \text{YR}_t + \text{IND}_i + \varepsilon_{i,t},
\end{aligned}$$

$$\begin{aligned}
\text{(3b)}\quad \text{NSKEW}_{i,t} = {} & \beta_0 + \beta_1\text{LIQ}_{i,t-1} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} \\
& + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} \\
& + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} \\
& + \text{YR}_t + \text{IND}_i + \varepsilon_{i,t}.
\end{aligned}$$

Here, i denotes the firm, t denotes the year, YR_t denotes the year fixed effects, IND_i denotes the industry fixed effects based on 2-digit Standard Industrial

Classification (SIC) codes, and $\varepsilon_{i,t}$ is the error term. We estimate equation (3a) using the logit model and equation (3b) using ordinary least squares (OLS). Both z- and t-statistics are computed using standard errors adjusted for heteroskedasticity and clustering at the firm level. Because all explanatory variables are lagged 1 year, the sample size for these tests is reduced from 58,533 (as in Table 2) to 48,176 observations.

Table 4 gives the baseline regression results. Column 1 shows the results for the crash dummy. The coefficient of stock liquidity is positive and statistically significant (z-statistic $= 7.439$), suggesting that firms with higher liquidity are more likely to experience a stock price crash in the future. The marginal effect of stock liquidity on crash dummy (evaluated at the mean values of the explanatory variables) is 0.033, suggesting that a 1-standard-deviation rise in stock liquidity (i.e., 0.826) is associated with a $0.826 \times 0.033 = 0.027$ increase in crash probability. Given that our sample mean of crash dummy is 0.188, the effect of stock liquidity on crash risk is not only statistically significant, but also economically meaningful.

TABLE 4

Stock Liquidity and Crash Risk: Main Results

Table 4 presents regression results for the relation between stock liquidity and crash risk. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. Other variable definitions are in the Appendix. All variables are winsorized the variables at both the 1st and 99th percentiles. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effects are included in the regressions. The regression in column 1 is estimated using logit; that in column 2 is estimated using ordinary least squares. $z(t)$-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$CRASH_t$	$NSKEW_t$
Variable	1	2
LIQ_{t-1}	0.216***	0.057***
	(7.439)	(9.008)
$NSKEW_{t-1}$	0.055***	0.022***
	(3.423)	(4.176)
$SIGMA_{t-1}$	7.102***	5.231***
	(4.345)	(11.745)
RET_{t-1}	0.980***	0.574***
	(4.880)	(11.094)
$DTURN_{t-1}$	0.448***	0.207***
	(3.805)	(5.743)
$SIZE_{t-1}$	0.015	0.045***
	(1.540)	(16.040)
MB_{t-1}	0.008***	0.004***
	(2.957)	(5.048)
LEV_{t-1}	−0.034	−0.012
	(−0.467)	(−0.539)
ROA_{t-1}	−0.313***	−0.124***
	(−4.074)	(−4.707)
$ACCM_{t-1}$	0.079**	0.023*
	(2.055)	(1.792)
No. of obs.	48,176	48,176
R^2	0.021	0.041

Column 2 of Table 4 shows the results for negative skewness. The coefficient of stock liquidity is positive and statistically significant (t-statistic = 9.008), which suggests that future stock returns of firms with higher liquidity are, on average, more negatively skewed. In terms of economic significance, increasing stock liquidity by 1 standard deviation (0.826) raises negative skewness by $0.826 \times 0.057 = 0.047$. To put this in perspective, a 1-standard-deviation increase in MB, which is shown in prior studies (e.g., Chen et al. (2001)) to be one of the most important determinants of crash risk, increases negative skewness by $4.478 \times 0.004 = 0.018$. Overall, these findings further confirm a positive and significant association between stock liquidity and crash risk.

The results for control variables are largely consistent with the prior literature. Specifically, crash risk is positively associated with past stock returns, stock turnover, market-to-book ratio, stock return volatility, and discretionary accruals. It is negatively correlated with firm profitability. Untabulated statistics show that the largest variance inflation factor (VIF) is below 5, suggesting that multicollinearity does not pose a serious problem in our setting (O'Brien (2007)).

C. Robustness Tests

We conduct further analyses to ensure our baseline results are robust to alternative model specifications and variable definitions. We report the results in Table 5. For brevity, we tabulate only the coefficients of stock liquidity.

We begin by considering alternative measures of crash risk and conduct three sets of analyses. In the first set, we use alternative firm-specific thresholds to identify crash weeks. The purpose is to mitigate the concern that our results may be driven by a particular threshold (3.09 standard deviations) used in defining the crash risk dummy. Specifically, we define crash weeks as those weeks during which a firm experiences firm-specific weekly returns that are 3.5, 4, or 4.5 standard deviations below the mean firm-specific weekly returns over the fiscal year. In the second set, we use general instead of firm-specific thresholds to identify crash weeks. Firm-specific thresholds are subject to the concern that, for example, 3.09 standard deviations below mean returns may not be economically significant enough to be a crash for stocks with low volatility. To mitigate this concern, we alternatively define crash weeks as those during which firms experience firm-specific weekly returns that are below −10%, −15%, or −20%. Finally, we consider the number of crash weeks within a fiscal year as an alternative measure of crash risk. Although the crash dummy has been widely used in prior research (e.g., Hutton et al. (2009), Kim et al. (2011a), (2011b)), it is expected to have less variation in the outcomes, and thus to be less informative, than the number of crash weeks over a fiscal year. However, our (untabulated) results indicate that the number of observations with more than 1 crash week is very small (less than 0.6% of the sample), consistent with the notion that the crash dummy captures a rare negative stock event. Thus, using the number of crashes within a year as the dependent variable in the OLS regression is empirically very similar to estimating a binary choice model using the crash dummy as the dependent variable. Nevertheless, for completeness we reestimate equation (3a) using OLS and using the number of crashes as the dependent variable. The results of these tests are tabulated in Panel A of Table 5. For each test, the coefficient for stock liquidity

TABLE 5
Stock Liquidity and Crash Risk: Additional Analysis

Table 5 presents the results for the robustness tests. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. Other variable definitions are in the Appendix. The constant terms, control variables, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effects are included in all regressions. $z(t)$-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Coefficients of Stock Liquidity	
	$CRASH_t$	$NSKEW_t$
	1	2
Panel A. Alternative Definitions of Crash Risk		
(1) 3.5 standard deviations below the mean	0.213***	—
	(7.241)	—
(2) 4 standard deviations below the mean	0.182***	—
	(7.352)	—
(3) 4.5 standard deviations below the mean	0.181***	—
	(7.346)	—
(4) Firm-specific return below −10%	0.237***	—
	(6.869)	—
(5) Firm-specific return below −15%	0.215***	—
	(6.986)	—
(6) Firm-specific return below −20%	0.203***	—
	(7.373)	—
(7) No. of crash weeks as the dependent variable	0.026***	—
	(7.648)	—
Panel B. Alternative Stock Liquidity Measures		
(1) Price impact (Amihud (2002))	0.002***	0.001***
	(6.439)	(10.250)
(2) Implicit bid–ask spread (Hasbrouck (2009))	0.191***	0.043***
	(7.613)	(7.508)
(3) Percentage of zero returns (Lesmond (2005))	0.022***	0.009***
	(7.778)	(11.208)
Panel C. Additional Controls		
(1) Including firm fixed effects	0.122***	0.036***
	(2.749)	(2.812)
(2) Including additional control variables	0.733***	0.145**
	(2.633)	(2.435)

is positive and significant (smallest z-statistic for the crash dummy = 6.869 and t-statistic for the number of crashes = 7.648), suggesting that our findings are robust to alternative measures of crash risk.

Next, we consider the possibility that the documented stock liquidity–crash risk relation is driven by our choice of stock liquidity measure. To alleviate this concern, we consider the following alternative measures of stock liquidity: Amihud's (2002) price impact measure, Hasbrouck's (2009) implicit bid–ask spread measure, and Lesmond's (2005) percentage of zero daily returns measure.[11] We again multiply each measure by −1 so that higher values imply higher liquidity.

[11] Amihud's (2002) price impact measure captures the stock price changes per $millions of trading volume. The implicit bid–ask spread is the Gibbs sampler estimate of the square root of the negative daily autocorrelation of individual stock returns. Implicit bid–ask spread data are from Joel Hasbrouck's Web page (http://people.stern.nyu.edu/jhasbrou/Research/). The percentage of zero daily

The results are in Panel B of Table 5. The coefficient of stock liquidity is positive and significant for each liquidity measure in both the crash dummy and negative skewness regressions (smallest z-statistic = 6.439 and smallest t-statistic = 7.508). This suggests our findings are robust across alternative measures of stock liquidity.

For completeness, we conduct several additional (untabulated) tests. The results show that our findings are robust to using down–up volatility as an alternative measure of crash risk (Chen et al. (2001)),[12] excluding the recent financial crisis (2008–2009) to address the concern that our results may be driven by the excess market volatility during that period, and using the post-Sarbanes–Oxley (SOX) sample period (2003–2010) to control for changes in the regulatory environment (Hutton et al. (2009)).

D. Endogeneity

Although we document a strong positive association between stock liquidity and crash risk, the results are potentially subject to endogeneity arising from either omitted variables or reverse causality running from crash risk to liquidity. We perform several tests to alleviate these concerns. In Panel C of Table 5, we augment our baseline regression models by including firm fixed effects to account for potential firm-specific time-invariant omitted variables. We obtain qualitatively similar results. Next, we modify our baseline regression models by including a set of additional control variables that could be correlated with both stock liquidity and crash risk. We control for high-frequency trading to mitigate the concern that its rise in recent years could affect both stock liquidity and crash risk. We follow Zhang (2010) in constructing this measure. We also control for the effects of tax avoidance and executive equity incentives on crash risk (as documented by Kim et al. (2011a), (2011b)). We include the estimated probability of engaging in a tax shelter based on Wilson's (2009) prediction model, and CFO option sensitivity to stock price changes estimated following Core and Guay (2002).[13] Prior research suggests that managers' propensity to hoard bad news, and thus crash risk, could be related to firms' corporate governance and auditor characteristics (Beasley (1996), Dunn and Mayhew (2004)). Therefore, we include board independence, the CEO duality dummy, the big auditor dummy, and the auditor industry specialization dummy as additional controls.[14] Furthermore, we include a high

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returns is the number of trading days with zero daily returns and positive trading volume, divided by the number of trading days over the fiscal year.

[12]We calculate the down-up volatility measure as per Chen et al. (2001). For each firm-year, we divide weeks into "down" (weeks with firm-specific returns below the annual mean) and "up" (those with firm-specific returns above the annual mean). We then calculate the standard deviation of firm-specific weekly returns for the two subsamples separately and define down-up volatility as the natural log of the ratio of standard deviation on down weeks to that on up weeks. The coefficient of stock liquidity remains positive and significant (t-statistic = 9.681).

[13]We control for CFO option incentives following Kim et al. (2011b). They show that CFO option incentives dominate CEO option incentives in determining future crash risk and conclude that CFOs are more influential in firms' bad news hoarding decisions. As a robustness test, we include CEO (rather than CFO) option sensitivity to stock price changes as an additional control. The results (untabulated) remain qualitatively the same.

[14]Board independence is the proportion of independent directors on a board. The CEO duality dummy equals 1 if the CEO is also the chairman of the board, and 0 otherwise. The big auditor

litigation industry membership dummy to control for litigation risk (Matsumoto (2002)), and a KMV distance-to-default measure constructed as per Bharath and Shumway (2008) to control for financial distress risk. Because of missing values for these additional controls, we perform our analysis with a much smaller sample of 7,674 firm-year observations. Our main results, however, are unaffected.

To further address endogeneity concerns, we follow prior studies (e.g., Fang et al. (2009), Bharath, Jayaraman, and Nagar (2013)) and use a decimalization event as a quasi-natural experiment. On Jan. 29, 2001, the NYSE and AMEX began quoting and trading stocks in decimal increments (as opposed to increments of $1/16). The NASDAQ also changed its tick size to decimals between Mar. 12, 2001 and Apr. 9, 2001. Prior research (e.g., Chordia et al. (2008)) shows that decimalization resulted in an increase in stock liquidity, making it an appealing framework in which to examine the effect of stock liquidity on crash risk.

We examine the changes in crash risk around decimalization using regression analysis. We rely on firms for which data are available for both the fiscal year before and the fiscal year after decimalization. The post-shock dummy (POST) equals 1 for the fiscal year after the decimalization, and 0 for the fiscal year before the event. The regression models are estimated as follows:

$$\text{(4a)}\quad \text{CRASH}_{i,t} = \beta_0 + \beta_1\text{POST}_{i,t} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} + \text{IND}_i + \varepsilon_{i,t},$$

$$\text{(4b)}\quad \text{NSKEW}_{i,t} = \beta_0 + \beta_1\text{POST}_{i,t} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} + \text{IND}_i + \varepsilon_{i,t}.$$

The notations are the same as in equations (3a) and (3b). We report the results in Panel A of Table 6. Column 1 gives results for the crash dummy, and column 2 for negative skewness. For each measure, the coefficient for the post-shock dummy is positive and significant (z-statistic = 2.434 and t-statistic = 4.136, respectively), suggesting that crash risk has increased in response to the liquidity-increasing shock.

However, an increase in crash risk may be capturing the effects of other marketwide confounding events in 2001, rather than the effect of decimalization per se. To address this concern, we conduct two tests. In the first test, we adopt an identification approach suggested by Edmans et al. (2013), who note that moving from $1/16 to $1/100 increments is a greater proportional change for, and thus should have a greater effect on, liquidity of low-priced stocks. Consistent with this, they document that decimalization has a stronger effect on the liquidity of low-priced stocks. We create a low price dummy (LOWPRC) that is equal to 1 if a firm's closing stock price in the fiscal year before the decimalization was below

dummy equals 1 if the company is audited by one of the big auditors, and 0 otherwise. The actual number of big auditors has varied over time from 8 during the 1980s to 4 currently due to mergers and the dissolution of Arthur Andersen. The auditor industry specialization dummy equals 1 if the firm is audited by an industry specialist auditor, defined as the auditor with the largest market share among all auditors in the firm's 2-digit SIC industry code.

TABLE 6

Stock Liquidity and Crash Risk: Tests on 2001 Decimalization

Table 6 presents the results of changes in crash risk around the 2001 decimalization. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. POST equals 1 for the fiscal year after the decimalization, and 0 for the fiscal year before the decimalization. LOWPRC equals 1 if a firm's closing stock price in the fiscal year before the decimalization is below the sample median, and 0 otherwise. Other variable definitions are in the Appendix. The constant term and industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes are included in all regressions in Panel A. The regressions in columns 1 and 3 are estimated using a logit model; those in columns 2 and 4 are estimated using ordinary least squares. $z(t)$-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Regression Analysis

	CRASH_t	NSKEW_t	CRASH_t	NSKEW_t
Variable	1	2	3	4
POST_t	0.182**	0.095***	0.023	0.018
	(2.434)	(4.136)	(0.209)	(0.534)
$\text{POST}_t \times \text{LOWPRC}$			0.186***	0.153***
			(2.620)	(3.451)
LOWPRC			−0.059	−0.055
			(−1.268)	(−1.512)
NSKEW_{t-1}	0.043	0.017	0.027	0.011
	(0.827)	(0.932)	(0.518)	(0.580)
SIGMA_{t-1}	7.520	6.685***	8.714*	7.160***
	(1.564)	(4.647)	(1.789)	(4.931)
RET_{t-1}	0.640	0.582***	0.752	0.626***
	(1.142)	(3.587)	(1.326)	(3.828)
DTURN_{t-1}	0.331	0.196*	0.206	0.144
	(0.969)	(1.654)	(0.602)	(1.211)
SIZE_{t-1}	0.092***	0.073***	0.087***	0.071***
	(4.192)	(10.789)	(3.499)	(9.317)
MB_{t-1}	0.017**	0.004*	0.017**	0.004*
	(2.317)	(1.649)	(2.404)	(1.749)
LEV_{t-1}	0.470**	0.170**	0.471**	0.171**
	(2.182)	(2.394)	(2.178)	(2.401)
ROA_{t-1}	0.100	0.037	0.134	0.050
	(0.465)	(0.496)	(0.624)	(0.667)
ACCM_{t-1}	0.310***	0.079*	0.313***	0.078*
	(2.872)	(1.864)	(2.879)	(1.861)
No. of obs.	4,546	4,546	4,546	4,546
R^2	0.026	0.050	0.028	0.052

Panel B. Difference-in-Difference Analysis

Variable	Before	After	Change	t-Statistic
CRASH				
Mean CRASH (U.S. market)	0.185	0.229	0.044***	(4.278)
Mean CRASH (non-U.S. markets)	0.180	0.192	0.012*	(1.836)
Difference-in-difference			0.032*	(1.701)
NSKEW				
Mean NSKEW (U.S. market)	0.052	0.170	0.118***	(6.158)
Mean NSKEW (non-U.S. markets)	−0.098	−0.061	0.037**	(2.490)
Difference-in-difference			0.081**	(2.392)

the sample median, and 0 otherwise. Next, we modify equations (4a) and (4b) to include LOWPRC and the interaction term between POST and LOWPRC. We report the results in Panel A of Table 6. Column 3 gives results for crash dummy, and column 4 for negative skewness. For each measure, the coefficient of the interaction term between POST and LOWPRC is positive and significant

(z-statistic = 2.620 and t-statistic = 3.451, respectively), suggesting that an increase in crash risk following decimalization was more pronounced for the low-priced stocks. These findings confirm that the crash risk increase was attributable to decimalization.[15]

In the second test, we compare the changes in crash risk around 2001 in the United States with those in major non-U.S. markets that did not experience an event comparable to decimalization. We expect the changes in crash risk to be more positive for the U.S. market.[16] The results are reported in Panel B of Table 6. For the U.S. market, the mean crash dummy increases by 0.044 and mean negative skewness by 0.118. For the non-U.S. markets, the average change in the mean crash dummy is 0.012 and the average change in mean negative skewness is 0.037. More importantly, the difference between the change in crash risk in the U.S. market and that in the non-U.S. markets is positive and statistically significant for both measures of crash risk (t-statistics = 1.701 and 2.392 for the crash dummy and negative skewness, respectively). We obtain similar (untabulated) results using median values. Overall, these findings are consistent with the view that the increase in crash risk around 2001 is driven by decimalization. Taken together, the totality of the evidence from our identification tests suggests a positive causal relation running from stock liquidity to stock price crash risk.

V. Stock Liquidity and Crash Risk: Which Channel Matters?

Our baseline results suggest that higher stock liquidity leads to higher crash risk. As discussed in Sections I and II, such an effect can occur through the transient investor channel or through the blockholder channel. In this section, we develop several tests to evaluate which channel is more important in driving the stock liquidity–crash risk relation.

A. Institutional Ownership and the Liquidity–Crash Relation

The transient investor channel suggests that stock liquidity encourages the cutting-and-running type of selling by transient institutional investors upon bad news disclosures. This, in turn, may induce managers to withhold bad news, resulting in bad news accumulation and, consequently, an increased probability of a future crash. Thus, if the transient investor channel plays an important role in shaping the positive liquidity–crash relation, the effect of stock liquidity on future crash risk should be more pronounced for firms with a higher proportion of transient institutional ownership. In contrast, if liquidity influences crash risk mainly through the blockholder channel, the liquidity–crash relation should be stronger when blockholder ownership is higher.

[15]We perform several additional analyses (untabulated) to ensure the robustness of our results. None of the following has a major effect on regression results: including firm fixed instead of industry fixed effects in equations (4a) and (4b), using the number of crash weeks (instead of crash dummy) as the dependent variable in columns 1 and 3 of Table 6, and examining a different positive shock to liquidity, the change in minimum tick size from $1/8 to $1/16 in 1997 by the NYSE, AMEX, and NASDAQ (Fang et al. (2014)).

[16]We obtain the data used to construct crash risk measures for non-U.S. markets from Compustat Global and Datastream. Non-U.S. markets include Germany, France, Great Britain, Japan, and Italy.

Prior studies suggest that institutional investors are a generally heterogeneous class, with many different types of investors who have differing investment horizons and monitoring intensities. We categorize institutions in two ways to account for this heterogeneity. First, we categorize institutions as either transient (TRAIO) or nontransient (NONTRAIO) by following Bushee (1998), who classifies institutional investors using a factor analysis based on characteristics of past behavior (e.g., portfolio turnover, diversification, and momentum trading). Transient institutions are characterized as having high portfolio turnovers, highly diversified portfolio holdings, and a strong interest in short-term trading profits. Nontransient institutions include quasi-indexer and dedicated institutions, which are characterized as having low portfolio turnovers, monitoring firm management intensely, and relying on information beyond current earnings to assess managers' performance (e.g., Gaspar, Massa, and Matos (2005), Fang et al. (2014)).[17] Second, we partition institutions into blockholders and nonblockholders. Following prior research (e.g., Roosenboom, Schlingemann, and Vasconcelos (2014)), we define blockholders (BLOCK) as institutions that own more than 5% of a firm's shares outstanding, and nonblockholders (NONBLOCK) as the remaining institutions. Edmans and Manso (2011) and Roosenboom et al. (2014) argue that blockholders are typically dedicated and long-term-oriented institutional investors that monitor management via their threat of exit. They posit that nonblockholders consist mainly of short-term-oriented institutions that do not actively monitor or gather information.

Table 7 shows our regression results. As a preliminary analysis, we first examine the effect of total institutional ownership on the stock liquidity–crash risk relation. We define total institutional ownership (IO) as the number of shares held by all institutional investors, divided by the total shares outstanding. In Panel A, we augment our baseline models by adding total institutional ownership and its interaction with stock liquidity. The coefficient of the interaction term is positive and significant in the crash dummy regression, and positive but insignificant in the negative skewness regression. These results provide some evidence that higher institutional ownership increases the positive effect of stock liquidity on crash risk.

Next, to explore which type of institutions drives the documented effect, Panel B of Table 7 decomposes total institutional ownership into transient and nontransient, and interacts each ownership variable with stock liquidity. The results show that the coefficients of the interaction term between stock liquidity and transient institutional ownership are positive and statistically significant in both regressions (z-statistic $= 2.186$ and t-statistic $= 2.535$, respectively). This suggests that the effect of stock liquidity on future crash risk is stronger for firms held by more transient institutions, consistent with the transient investor channel. Conversely, the interaction terms between stock liquidity and

[17]Quasi-indexers differ from dedicated institutions in that the former hold highly diversified portfolios and generally follow indexing and buy-and-hold investing strategies, whereas the latter have a high stockholding concentration and undertake more of a "relationship investing" role (Porter (1992)). Similar to dedicated institutions, however, quasi-indexers are long-term oriented. Recent studies show that they exert influence through proxy voting and by facilitating other blockholders' activism (e.g., Appel, Gormley, and Keim (2016), Mullins (2014)). Untabulated robustness checks show our results are unaffected if we exclude quasi-indexers from nontransient institutions.

TABLE 7

Stock Liquidity and Crash Risk: The Role of Institutional Investors

Table 7 presents the results regarding the effects of institutional ownership on the liquidity–crash relation. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. IO, TRAIO, NONTRAIO, BLOCK, and NONBLOCK are total institutional ownership, transient institutional ownership, nontransient institutional ownership, blockholder ownership, and nonblockholder ownership, respectively. The constant term, control variables, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effects are included in all regressions. The regressions in column 1 are estimated using a logit model; those in column 2 are estimated using ordinary least squares. $z(t)$-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable	$CRASH_t$ 1	$NSKEW_t$ 2
Panel A. The Effect of Total Institutional Ownership (N = 48,176)		
LIQ_{t-1}	0.099*** (3.181)	0.036*** (5.017)
$LIQ_{t-1} \times IO_{t-1}$	0.233** (2.514)	0.021 (0.927)
IO_{t-1}	0.598*** (10.078)	0.180*** (10.640)
Panel B. The Effects of Transient and Nontransient Institutional Ownership (N = 48,176)		
LIQ_{t-1}	0.098*** (3.145)	0.036*** (4.995)
$LIQ_{t-1} \times TRAIO_{t-1}$	0.142** (2.186)	0.171** (2.535)
$TRAIO_{t-1}$	1.397*** (9.025)	0.657*** (12.722)
$LIQ_{t-1} \times NONTRAIO_{t-1}$	0.382 (1.436)	0.061 (0.827)
$NONTRAIO_{t-1}$	0.281 (1.478)	−0.002 (−0.068)
Panel C. The Effects of Block and Nonblock Ownership (N = 48,176)		
LIQ_{t-1}	0.139*** (4.189)	0.044*** (5.988)
$LIQ_{t-1} \times NONBLOCK_{t-1}$	0.105* (1.703)	0.198*** (4.973)
$NONBLOCK_{t-1}$	0.777*** (10.009)	0.220*** (9.848)
$LIQ_{t-1} \times BLOCK_{t-1}$	0.002 (0.016)	0.010 (0.291)
$BLOCK_{t-1}$	0.115 (1.023)	0.048 (1.432)

nontransient institutional ownership are insignificant in both regressions, suggesting that long-term-oriented institutions have no discernible effect on the liquidity–crash relation.[18]

[18] As robustness tests, we classify institutional investors as short or long term using alternative measures of investor horizons proposed by Yan and Zhang (2009) and Derrien, Kecskes, and Thesmar (2013). We sort all institutional investors based on their average churn rate (i.e., portfolio turnover) over the past 4 quarters, as per Yan and Zhang, and based on the fraction of their portfolios turned over during the past 12 quarters, as per Derrien et al. The (untabulated) results are qualitatively the same.

Panel C of Table 7 divides total institutional ownership into block and nonblock ownership, and interacts them separately with stock liquidity. The results show that the interaction terms between stock liquidity and block ownership are insignificant. Thus, we find no evidence that the strength of the stock liquidity–crash risk relation varies with the level of block ownership. In contrast, the coefficients of the interaction term between stock liquidity and nonblock ownership are positive and significant in both regressions (z-statistic $= 1.703$ and t-statistic $= 4.973$, respectively). This suggests that the effect of liquidity on crash risk is stronger when firms are held by more nonblockholders, who are typically viewed as short-term-oriented investors. These findings provide further support for the transient investor channel, but not for the blockholder channel.

B. Stock Liquidity and Future Bad News Releases

Our second set of tests revolves around the link between stock liquidity and the intensity of bad news releases during crash weeks. Recall that transient investor channel implies accumulation of bad news over time, until the point when all bad news is released at once and the crash occurs. Thus, if the documented liquidity–crash risk relation occurs through the transient investor channel, we should observe a higher intensity of very bad news releases during crash weeks than during noncrash weeks. Furthermore, and more importantly, we should observe a positive association between stock liquidity and the subsequent probability of unexpected very bad news releases. Conversely, the blockholder channel implies a negative association between stock liquidity and the subsequent probability of unexpected very bad news releases. This is because higher liquidity enhances blockholders' monitoring of firm management, which dissuades management underperformance to begin with and encourages blockholders to gather information and trade on it, which limits manager's ability to pile up bad news.

For intensity of bad news releases, we examine whether the magnitude of negative unexpected earnings and the frequency of negative managerial earnings guidance are higher during crash weeks than during noncrash weeks for both quarterly and annual earnings. We first identify firms that experienced crashes and announced earnings or released earnings guidance during crash weeks, and label them as crash firms. We then match each crash firm with a control firm that also announced earnings or released earnings guidance during the crash firm's crash week, but did not experience a crash. The control firm is matched using propensity scores based on industry, market capitalization, and the market-to-book ratio in the previous month. Finally, for both crash and control firms, we compute unexpected earnings (UE) and the proportion of observations that fall into each earnings guidance category (as described below) and compare mean values across the two samples.

We estimate quarterly unexpected earnings as a firm's net income in the current quarter minus its net income for the same quarter in the previous fiscal year, scaled by its lagged market value of equity (Livnat and Mendenhall (2006)). We estimate annual unexpected earnings as a firm's income before extraordinary items in the current year minus its income before extraordinary items in the previous fiscal year, scaled by its lagged market value of equity (Kothari, Lewellen, and Warner (2006)).

We classify earnings guidance into 4 categories: SHORTFALL, MEET, BEAT, and OTHER. SHORTFALL refers to the announcement that the firm is not expected to meet the earnings target (i.e., management's prior expectation of earnings for the period). MEET means the firm will meet the target. BEAT means the firm is expected to beat the target. OTHER means the firm provided earnings guidance but did not specify its expectations precisely.

We report the comparison results in Panel A of Table 8. The mean quarterly unexpected earnings for crash firms is negative and significant at the 1% level. In contrast, the mean unexpected earnings for control (noncrash) firms is not significantly different from 0. The difference between the two means is negative (−0.010) and significant at the 1% level (t-statistic = −4.132). The mean quarterly SHORTFALL for crash firms is 0.656 versus 0.309 for noncrash firms, and the difference is significant (t-statistic = 18.550). During crash weeks, crash firms also have significantly lower frequencies of meeting or beating earnings targets than noncrash firms. The results are qualitatively similar for the annual items. Collectively, these results suggest that a typical crash firm is characterized by a higher intensity of bad news releases than is a noncrash firm.

Next, we examine whether higher stock liquidity is associated with a higher or lower subsequent probability of unexpected very bad news releases. To that end, we construct two variables, SURP_UE and SURP_G. SURP_UE is a dummy variable that equals 1 if the firm's unexpected earnings in the current fiscal year are in the bottom decile and its unexpected earnings in the previous fiscal year are non-negative, and 0 otherwise. SURP_G is a dummy variable that equals 1 if a firm issued a SHORTFALL guidance in the current fiscal year but not in the previous fiscal year, and 0 otherwise. The idea behind these variables is to identify firms for which the release of very bad news is not expected based on firms' prior announcements and thus comes as a surprise to the market. We then estimate the following regressions using the logit model:

$$\text{(5a)}\quad \text{SURP\_UE}_{i,t} = \beta_0 + \beta_1\text{LIQ}_{i,t-1} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} + \text{IND}_i + \text{YR}_t + \varepsilon_{i,t},$$

$$\text{(5b)}\quad \text{SURP\_G}_{i,t} = \beta_0 + \beta_1\text{LIQ}_{i,t-1} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} + \text{IND}_i + \text{YR}_t + \varepsilon_{i,t}.$$

We use the same control variables as in equations (3a) and (3b). The results are given in Panel B of Table 8. Column 1 shows results for the SURP_UE dummy; column 2 shows results for the SURP_G dummy. For each variable, the coefficient for stock liquidity is positive and significant (smallest z-statistic = 5.293). The results suggest that stock liquidity is positively associated with the subsequent probability of unexpected very bad news releases.

Collectively, the results in Table 8 indicate that crash weeks are characterized by a higher intensity of bad news releases than are noncrash weeks, and that the

TABLE 8
Stock Liquidity, Stock Price Crashes, and Bad News Releases

Table 8 presents the results of the tests on bad news releases during crash weeks. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1993 and 2010. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The crash dummy (CRASH) is defined as a dummy variable equal to 1 if there is one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise. Negative skewness (NSKEW) is −1 times the skewness of weekly returns over the fiscal year. Crash weeks are identified if weekly returns fall 3.09 standard deviations below the mean weekly returns over the fiscal year. Crash firms are matched with control firms in the same industry and with the closest market capitalization and the book-to-market ratio. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the difference between the trade price and the midpoint of the bid–ask quote over the trade price. Quarterly UE is a firm's net income in the current quarter minus its net income for the same quarter in the previous fiscal year, scaled by its lagged market value of equity. Annual UE is a firm's income before extraordinary items in the current year minus its income before extraordinary items in the previous fiscal year, scaled by its lagged market value of equity. SHORTFALL, MEET, and BEAT refer to the announcement that a firm is expected to fall short of, meet, or beat their earnings targets, respectively. OTHER indicates cases where an earnings target is not mentioned. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effects are included in the logit regressions reported in Panel B. $z(t)$-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. News Releases for Crash versus Noncrash Firms

Variable	Crash Firms	Control Firms	Difference	t-Statistics
Quarterly items				
Mean UE ($N=3,111$)	−0.011***	−0.001	−0.010***	(−4.132)
Guidance ($N=1,236$)				
%SHORTFALL	0.656	0.309	0.346***	(18.550)
%MEET	0.122	0.327	−0.205***	(−12.623)
%BEAT	0.018	0.129	−0.110***	(−10.763)
%OTHER	0.203	0.233	−0.030	(−1.220)
Annual items				
Mean UE ($N=8,492$)	−0.062***	−0.024**	−0.037***	(−7.444)
Guidance ($N=974$)				
%SHORTFALL	0.571	0.1797	0.392***	(19.531)
%MEET	0.281	0.500	−0.218***	(−10.139)
%BEAT	0.031	0.194	−0.162***	(−11.688)
%OTHER	0.115	0.126	−0.011	(0.560)

Panel B. Stock Liquidity and Bad News Releases

Variable	SURP_UE_t 1	SURP_G_t 2
LIQ_{t-1}	0.221*** (5.293)	1.692*** (7.402)
NSKEW_{t-1}	−0.153*** (−5.855)	0.139*** (3.792)
SIGMA_{t-1}	47.878*** (16.759)	6.128 (1.206)
RET_{t-1}	3.265*** (10.372)	0.216 (0.282)
DTURN_{t-1}	0.444** (2.436)	1.079*** (3.749)
SIZE_{t-1}	−0.108*** (−5.879)	0.011 (0.432)
MB_{t-1}	0.013** (2.262)	−0.016** (−2.214)
LEV_{t-1}	−0.577*** (−4.019)	0.310* (1.784)
ROA_{t-1}	3.091*** (13.132)	1.423*** (4.909)
ACCM_{t-1}	0.606*** (10.654)	0.199* (1.875)
No. of obs.	47,885	21,272
R^2	0.144	0.090

subsequent probability of unexpected very bad news releases is higher for firms with higher stock liquidity. These findings provide further support for the transient investor channel but are inconsistent with the blockholder channel.

C. Stock Liquidity and Institutional Selling on Crash Weeks

In our last set of tests, we explore whether stock liquidity leads to higher institutional selling on crash weeks, and if it does, which type of exit (the cutting-and-running type of exit by transient institutions or blockholders' exit) drives the institutional selling on crash weeks. Both the transient investor channel and the blockholder channel suggest that higher stock liquidity facilitates institutional selling when bad news about a firm is revealed. However, the difference lies in which type of institutions primarily contribute to the enhanced selling pressures. The cutting-and-running exit occurs when transient institutions reduce their stakes in a firm in response to bad news disclosures. Blockholders' exit occurs when blockholders use their information advantage to make trading profits based on bad news disclosures.

To begin, we examine whether crash weeks are characterized by abnormal institutional selling. We use the standardized abnormal selling volume (SASV) measure proposed by Lakonishok and Vermaelen (1986), constructed as follows. For each stock, we define "normal" institutional selling volume (NSVOL) as the average number of shares sold by institutional investors in the [−9, −2] week window, for which week 0 is the crash week.[19] To estimate weekly institutional selling volume (SVOL), we aggregate daily volume into weekly sums. The abnormal institutional selling volume (ASVOL) of stock i in week j for $j=-1, 0, 1, 2, 3$ is then written as:

$$(6) \qquad \mathrm{ASVOL}_{i,j} = \frac{\mathrm{SVOL}_{i,j} - \mathrm{NSVOL}_{i,j}}{\mathrm{NSVOL}_i}.$$

Finally, the SASV for stock i in week j for $j=-1, 0, 1, 2, 3$ is computed as:

$$(7) \qquad \mathrm{SASV}_{i,j} = \frac{\mathrm{ASVOL}_{i,j}}{\sigma(\mathrm{ASVOL}_i)},$$

where $\sigma(\mathrm{ASVOL}_i)$ is the standard deviation of abnormal volume computed between weeks −9 and −2.

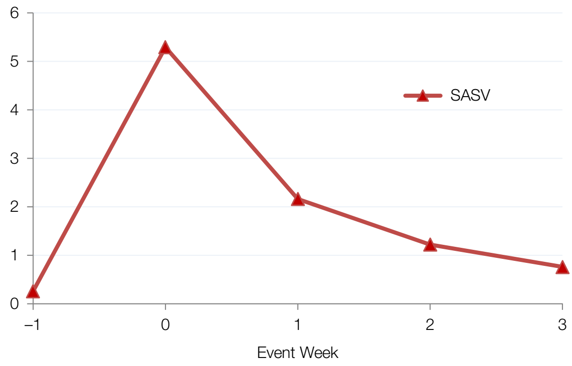
Figure 2 depicts the mean SASV during weeks −1, 0, 1, 2, and 3 across all firms that experienced a stock price crash. The results show a positive and significant spike in mean SASV during week 0 (t-statistic = 2.340). The mean values are not significantly different from 0 for weeks −1, 1, 2, and 3 (largest t-statistic = 0.961). These results suggest that crash weeks are characterized by abnormal institutional selling activity.

[19]Following Barber, Odean, and Zhu (2009), we identify institutional selling if the total market value of shares sold in a transaction exceeds US$50,000. Our sample starts in 1995 because of data restrictions from the vendor and ends in 2002 because of the increased popularity of high-frequency trading afterward, which makes it difficult to identify institutional trading from trading size (Barber et al. (2009)). Because we identify institutional selling by trading size, for this test we are unable to compute selling volume from various types of institutions. For robustness, we also use the standardized abnormal net selling volume (i.e., selling volume minus buying volume). The results (untabulated) are qualitatively similar.

FIGURE 2

Plot of Institutional Selling Activity around Crash Weeks

Figure 2 presents the institutional standardized abnormal selling volume around stock price crash weeks. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1995 and 2002. Standardized abnormal selling volume (SASV) is the abnormal weekly institutional selling volume deflated by the standard deviation of abnormal selling volume over the [−9, −2] week period.



Next, we examine whether the abnormal institutional selling during crash weeks is stronger for higher liquidity firms. We estimate the following regression model:

$$\text{(8)}\quad \text{SASV}_{i,t} = \beta_0 + \beta_1\text{LIQ}_{i,t-1} + \beta_2\text{NSKEW}_{i,t-1} + \beta_3\text{SIGMA}_{i,t-1} + \beta_4\text{RET}_{i,t-1} + \beta_5\text{DTURN}_{i,t-1} + \beta_6\text{SIZE}_{i,t-1} + \beta_7\text{MB}_{i,t-1} + \beta_8\text{LEV}_{i,t-1} + \beta_9\text{ROA}_{i,t-1} + \beta_{10}\text{ACCM}_{i,t-1} + \text{IND}_i + \text{YR}_t + \varepsilon_{i,t}.$$

We use the same control variables as in equations (3a) and (3b). The results in column 1 of Table 9 show that the coefficient for stock liquidity is positive and significant (t-statistic = 8.056). This suggests that, on average, the abnormal institutional selling activity during crash weeks is more intense for firms with higher stock liquidity. These results indicate that institutional selling plays an important role in driving the stock liquidity–crash risk relation.

As discussed above, higher stock liquidity may facilitate institutional selling by enhancing the response of transient institutional investors to bad news releases (cutting and running) or by facilitating blockholders' exit. Thus, finally, we attempt to identify which type of exit predominantly drives the relation between stock liquidity and abnormal institutional selling during crash weeks.

We report the results for these tests in columns 2–4 of Table 9. Column 2 shows the results for the ownership of all institutional investors; column 3 shows results for the division between transient and nontransient institutions; and column 4 shows results for the division between blockholders and nonblockholders. Column 2 reveals that the coefficient for the interaction term between total institutional ownership and stock liquidity is not significant in the regression. More importantly, column 3 indicates that the coefficient for the interaction term between transient institutional ownership and stock liquidity is

TABLE 9

Institutional Abnormal Selling around Crash Weeks

Table 9 gives the results of the tests for the effects of stock liquidity on abnormal institutional selling around stock price crash weeks. The sample consists of firm-years jointly covered in the merged Compustat/Center for Research in Security Prices (CRSP) database and Trade and Quote (TAQ) database between 1995 and 2002. Stock liquidity (LIQ) is defined as −100 times relative effective spread, which is the ratio of the absolute difference between the trade price and the midpoint of the bid–ask quote over the trade price. The dependent variable (SASV) is the abnormal weekly institutional selling volume deflated by the standard deviation of abnormal selling volume over the [−9, −2] week period. Other variable definitions are in the Appendix. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effects are included in all the regressions, which are performed by ordinary least squares. t-statistics (reported in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: $SASV_t$			
Variable	1	2	3	4
LIQ_{t-1}	2.248*** (8.056)	1.736*** (5.758)	1.670*** (5.477)	1.856*** (5.551)
$LIQ_{t-1} \times IO_{t-1}$		−0.092 (−0.091)		
IO_{t-1}		3.765*** (3.997)		
$LIQ_{t-1} \times TRAIO_{t-1}$			0.528** (2.428)	
$TRAIO_{t-1}$			6.012** (2.375)	
$LIQ_{t-1} \times NONTRAIO_{t-1}$			−3.592 (−1.050)	
$NONTRAIO_{t-1}$			2.544 (1.091)	
$LIQ_{t-1} \times BLOCK_{t-1}$				−3.807* (−1.700)
$BLOCK_{t-1}$				2.189 (0.864)
$LIQ_{t-1} \times NONBLOCK_{t-1}$				3.243** (2.277)
$NONBLOCK_{t-1}$				3.781*** (2.901)
$NSKEW_{t-1}$	0.090 (0.378)	0.021 (0.085)	0.063 (0.259)	0.024 (0.098)
$SIGMA_{t-1}$	128.555*** (6.652)	120.077*** (6.232)	105.889*** (5.389)	115.755*** (5.911)
RET_{t-1}	12.504*** (5.955)	11.440*** (5.450)	10.307*** (4.888)	11.090*** (5.180)
$DTURN_{t-1}$	0.934 (0.573)	0.383 (0.236)	−0.016 (−0.010)	0.064 (0.039)
$SIZE_{t-1}$	0.805*** (5.853)	0.698*** (4.932)	0.702*** (4.948)	0.665*** (4.263)
MB_{t-1}	0.058 (1.117)	0.068 (1.331)	0.061 (1.181)	0.068 (1.316)
LEV_{t-1}	2.582** (2.139)	2.246* (1.884)	2.299* (1.927)	2.350** (1.993)
ROA_{t-1}	1.129 (1.033)	0.817 (0.747)	0.662 (0.608)	0.873 (0.783)
$ACCM_{t-1}$	0.142 (0.245)	0.258 (0.451)	0.199 (0.349)	0.281 (0.485)
No. of obs.	3,586	3,586	3,586	3,568
R^2	0.100	0.106	0.108	0.107

positive and significant (t-statistic = 2.428). Column 4 shows that the coefficient for the interaction term between nonblockholder institutional ownership and stock liquidity is positive and significant (t-statistic = 2.277). Interestingly, the interaction term between blockholder ownership and stock liquidity is negative and significant at the 10% level (t-statistic = 1.700), suggesting that liquidity discourages blockholders from selling upon public bad news. A potential explanation for this result is that stock liquidity encourages blockholders to gather private information and thus trade more aggressively on private rather than public signals. Overall, we find no evidence that the effect of stock liquidity on crash risk is amplified for firms with higher block ownership or for firms with a higher proportion of nontransient institutions.

To summarize, these results suggest that institutional exit is important in shaping the relation between stock liquidity and crash risk. They also suggest that institutional exit on crash weeks occurs primarily through the selling activities of transient institutions or nonblockholders, rather than through that of blockholders. Collectively, our results in Section V are consistent with stock liquidity positively affecting crash risk through increasing short-termism-induced managerial bad news hoarding, and through facilitating transient institutional exits in response to bad news releases.

VI. Conclusions

Stock price crashes can severely damage investors' welfare and confidence. Using a large sample of U.S. firms for 1993–2010, we find that higher stock liquidity gives rise to higher crash risk. To understand the mechanisms underlying this effect, we explore both ex ante and ex post channels. Our analysis suggests that high stock liquidity induces short-termist pressure and increases managers' ex ante incentives to withhold bad news. Moreover, high liquidity facilitates the exit of transient institutions, thus magnifying the ex post stock price reactions to bad news releases.

Our results suggest that stock liquidity can increase managers' incentives to withhold bad news and weaken financial market stability. Nonetheless, given that the prior literature has documented various beneficial effects of stock liquidity on corporate governance, information environment, and firm value (Holden et al. (2014)), we do not conclude that stock liquidity is on balance a negative attribute. Rather, it has both positive and negative effects, and our study identifies one negative side: its effect on crash risk through the transient investor channel. Thus, our results further emphasize the need for regulators to determine the optimal level of stock liquidity based on the trade-off between its benefits and costs.

Finally, prior research (e.g., Ang, Chen, and Xing (2006), Chang, Christoffersen, and Jacobs (2013)) documents a significant risk premium for downside risk. However, the documented effect of liquidity on crash risk does not necessarily imply that more liquid stocks should have higher expected returns. Rather, our findings suggest that to understand the net effect of liquidity on expected stock returns, one may need to consider not only its beneficial aspects (e.g., Amihud and Mendelson (1986)), but also its effect on crash risk. We leave this issue for future research.

Appendix. Variable Definitions

ACCM: Moving sum of the absolute value of annual discretionary accruals over the prior 3 years, where accruals are calculated using the modified Jones model of Dechow, Sloan, and Sweeney (1995).

CRASH: Dummy variable equal to 1 for one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and 0 otherwise.

DISP: Standard deviation of analysts' earnings per share forecasts divided by the mean of analysts' forecasts.

DTURN: Average monthly stock turnovers over the current fiscal year minus those over the previous fiscal year. Monthly stock turnover is calculated as the ratio of monthly trading volume over the number of shares outstanding.

IO: Proportion of shares held by institutional investors. We classify further into TRAIO, the proportion held by transient institutional investors; NONTRAIO, the proportion held by nontransient institutional investors; BLOCK, the proportion held by institutional blockholders; and NONBLOCK, the proportion held by nonblockholders.

LEV: Ratio of long-term debt (DLTT) over the book value of total assets (AT).

LIQ: -100 times the relative effective spread, which is the ratio of the absolute value of the difference between the trade price and the midpoint of the bid–ask quote over the trade price.

LOWPRC: Dummy variable equal to 1 if a firm's closing stock price in the fiscal year before the decimalization is below the sample median, and 0 otherwise.

MB: Ratio of the market value of equity over the book value of equity (CEQ). Market value of equity is the product of stock price (PRCC_F) and the number of shares outstanding (CSHPRI).

NSKEW: Ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by -1.

POST: Dummy variable equal to 1 for the fiscal year after the decimalization, and 0 for the fiscal year before the event.

RET: 100 times the mean of firm-specific weekly returns over the fiscal year.

ROA: Ratio of income before extraordinary items (IB) over book value of total assets (AT).

SASV: Abnormal weekly institutional selling volume deflated by the standard deviation of abnormal selling volume over the $[-9, -2]$ week period.

SI: Ratio of the number of shares held short over the number of shares outstanding.

SIGMA: Standard deviation of firm-specific weekly returns over the fiscal year.

SIZE: Natural log value of the market value of equity.

SURP_G: Dummy variable equal to 1 if the firm released a SHORTFALL guidance in the current fiscal year but not in the previous fiscal year, and 0 otherwise. For firms with no recorded earnings guidance, the variable equals 0.

SURP_UE: Dummy variable equal to 1 if the unexpected earnings are in the lowest decile for the current fiscal year and non-negative in the previous fiscal year, and 0 otherwise.

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