Customer Satisfaction and Stock Crash Risk

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Abstract

We find that firms with a higher level of customer satisfaction are associated with lower stock crash risk in the future. Our main findings are robust to a series of robustness tests for endogeneity concerns, including instrumental variable and difference-in-difference analysis based on the Gramm-Leach-Bliley Act. Our results support the view that customer satisfaction reduces stock crash risk by reducing the negative impact of stock price volatility feedback and differences of opinion among investors. However, we do not find significant evidence that the bad news hoarding theory contributes to the negative relationship.

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There is only one boss. The customer. And he can fire everybody in the company from the chairman on down, simply by spending his money somewhere else.

-By Sam Walton, Founder of Walmart, and Sam's Club

1. Introduction

Customer satisfaction is widely regarded as a pivotal element in successful businesses. Firms with higher levels of customer satisfaction tend to experience fewer customer complaints, more customer loyalty, and fewer litigations (Fornell et al., 1996), benefit from word of mouth (Anderson, 1998), achieve better accounting performance (Barger and Grandey, 2006; Ittner and Larcker, 1998; Rust et al., 2004), and reduce cash flow volatility (Fornell and Mazvancheryl, 2004). Furthermore, a large body of research suggests that these positive impacts on the firm's business are associated with favourable risk-adjusted stock returns (Fornell et al., 2006; Fornell et al., 2016; Aksoy et al., 2008; Sorescu & Sorescu, 2016) and reduced stock return volatility (Tuli and Bharadwaj, 2009).

The purpose of the study is to investigate another risk channel where effects of customer satisfaction may manifest – the risk of a stock price crash. The likelihood of extreme losses holds important implications for portfolio theories and for asset pricing models (Harvey and Siddique, 2000; Kim and Zhang, 2016). If customer satisfaction indeed contributes to diminishing the overall risk of a firm, it follows that a similar pattern would be observed in relation to stock price crash risk. On the other hand, mangers might exploit favourable customer satisfaction to engage in opportunistic behaviour such as withholding negative information, potentially elevating the firms' stock price crash risk.

Our empirical findings reveal an inverse relation between our measure of customer satisfaction, the American Customer Satisfaction Index (ACSI), and all three proxies for stock price crash risk. This negative relationship is both economically and statistically significant. For instance, a one standard deviation increase in ACSI leads to a substantial 154% reduction in the negative skewness of firm-specific weekly returns compared to its sample mean. Importantly, our results remain robust when we employ a two-stage least square model and a difference-in-difference approach utilising the Gramm-Leach-Bliley Act as an exogenous shock to alleviate endogeneity concerns.

Furthermore, our results provide insights into the mechanisms through which the reduction in crash risk is attained. We find that the negative relation between ACSI and stock crash risk is more pronounced 1) when stock return volatility is high and 2) when analysts' earnings forecasts are more dispersed. These findings support the notion that the reduction in crash risk is, at least in part, attributable to favourable customer satisfaction mitigating the adverse price impacts of 1) heightened volatility (volatility feedback effect) and 2) differences in opinion among investors. However, our results do not support the hypothesis that customer satisfaction moderate the crash risk arising from managers' tendencies to withhold negative information (bad news hoarding). Our proxies for such tendencies, financial report readability and timeliness of loss recognition, do not influence the strength of the negative relation bet ween ACSI and stock crash risk.

Our contributions to the existing literature are three-fold. Firstly, we complement the vast literature on the significance of customer satisfaction by underscoring its role in mitigating firms' stock price tail risk - another important risk metric for investors alongside return variance. To the best of our knowledge, ours is the first study to delve into the relation between customer satisfaction and firms' stock crash risk. Our paper is also related to another strand of literature on stock crash risk in financial markets. Previous studies primarily focus on the connection between price crash risk and factors within firms including firm characteristics,[2]

[2] For example, corporate tax avoidance (Kim et al., 2011b), corporate social responsibility (Kim, Li, & Li, 2014), stock liquidity (Chang, Chen, & Zolotoy, 2017), divergence of cash flow and voting rights (Hong, Kim, & Welker, 2017), stock synchronicity An & Zhang, 2013), and intangible intensity (Wu & Lai, 2020).

accounting policies,[3] and management team.[4] While there are some studies exploring whether participants outside the firm affect stock crash risk[5], little attention has been directed towards non-financial stakeholders. Our study is among the first to shed light on how customers, crucial nonfinancial stakeholder, may influence the downside risk of stock prices. Notably, Wu and Lai (2020) provide evidence that intangible assets, such as goodwill, increases stock crash risk through the information channel. In contrast, our findings suggest that certain intangible assets, specifically customer satisfaction, may act as a mitigating factor against stock crash risk. Lastly, we present empirical evidence pointing to potential channels through which customer satisfaction could mitigate stock crash risk.

The rest of the paper is organized as follows. Section 2 provides an overview of the sample selection and variable constructions. Section 3 outlines the baseline models and reports the main empirical results. Section 4 presents the robustness test alleviating possible endogeneity concerns. Section 5 analyses the possible channels. Section 6 summarizes and concludes.

2. Sample and Variable Constructions

2.1 Sample Selections

To measure annual firm-specific crash risk, we obtain weekly stock returns from the Center for Research in Security Prices (CRSP). We use 12-month period weekly returns for each firm-year ending three months after a firm's fiscal year-end (Kim et al., 2011a, 2011b).

[3] For example, mandatory IFRS adoption (DeFond et al., 2014), financial report opacity (Hutton et al., 2009; Kim & Zhang, 2014), financial report comparability (Kim, Li, Lu, & Yu, 2016), financial report readability (Kim, Wang, & Zhang, 2019), and accounting conservatism (Kim & Zhang, 2016).

[4] For example, option-based compensation (Kim et al., 2011a), insurance benefits (Yuan, Sun, & Cao, 2016), excess perk consumption (Xu et al., 2014), religion (Callen & Fang, 2015a), overconfidence (Kim et al., 2016), and employee welfare (Ben-Nasr & Ghouma, 2018).

[5] For example, short interest (Callen & Fang, 2015b), government monitoring (Chen, Kim, Li, & Liang, 2017), institutional investors (An & Zhang, 2013; Deng et al., 2018), media and analyst coverage (An, Chen, Naiker, & Wang, 2020; Kim, Lu, & Yu, 2019), and market (An, Chen, Li, & Xing, 2018; Chen et al., 2017; Li & Zhan, 2018).

The three-month lag ensures that investors have access to the financial data and incorporate it into their trading behaviour (Kim et al., 2011a). We also require each firm to have at least 26 weekly returns for each fiscal year. Observations are excluded if the firm has non-positive book equity, non-positive total assets, or fiscal year-end stock prices less than $1. We exclude firms in utility (4000 <=SIC<=4999) and financial (6000<= SIC <=6999) industry due to their different competition landscapes and regulations with other industries.

2.2 Stock Crash Risk Measurements

Following previous studies, we use two steps to measure stock crash risk (Hutton 2009). First, we regress weekly stock returns on leads and lags of weekly market returns.[6] Firm-specific (i.e., market adjusted) weekly returns are calculated by the natural logarithm of one plus the residuals ($W_{i,w} = \ln(1 + \hat{\varepsilon}_{i,w})$) from the following model:

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

where $r_{i,w}$ is the return on stock *i* in week *w*, $r_{m,\mathrm{w}}$ is the return on the CRSP value-weighted market index in week *w* and $\varepsilon_{i,w}$ is the residual return in week *w*.

The second step uses the (log) residual $W_{i,w}$ to construct three commonly used annual stock crash risk proxies, which are *NCSKEW*, *DUVOL*, and *CRASH* (An & Zhang, 2013; Kim et al., 2011a, 2011b; Li & Zhan, 2018). Specifically, the first proxy, *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns (Chen et al., 2001). We take the third moment of firm-specific weekly returns $W_{i,w}$ for each firm-year and then divide it by the standard deviation of firm-specific weekly returns raised to the third power:

[6] The use of leads and lags in the regression account for the nonsynchronous trading problem as proposed by Dimson (1979). Dimson argued that the closing price of a stock with low trading frequency may not reflect that period's information because of no transaction. Instead, the information will be reflected in the next period's price.

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,w}^{3}}{(n-1)(n-2)(\sum W_{i,w}^{2})^{\frac{3}{2}}} \tag{2}$$

where $W_{i,\mathrm{w}}$ is stock returns for firm *i* in week *w*; *n* is the number of observations on weekly returns for firm *i* in year *t*. In line with prior research (Chen et al., 2001), the skewness is scaled by the standard deviation of weekly returns to allow for comparison across different stocks. The negative sign in front of the formula allows easier interpretation of the measure so that a higher value of *NCSKEW* is associated with a more left-skewed distribution of firm-specific weekly returns. Thus, a higher value of *NCSKEW* indicates a higher stock price crash risk.

Our second measure of crash risk is the down-to-up volatility (*DUVOL*) of firm-specific weekly returns. For each firm *i* over year *t*, a firm-week is defined as an up (down) week if the firm-specific weekly return is above (below) the annual mean. We then calculate *DUVOL* as follows:

$$DUVOL_{i,t} = log\left[\frac{(n_u-1)\sum_{down} W_{i,d,w}^{2}}{(n_d-1)\sum_{up} W_{i,u,w}^{2}}\right] \tag{3}$$

where n_u and n_d are the number of up and down weeks, $W_{i,u,w}$ and $W_{i,\mathrm{d},w}$ are the weekly returns of up and down weeks for firm *i*. Similar to the first crash risk measure, a higher value of *DUVOL* corresponds to a stock having a more left-skewed distribution and, thus, more prone to crash.

Our third measure of crash risk is $CRASH_{i,t}$, which equals one when a firm experiences one or more crash weeks in a given year, and zero otherwise. Following Hutton et al. (2009), we define the crash week as the week during which the firm-specific returns are smaller than 3.2 standard deviation of its annual average return. We choose the 3.2 threshold so that the crash events account for 0.07% of the frequency in the normal distribution. One could expect to observe 0.07% of the sample observation to crash in any week[7].

2.3 Customer Satisfaction Measurement

Our primary measure of customer satisfaction is the American Customer Satisfaction Index (*ACSI*). The index is designed to evaluate the quality of goods and services purchased in the U.S. and produced by domestic and foreign firms with substantial U.S. market shares (Fornell et al. 1996). The *ACSI* represents the experience of individual customers' view of the company's product and service, instead of expert rating (e.g., Consumer Reports) or managers' perceptions (e.g., PIMS). It accounts for more than 43% of the U.S. economy and spans all major economic sectors. More than 50,000 household consumers, who have passed screening questions, are polled quarterly. Each firm will have an *ACSI* score ranging from 0 to 100 each year, with 100 as the highest level of customer satisfaction. The *ACSI* employs the same survey questionnaire, random sampling, and estimation modelling across firms and years. The marketing literature proves the validity and reliability of the measurement with comprehensive tests (Fornell et al., 1996; Fornell et al., 2006). Different industries may have a different type of customer satisfaction (e.g., high tech industry customers focus on product quality, while financial industry customers care more about service quality). Thus, we scaled each firm's *ACSI* score with its industry *ACSI* score as below:

$$ACSI_{i,t} = \frac{ACSI_{firm,t}}{ACSI_{industry,t}} - 1 \quad (4)$$

where $ACSI_{firm,t}$ is the customer satisfaction score of a firm at year *t*, $ACSI_{industry,t}$ is the customer satisfaction score of the firm's industry at year *t*. A higher value of *ACSI* represents a higher customer satisfaction level of the firm's products or services.

[7] We also use a 3.09 threshold instead of 3.2 (Hutton et al, 2009). 3.09 threshold will generate a crash frequency of 0.1%. We obtain similar results with this alternative measure.

Table 1 Summary Statistics

This table reports the descriptive statistics for crash risk, customer satisfaction, and control variables employed in this study. The measurements of crash risk are *CRASH*, *NCSKEW*, and *DUVOL* at year *t*. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. The definitions of all other variables can be found in Appendix A. The sample contains 3,596 unique firm-year observations for publicly traded U.S. firms that have ACSI index over the period 1994 to 2019. All variables are winsorized at 1% and 99%.

Variables	N	Mean	SD	p25	Median	p75
Dependent Variables						
CRASH	3,596	0.205	0.404	0	0	0
NCSKEW	3,596	0.044	0.722	-0.383	-0.003	0.402
DUVOL	3,596	0.014	0.225	-0.125	0.004	0.145
Independent Variable						
ACSI	3,596	0.000	0.064	-0.033	0.008	0.042
Control Variables						
DTURN	3,596	0.030	0.725	-0.167	0.021	0.226
RET	3,596	-0.073	0.098	-0.081	-0.041	-0.023
SIGMA	3,596	0.034	0.018	0.022	0.029	0.041
SIZE	3,596	10.062	1.648	9.005	10.042	11.237
LEVERAGE	3,596	0.272	0.179	0.153	0.261	0.356
ROA	3,596	0.051	0.065	0.019	0.044	0.082
MB	3,596	6.345	13.881	1.584	2.605	5.112

Table 1 presents the summary statistics of all variables used in our analysis. Apart from sample selection criteria discussed in section 2.1, we also delete observations with missing control variables. Our analysis sample contains 3,596 unique firm-year observations constructed from public-traded U.S. firms with the *ACSI* index between 1994 and 2019. On average, 20% of the sample firm-year observations experience one or more crash weeks each year. The averages of negative skewness (*NCSKEW)* and down-to-up volume (*DUVOL)* are 0.081 and 0.014, respectively, similar to statistics reported in the literature (Kim et al., 2011b; Li & Zhan, 2018). These positive values indicate that sample firms have more left-skewed firm-specific weekly returns on average.

Table 2 presents the correlations between these variables. The three crash risk measures are highly correlated, with a significant value of 0.62 (between *CRASH* and *NCSKEW*), 0.56 (between *CRASH* and *DUVOL*), and 0.81 (between *NCSKEW* and *DUVOL*). The customer satisfaction measure, *ACSI*, is significantly and negatively related across three measurements of crash risks. Specifically, the correlation between *ACSI* and *CRASH* dummy is -0.04 (-0.07 for *NCSKEW* indicator and -0.05 for *DUVOL* indicator). These correlations provide an informal suggestion that firms with a higher level of customer satisfaction are less likely to have a stock crash in the future.

3. Regression Analysis

To formally test the competing predictions about the relationship between customer satisfaction and stock price crash risk, we run the following panel regression:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (5)$$

where the firm is indexed by *i* and year indexed by *t*. *CRASH_Risk* is one of the three crash-risk measures discussed in Section 2.2, including *CRASH*, *NCSKEW*, and *DUVOL*. Customer satisfaction (*ACSI*) is our primary variable of interest and is calculated as discussed in Section

2.3. A positive (negative) and significant coefficient estimate on *ACSI* would indicate that higher customer satisfaction is associated with a higher (lower) level of stock price crash risk.

Table 2 Pearson Correlations

This table reports the descriptive statistics for crash risk, customer satisfaction, and control variables employed in this study. The measures measurements of crash risk are *CRASH*, *NCSKEW*, and *DUVOL* at year t. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. The definitions of all other variables can be found in Appendix A. *ACSI* and other control variables are measured at year t-1. The sample contains 3,596 unique firm-year observations for publicly traded U.S. firms who that have has ACSI index over the period 1994 to 2019. All variables are winsorized at 1% and 99%.

	CRASH	*NCSKEW*	*DUVOL*	*ACSI*	*DTURN*	*RET*	*SIGMA*	*SIZE*	*LEVERAGE*	*ROA*	*MB*
CRASH	1										
NCSKEW	0.64	1									
	(0.00)										
DUVOL	0.56	0.82	1								
	(0.00)	(0.00)									
ACSI	-0.04	-0.07	-0.05	1							
	(0.01)	(0.00)	(0.00)								
DTURN	-0.02	0.02	0.03	-0.03	1						
	(0.22)	(0.36)	(0.07)	(0.05)							
RET	-0.01	0.02	0.01	0.13	-0.15	1					
	(0.4)	(0.14)	(0.76)	(0.00)	(0.00)						
SIGMA	0.02	-0.02	0	-0.13	0.16	-0.96	1				
	(0.13)	(0.21)	(0.89)	(0.00)	(0.00)	(0.00)					
SIZE	-0.04	0.01	-0.01	-0.1	-0.03	0.3	-0.34	1			
	(0.03)	(0.62)	(0.71)	(0.00)	(0.1)	(0.00)	(0.00)				
LEVERAGE	0	0.01	0	-0.17	0.09	-0.05	0.04	-0.22	1		
	(0.81)	(0.52)	(0.84)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)			
ROA	0.03	0.01	0.01	0.1	-0.1	0.39	-0.36	-0.11	-0.04	1	
	(0.07)	(0.39)	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)		
MB	0.01	-0.01	-0.01	-0.03	0.01	0.03	-0.03	-0.18	0.3	0.2	1
	(0.41)	(0.5)	(0.46)	(0.05)	(0.39)	(0.08)	(0.1)	(0.00)	(0.00)	(0.00)	

Following the literature on determinants of stock crash risk (Callen & Fang, 2015a; Hutton et al., 2009; Kim et al., 2011a, 2011b), we control for a range of variables including the detrended turnover (*DTURN*), mean and standard deviation of firm-specific weekly returns (*RET* and *SIGMA*), the log value of firm size (*SIZE*), financial leverage (*LEVERAGE*), return on assets (*ROA*), market-to-book ratio (*MB*), and one-year lagged *NCSKEW*.[8] We also include industry fixed effects ($Industry_i$) and year fixed effects ($Year_t$) to capture unobserved heterogeneity across industry and year. Standard errors are clustered at the firm level to alleviate the heteroscedasticity concern (Petersen, 2009). The details of the variables employed in our analysis are described and defined in Appendix A.

In Table 3, we report the effects of customer satisfaction (*ACSI*) on these three crash indicators (*CRASH*, *NCSKEW*, and *DUVOL*) from estimating equation (5). To be noted, we employ the Probit Model to examine the relationship between customer satisfaction and *CRASH* since it is a dummy variable. In Column 1 of Table 3, the coefficient based on the *CRASH* is -1.333 (with t-value equals -2.4). The result is also economically significant. Specifically, given a one standard deviation increase in *ACSI*, the probability of crash decreases by 8.5% in the following year.[9] This is compared to the average crash frequency of 20.5% (out of all sample observations) with a standard deviation of 40.4%. Columns 2 and 3 of Table 3 also report significantly negative coefficient on *ACSI* when conducting OLS regression with *NCSKEW* and *DUVOL* as the dependent variable.[10]

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[8] We control for the firm size (*SIZE*) as it has been found to affect a firm's stock price volatility (Pástor & Veronesi, 2003), credit risk (Beaver et al., 2005), and crash risk (Chen et al., 2001; Hutton et al., 2009). We control for leverage (*LEVERAGE*) as higher leverage is found to be associated with higher bankruptcy risk (Ross, 1977, Beaver et al., 2005). Prior studies suggest that firms with a higher market-to-book ratio are more likely to involve bubbles and are more prone to crash (Harvey and Siddique, 2000, Chen et al., 2001). Thus, we also control for the market-to-book ratio (*MB*). Finally, we control for a firm's crash risk in the previous year as the experience of a crash may increase investors′ aversion to future crash risk (Bates, 2000).

[9] Given a one standard deviation increase in *ACSI* (0.064), the probability of crash decreases by -1.333*0.064=-0.085.

[10] The coefficient on *ACSI* is -1.059 in Column 2 and translates to 0.068 (-1.059*0.064) change in *NCSKEW*. It is also economically significant as the magnitude is large compared to the average *NCSKEW* of 0.044. Similarly,

Overall, our main regression results provide strong support for the view that firms with higher customer satisfaction are less exposed to stock crash risk in the future. However, endogeneity issues may exist due to the following considerations. First, the negative relationship between customer satisfaction and stock crash risk could be driven by unobserved shocks and omitted variables, such as macroeconomic shocks that we cannot control for. Second, our results may be affected by a reverse causality relationship. For instance, shareholders from firms with poor firm performance and high crash risk may pressure managers into improving short-term financial performance by sacrificing the product and service quality, which leads to lower customer satisfaction. We attempt to address these endogeneity concerns in the next section, using a firm fixed effects model, an instrumental variable (IV) approach, and a natural experiment that acts as an exogenous shock to customer satisfaction.

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the coefficient on *ACSI* is -0.271 in Column 3 and translates to 0.017 (-0.271*0.064) change in *DUVOL,* which has a mean of 0.014.

Table 3 Does Customer Satisfaction Affect Stock Price Crash Risk?

This table reports the regression results for the impact of customer satisfaction on stock crash risk. The measurements of crash risk are *CRASH*, *NCSKEW*, and *DUVOL* at year t. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *ACSI* and other control variables are measured at year t-1. In each regression, we control firm-level variables including *DTURN*, *RET*, *SIGMA*, *NCSKEW*, *SIZE*, *LEVERAGE*, *ROA*, and *MB*. The definitions of these variables can be found in Appendix A. Year fixed effects and industry fixed effects are also included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables (t)	*CRASH*	*NCSKEW*	*DUVOL*
Independent Variable (t-1)			
ACSI	-1.333**	-1.059***	-0.271***
	(0.549)	(0.228)	(0.063)
Control Variables (t-1)			
DTURN	-0.025	0.028	0.012*
	(0.049)	(0.019)	(0.007)
RET	1.390	0.274	0.138
	(1.228)	(0.510)	(0.175)
SIGMA	6.109	-1.881	0.026
	(6.847)	(3.088)	(1.011)
NCSKEW	0.029**	0.018	0.001
	(0.013)	(0.021)	(0.002)
SIZE	-0.080***	-0.018	-0.006*
	(0.030)	(0.013)	(0.003)
LEVERAGE	-0.228	-0.087	-0.012
	(0.217)	(0.102)	(0.029)
ROA	0.087	-0.073	0.014
	(0.588)	(0.296)	(0.094)
MB	-0.001	-0.001	-0.000
	(0.003)	(0.001)	(0.000)
Constant	-0.848**	-0.087	-0.013
	(0.345)	(0.187)	(0.059)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Num of Observations	3,486	3,486	3,486
R-square	0.0413	0.0530	0.0387

4. Robustness Tests

This section presents three methods to mitigate endogeneity concerns we discussed in Section 3.

4.1 Evidence from Firm Fixed Effects Model

The baseline regression control for year fixed effects and industry fixed effects. To control for the impact of time-invariant correlated variables at the firm level, we add firm fixed effects to the following model,

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \lambda * Control_{i,t-1} + Firm_i + Year_t + \varepsilon_{i,t} \quad (6)$$

Table 4 presents the above regression results that use the same variable definitions except replacing industry fixed effects with firm fixed effects. The coefficient on *ACSI* remains significant and negative across all three crash measurements. Thus, the results with firm fixed effects confirm the findings in Table 3 that higher customer satisfaction is associated with lower stock crash risk in a more restricted setting.

4.2 Evidence from Instrumental Variable Regressions

To alleviate endogeneity from omitted variables or reverse causality, we also use two-stage least squares regression based on two instrument variables (IVs) related to customer satisfaction while are unlikely to affect stock crash risks directly.

The first IV is the advertisement expense (Ad_Exp) scaled by sales at the beginning of each year. Ha, John, Janda, and Muthaly (2011) provide evidence that advertising spending has simultaneously positive effects on customer's store image, perceived quality, and satisfaction on brand loyalty. On the other hand, it is unlikely that a firm's crash risk is directly affected by advertisement spending.

Table 4 Firm- and Year-fixed Effects Regression

This table reports the regression results for the impact of customer satisfaction on stock crash risk. The measurements of crash risk are *CRASH*, *NCSKEW*, and *DUVOL* at year t. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *ACSI* and other control variables are measured at year t-1. In each regression, we control firm-level variables including *DTURN*, *RET*, *SIGMA*, *NCSKEW*, *SIZE*, *LEVERAGE*, *ROA*, and *MB*. The definitions of these variables can be found in Appendix A. Year fixed effects and firm fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables (t)	*CRASH*	*NCSKEW*	*DUVOL*
Independent Variable (t-1)			
ACSI	-3.795*	-0.797**	-0.258**
	(2.216)	(0.372)	(0.117)
Control Variables (t-1)			
DTURN	0.093	0.022	0.012
	(0.085)	(0.021)	(0.007)
RET	1.861	-0.260	0.039
	(3.051)	(0.594)	(0.213)
SIGMA	-7.173	-5.114	-0.632
	(16.961)	(3.611)	(1.241)
NCSKEW	-0.007	-0.085***	-0.006***
	(0.033)	(0.021)	(0.002)
SIZE	0.476**	0.084**	0.023**
	(0.212)	(0.039)	(0.011)
LEVERAGE	1.753*	-0.219	-0.043
	(0.932)	(0.159)	(0.048)
ROA	-2.012	-0.088	-0.037
	(2.204)	(0.433)	(0.139)
MB	0.004	0.000	0.000
	(0.008)	(0.001)	(0.000)
Constant	-3.584	-0.113	-0.034
	(4.740)	(0.234)	(0.077)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Num of Observations	3,486	3,486	3,486
R-square	0.079	0.182	0.151

Moreover, previous studies show that the firm's service quality positively affects customer satisfaction (Barger & Grandey, 2006; Olorunniwo, Hsu, & Udo, 2006). Meanwhile, the staff expense is also unlikely to relate to the occurrence of a firm crash directly in the future. Thus, as a proxy for the staff quality, the second IV is the staff expense (*Staff_Exp*) scaled by sales at the beginning of each year. Both IVs satisfy the exclusion condition so that it can be used in our analysis.

Columns 1 to 3 of Table 5 present results using the sub-sample with non-missing values of the two instrumental variables. Similarly, both the Probit model and the OLS regression provide evidence that low level of customer satisfaction leads to high crash risk. The Probit model is significant at the 10% level, and the OLS model significant at the 5% level.

Columns 4 to 7 of Table 5 present the two-stage least squares (2SLS) regression results. We first regress customer satisfaction, *ACSI,* on the *advertisement expense, staff expense,* firm-level control variables, and industry- and year-fixed effects in Column (7). We find that advertising expense is significant in predicting *ACSI*, which indicates that an increase in advertising will significantly increase customer satisfaction. The F-statistic of 25.27 rejects the null hypothesis that these two instrumental variables are jointly zero, indicating that IVs are robust to weak instrument concerns in our analysis.

We then replace *ACSI* with the predicted value of *ACSI* from the first stage regression and present IV estimates in Columns 4 to 6 for the three crash measures. To consider the over-identifying restriction of instrument variables, we also conduct the Hansen J-statistics test with the null hypothesis that there exists a zero correlation between IV and the error term. The p-values of three second-stage models are 0.92, 0.50, and 0.46, respectively, indicating that the two IVs have no correlation with the stock crash risk and satisfy the exclusion condition.

Table 5 Instrumental Variables-Regression Results

This table reports the two-stage least squares (2SLS) regression results for the impact of customer satisfaction on stock crash risk. In the first stage, we regress *ACSI* on two instrumental variables (*Staff_Exp* and *Ad_Exp*) and extract the fitted value as the instrumented customer satisfaction ($\widehat{ACSI}$). *Staff_Exp* is firm's annual staff expense scaled with the sale in a given fiscal year. *Ad_Exp* is firm's advertisement expense scaled with the sale in a given year. The second stage regression is to regress $\widehat{ACSI}$ on crash risk measures. We control firm level variables in both stages and definitions of these variables can be found in Appendix A. Year fixed effects and firm fixed effects are included in each stage. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Probit	OLS		IV Second-stage Estimation			IV First-stage Estimation
	CRASH	*NCSKEW*	*DUVOL*	*CRASH*	*NCSKEW*	*DUVOL*	*ACSI*
Variables (t-1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ACSI	-2.048***	-1.336***	-0.282**	-9.088*	-5.286**	-1.110*	
	(0.764)	(0.443)	(0.109)	(4.734)	(2.497)	(0.586)	
Staff_Exp							0.109
							(0.119)
Ad_Exp							0.285***
							(0.104)
DTURN	0.011	0.038	0.012	0.007	0.035	0.012*	-0.001
	(0.049)	(0.035)	(0.009)	(0.052)	(0.025)	(0.007)	(0.002)
RET	2.216	0.211	0.168	1.695	0.059	0.136	-0.043
	(1.387)	(0.560)	(0.185)	(1.091)	(0.565)	(0.193)	(0.055)
SIGMA	15.580*	-1.618	0.782	11.536	-2.998	0.492	-0.432
	(8.736)	(4.243)	(1.391)	(7.153)	(4.092)	(1.411)	(0.410)
NCSKEW	0.025	-0.045	-0.013	-0.003	-0.060**	-0.016*	-0.003
	(0.068)	(0.039)	(0.013)	(0.062)	(0.029)	(0.009)	(0.003)
SIZE	-0.044	-0.007	-0.005	-0.090**	-0.034*	-0.010	-0.005*
	(0.034)	(0.014)	(0.004)	(0.041)	(0.019)	(0.007)	(0.003)
LEVERAGE	0.202	-0.218**	-0.050	0.193	-0.217*	-0.050	0.002
	(0.206)	(0.106)	(0.031)	(0.253)	(0.118)	(0.034)	(0.022)
ROA	-0.494	-0.397	-0.079	-0.755	-0.548	-0.111	-0.039
	(1.056)	(0.544)	(0.190)	(1.105)	(0.540)	(0.179)	(0.046)
MB	0.001	0.001	0.000*	0.001	0.001**	0.000***	0.000
	(0.003)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)

Table 5 Continued

Constant	-1.170**	-0.120	-0.021	-0.763	0.05	0.015	0.022
	(0.477)	(0.182)	(0.052)	(0.530)	(0.184)	(0.066)	(0.034)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num of Observations	1,471	1,471	1,471	1,471	1,471	1,471	1,471
R-square	0.071	0.065	0.068	0.07	0.004	0.039	0.145
Over-identification (Hansen's J-statistic p-value)				0.923	0.5	0.458	
Weak instrument (F-stats)							25.27

4.3 Evidence from Difference in Differences Approach

To further confirm the causal relationship between customer satisfaction and future stock crash risk, we employ a difference in difference (DiD) approach using an exogenous shock to customer service in the financial industry as a natural experiment. The Gramm-Leach-Bliley Act (GLBA), also known as the Financial Services Modernization Act of 1999, is an act to remove barriers in the financial market among banks, brokerages, and insurance companies. Before the Act, a financial institution was prohibited from acting as a combination of an investment bank, a commercial bank, and an insurance company. Individuals/customers had to open accounts in two different financial institutions for saving and investment purposes. Whereas after introducing this Act, financial institutions could provide convenience to their customers by offering both commercial and investment services.

An ideal natural experiment should satisfy both relevance and exclusion conditions. Regarding the relevance condition, customers tend to be more satisfied with their financial agents. They do not have to withdraw from one institution and deposit their money into another when adjusting investment strategy. Regarding the exclusion condition, the Act relaxed restrictions in the financial industry. It is reasonable to argue that the Act had no impact on other industries, which justifies the exclusion condition.

Thus, we define the treatment group as firms within the financial industry. We define pre-treatment years as the three-year period from 1996 through 1998 and the post-treatment period as years from 2000 to 2002. We run the following Probit and least squares regression model with the DiD framework to test the effect of the Act on the stock crash risk:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * Treat_{i,t-1} + \beta_2 * Post_{i,t-1} + \beta_3 * Treat_{i,t-1} * Post_{i,t-1} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (7)$$

where a firm is indexed by i and year by t. $CRASH\_Risk$ is one of the crash-risk variables, including *CRASH*, *NCSKEW*, and *DUVOL*. *Treat* equals one for firms in the financial industry, and zero otherwise. *Post* equals one for observations fall in the three years after the Gramm-Leach-Bliley Act, and zero for three years before the Act. The primary variable of interest,$Treat_{i,t-1} * Post_{i,t-1}$, is an interaction term of *Treat* and *Post*. A positive (negative) and significant coefficient estimate on this interaction, which is β_3 could indicate that higher customer satisfaction following the Act is associated with a higher (lower) level of stock price crash risk (relative to firms in the nonfinancial industry). Thus, if customer satisfaction could decrease the stock price crash risk, we expect a negative coefficient of this interaction variable.

Table 6 provides the results of DiD estimation. Consistent with our expectations, the coefficients of all three crash risk proxies are significantly negative, with a p-value of below 10% or 5%. Thus, the DiD approach supports the view that higher customer satisfaction leads to lower firm crash risk.

Table 6 Natural Experiment Test Results

This table reports the impact of Gramm-Leach-Bliley Act (GLBA) on stock crash risk using the difference in difference approach (DiD). The sample contains 675 unique firm-year observations ranging from 1996 to 2002. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *ACSI* and other control variables are measured at year t-1. In each regression, we control firm-level variables including *DTURN*, *RET*, *SIGMA*, *NCSKEW*, *SIZE*, *LEVERAGE*, *ROA*, and *MB*. The definitions of these variables can be found in Appendix A. *Treat* equals to one for the treatment firms in financing industry and zero otherwise. *Post* is a dummy variable equals one for three years after the Act (i.e., 2000 through 2002), and zero for three year before the Act (i.e., 1996 through 1998). Standard errors are shown in brackets and are robust for heteroscedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*CRASH*	*NCSKEW*	*DUVOL*
Treat	0.750**	0.397**	0.102**
	(0.318)	(0.167)	(0.050)
Post	0.419***	0.305***	0.065***
	(0.145)	(0.064)	(0.021)
*Treat*Post*	-0.921*	-0.578**	-0.125*
	(0.504)	(0.232)	(0.071)
DTURN	0.016	0.029**	0.006
	(0.025)	(0.012)	(0.005)
RET	0.593	0.838	0.342
	(1.948)	(0.820)	(0.268)
SIGMA	2.050	3.956	2.017
	(11.404)	(4.893)	(1.656)
NCSKEW	0.153*	-0.071	-0.033**
	(0.090)	(0.051)	(0.013)
SIZE	-0.012	-0.021	-0.010
	(0.042)	(0.019)	(0.006)
LEVERAGE	0.539	-0.083	-0.071
	(0.482)	(0.213)	(0.068)
ROA	3.411***	0.539	0.211
	(1.301)	(0.578)	(0.164)
MB	0.005	0.001	0.000
	(0.004)	(0.002)	(0.001)
Constant	-1.447***	-0.029	0.045
	(0.557)	(0.248)	(0.085)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Num of Observations	675	675	675
R-square	0.052	0.056	0.043

5. Exploring Channels of Reducing the Stock Crash Risk

The results thus far established a robust and negative causality from customer satisfaction to stock price crashes. We next explore possible channels that contribute the negative relationship between customer satisfaction and stock crash risk.

5.1 Volatility Feedback Channel

As we discussed in introduction, if customer satisfaction reduces the stock crash risk through the volatility feedback effect, we could expect higher customer satisfaction is associated with lower future stock price volatility. Moreover, we would observe the impact of customer satisfaction on the stock crash risk more pronounced for a group of firms with higher volatility.

We formally test these two arguments using the full sample. We define *Next_Sigma* as the standard deviation of firm-specific weekly returns in the following year. For the subsample test, we construct a dummy variable (*High_Sigma*) equals one for firms with above sample median standard deviation, and zero otherwise. We then expect an interaction term between *ACSI* and *High_Sigma* has a negative effect on crash risk. In other words, firms with higher volatility tend to have lower feedback if it has higher customer satisfaction. Lower volatility feedback reduces the level of crash risk. We estimate the following Probit and OLS model to test this mechanism:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \beta_2 * High\_Sigma_{i,t} + \beta_3 * ACSI_{i,t-1} * High\_Sigma_{i,t} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (8)$$

where the firm is indexed by i and year by t. *CRASH_Risk* is one of the three crash-risk variables, including *CRASH*, *NCSKEW*, and *DUVOL*. To define *High_Sigma*, we first calculate the standard deviation of firm-specific weekly returns at year t, *SIGMA*. *High_Sigma* is a dummy variable equals one if the firm's *SIGMA* is greater than the sample median, and zero otherwise. The primary variable of interest, the interaction between *ACSI* and *High_Sigma*, is expected to have a significant negative coefficient (β_3), suggesting that higher *ACSI* will reduce the crash risk induced by higher stock volatility.

The results in Table 7 provide evidence supporting the above conjectures. Column 1 shows the coefficient of *ACSI* on the next period stock volatility (*SIGMA*) is -0.02 with a significance level of 1%. Column 2 to 4 show the results of the above regression with the interaction term $ACSI_{i,t-1} * High\_Sigma_{i,t}$. Note that the model for the *CRASH* dummy (Column 2) is the Probit model. We find that the coefficient on *ACSI* becomes insignificant compared to our main results. The interaction term's coefficient is significant across all three measurements, indicating that the impact of customer satisfaction on stock crash risk is significant when the contemporaneous stock volatility is high.

Table 7 Volatility Feedback Channel

This table reports the regression results of testing the volatility feedback channel in triggering stock crash, conditional on the level of customer satisfaction (*ACSI*). *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *ACSI* and other independent variables are measured at year t-1. The definitions of other variables can be found in Appendix A. *High_Sigma* is a dummy variable equal to one if the firm's *SIGMA* is greater than the sample median, and zero otherwise. Our main variable of interest is the interaction between *ACSI* and *High_Sigma*. Year fixed effects and industry fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables (t)	*SIGMA* (1)	*CRASH* (2)	*NCSKEW* (3)	*DUVOL* (4)
Independent Variables (t-1)				
ACSI	-0.020***	0.163	-0.364	-0.038
	(0.006)	(0.790)	(1.182)	(0.090)
High_Sigma		0.543***	0.361*	0.023
		(0.107)	(0.205)	(0.021)
*ACSI *High_Sigma*		-1.704*	-4.255**	-0.400***
		(0.999)	(1.783)	(0.151)
Control Variables (t-1)				
DTURN	-0.000	-0.010	0.063	0.007
	(0.000)	(0.024)	(0.051)	(0.005)
RET	2.465	-74.849	-39.853	14.707
	(2.570)	(108.166)	(190.400)	(20.435)
SIGMA	0.739***	-10.852*	-15.861	-0.052
	(0.125)	(5.865)	(11.167)	(1.254)
NCSKEW	0.000	0.023*	0.018	0.000
	(0.000)	(0.013)	(0.026)	(0.004)
SIZE	-0.002***	-0.041*	0.006	-0.003
	(0.000)	(0.023)	(0.037)	(0.004)
LEVERAGE	-0.000	0.009	-0.105	-0.004
	(0.001)	(0.093)	(0.193)	(0.014)
ROA	-0.070***	0.311	0.047	-0.013
	(0.024)	(0.920)	(1.431)	(0.167)
MB	-0.000	-0.002	-0.004	-0.000
	(0.000)	(0.004)	(0.006)	(0.001)
Constant	0.028***	-1.048***	-0.472	-0.028
	(0.004)	(0.249)	(0.425)	(0.048)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	3,500	3,500	3,500	3,500
R-square	0.593	0.06	0.061	0.038

5.2 Differences of Opinion Channel

Hong and Stein (2003) provide a theoretical model that heterogeneity in investors' beliefs will lead to a stock crash. If customer satisfaction reduces the information uncertainty, the arbitragers will discover less unexpected information from bearish investors, which leads to a lower level of the crash. Thus, we could expect higher customer satisfaction is associated with a lower difference of opinion, and thus a lower level of stock crash risk. What's more, we can expect the impact of customer satisfaction on crash risk should be more pronounced for firms that have a higher level of differences of opinion.

We formally test the two arguments based on the full sample. We first define *Doo* as the standard deviation of analyst earnings forecasts in a fiscal year, which is the same year as the *ACSI* variable. For the subsample test, *High_Doo* is a dummy variable equals one if the firm's differences of opinion is greater than the sample median, and zero otherwise. We then expect an interaction term between *ACSI* and *High_Doo* has a negative effect on crash risk. In other words, a firm with a higher *Doo* will have a lower crash if it has higher customer satisfaction. We estimate the following Probit and OLS model to test this mechanism:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \beta_2 * High\_Doo_{i,t} + \beta_3 * ACSI_{i,t-1} * High\_Doo_{i,t} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (9)$$

where firm is indexed by i and year by t. *CRASH_Risk* is one of the three crash risk measurements. Our primary interest in this regression is the interaction between *ACSI* and *High_Doo*. If customer satisfaction reduces the stock crash risk by reducing the differences of opinion, we could expect a negative coefficient of β_3.

The results provided in Table 8 are consistent with the predictions above. Column 1 shows a negative relationship between *ACSI* and next period difference of opinion (*Doo*). The coefficient of *ACSI* on *Doo* is -0.474, which is significant at 5% level. Column 2 to 4 provide the full model results with the interaction term $ACSI_{i,t-1} * High\_Doo_{i,t}$. We find that the coefficient on customer satisfaction becomes insignificant compared to our main results. The coefficients on the interaction term are significantly negative across all three measures, indicating the impact of *ACSI* on the stock crash risk is more pronounced if contemporaneous analysts' difference of opinion on earnings is higher.

5.3 Bad News Hoarding Channel

To test this bad news hoarding channel, we conduct a series of empirical tests to investigate whether a higher customer satisfaction leads to less bad news hoarding and lower stock crash risk. We first consider the financial reporting opacity as it is a standard mechanism of measuring bad news hoarding (Hutton et al., 2009). Second, Hutton et al. (2009) also find that the opacity is associated with a higher level of stock synchronicity, measured using R-square of a market model. Thus, we also use R-square from the market model as a proxy of bad news hoarding. Third, following Basu (1997), we employ a profit-related measurement and examine the timeliness of loss recognition.

Table 8 Differences of Opinion Channel

This table reports the regression results of testing the difference of opinion channel in triggering stock crash. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *ACSI* and other independent variables are measured at year t-1. The definitions of other variables can be found in Appendix A. *Doo* is the standard deviation of analyst earnings forecasts in a fiscal year. *High_Doo* is a dummy variable equal to one if the firm's *Doo* is greater than the sample median, and zero otherwise. Year fixed effects and industry fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Doo* (1)	*CRASH* (2)	*NCSKEW* (3)	*DUVOL* (4)
ACSI	-0.474**	-0.261	-0.433	-0.013
	(0.210)	(0.608)	(1.038)	(0.089)
High_Doo		-0.121*	-0.216**	-0.025***
		(0.067)	(0.093)	(0.009)
ACSI High_Doo*		-1.596***	-4.374***	-0.400***
		(0.607)	(1.210)	(0.101)
Control Variables (t-1)				
DTURN	0.009	0.063*	0.137***	0.010**
	(0.009)	(0.036)	(0.044)	(0.004)
RET	77.108**	7.789	-128.018	1.551
	(30.283)	(60.556)	(102.485)	(9.054)
SIGMA	6.901***	-0.256	-17.018**	-0.280
	(2.286)	(4.036)	(8.159)	(0.772)
NCSKEW	-0.006	0.016	0.010	0.000
	(0.008)	(0.014)	(0.030)	(0.003)
SIZE	-0.000	-0.052***	-0.004	-0.001
	(0.019)	(0.019)	(0.035)	(0.003)
LEVERAGE	0.008	-0.015	-0.060	0.003
	(0.044)	(0.063)	(0.142)	(0.012)
ROA	-0.732**	0.327	-0.187	-0.015
	(0.373)	(0.463)	(0.596)	(0.065)
MB	0.000	-0.001	-0.002	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)
Constant	-0.038	-0.656***	0.318	-0.015
	(0.173)	(0.209)	(0.386)	(0.040)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	3,317	3,354	3,362	3,362
R-square	0.075	0.043	0.058	0.041

5.3.1 Financial Report Readability

This sub-section investigates the relationship between customer satisfaction, financial report readability, and the stock crash risk. Financial reports are one of the most important tools for managers to communicate with investors. Li (2008) argue that managers can easily hide adverse information from investors if the financial report is complex and hard to read. The author also provides four measurements of financial report readability using textual analysis, including the complexity and length of financial reports. Specifically, the *Fog index*, the first measurement, is defined as 0.4 multiply words per sentence plus 0.4 multiple percent of complex words in the financial report. Complex words are words with three syllables or more. The second measure, *NegFlesch*, is defined as 1.015 times words per sentence plus 84.6 times syllables per word minus 206.835. *Kincaid* is defined as 0.39 multiply words per sentence plus 11.8 times syllables per word minus 15.59. *Length* is the logarithm of the number of words in the annual report. Thus, a higher value of *Fog index*, *NegFlesch*, *Kincaid* and *Length* indicate a less readable financial report. If customer satisfaction decreases stock crash risk through the bad news hoarding channel, we expect a negative coefficient for customer satisfaction on those four measurements of financial report readability. The interaction term between *ACSI* and readability dummies could have a negative coefficient on crash risk. We estimate the following Probit and OLS model to test this mechanism:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \beta_2 * Readability\_dummy_{i,t-1} + \beta_3 * ACSI_{i,t-1} * Readability\_dummy_{i,t-1} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (10)$$

where the firm is indexed by *i* and year by *t*. *CRASH_Risk* is one of the crash-risk variables defined before. According to the four financial readability measurements discussed above, we create four readability dummies. These four dummies are *High_Fog, High_NegFlesch,* *High_Kincaid, and High_Length*[11], which equal one if the firm's readability measure is greater than the sample's median and zero otherwise. Our primary variable of interest, the interaction between *ACSI* and readability dummies, is expected to have a significant negative coefficient (β_3), suggesting that high *ACSI* score will reduce the crash risk by increasing information transparency (lower bad news hoarding).

The results in Table 9 do not support the bad news hoarding hypothesis. Column 1 of each panel provides evidence about the relation between *ACSI* and financial report readability index. The coefficients of *ACSI* on three out of four readability measurements are significantly negative, indicating that higher ACSI firms are associated with higher financial report readability. However, the full model results with the interaction term $ACSI_{i,t-1} * Readability\_dummy_{i,t-1}$, Columns 2 to 4 show that interaction terms' coefficients are insignificant across all three crash risk measures and four readability proxies. The results indicate that the impact of customer satisfaction on the stock crash risk does not link to the level of financial report readability.

[11] The financial report readability measure is obtained at the same year of *ACSI (t-1)*. The reason is that bad news hoarding will create price inflation and crash in the future, where volatility feedback channel will create crash at the concurrent period.

Table 9 Evidence of Financial Report Readability

This table reports the regression results of testing financial report readability in triggering stock crash. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. Four measures of financial report readability are included. The four readability dummies are *High_Fog*, *High_Negflesch*, *High_Kincaid*, and *High_Length* that equal one if the firm's financial report readability is greater than the sample median, and zero otherwise. A higher value of the measures indicates a less readable financial reports. The definitions of other control variables can be found in Appendix A. Year fixed effects and industry fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Readability Proxy-Fog index		Dependent Variables		
	Fog	*CRASH*	*NCSKEW*	*DUVOL*
ACSI	-3.466***	-1.385	-1.288	-0.109
	(1.331)	(0.962)	(1.772)	(0.163)
High_Fog		0.110	0.277	0.005
		(0.115)	(0.202)	(0.018)
*ACSI*High_Fog*		0.927	-2.317	-0.077
		(1.380)	(1.682)	(0.182)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	1,203	1,203	1,203	1,203
R-square	0.213	0.057	0.064	0.066
Panel B: Readability Proxy-Negflesch		Dependent Variables		
	Negflesch	*CRASH*	*NCSKEW*	*DUVOL*
ACSI	-5.377*	-0.071	-1.302	-0.132
	(3.221)	(0.817)	(1.472)	(0.130)
High_Negflesch		0.052	0.133	0.012
		(0.112)	(0.216)	(0.025)
*ACSI*High_Negflesch*		-1.640	-2.463	-0.026
		(1.181)	(1.777)	(0.143)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	1,203	1,203	1,203	1,203
R-square	0.362	0.057	0.062	0.066
Panel C: Readability Proxy-Kincaid		Dependent Variables		
	Kincaid	*CRASH*	*NCSKEW*	*DUVOL*
ACSI	-2.607**	-1.551	-1.712	-0.164
	(1.246)	(0.954)	(1.871)	(0.148)
High_Kincaid		0.043	0.150	-0.000
		(0.144)	(0.195)	(0.021)
*ACSI*High_Kincaid*		1.125	-1.563	0.024
		(1.474)	(2.306)	(0.196)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	1,203	1,203	1,203	1,203
R-square	0.240	0.056	0.061	0.066

Table 9 Continued

Panel D: Readability Proxy-Length	Dependent Variables			
	Length	*CRASH*	*NCSKEW*	*DUVOL*
ACSI	0.328	-0.549	-1.371	-0.181
	(0.367)	(1.011)	(1.661)	(0.128)
High_Length		0.084	0.027	0.017
		(0.146)	(0.222)	(0.020)
*ACSI*High_Length*		-0.707	-2.364	0.052
		(1.578)	(1.590)	(0.185)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	1,203	1,203	1,203	1,203
R-square	0.242	0.056	0.061	0.067

5.3.2 Information Transparency

Jin and Myers (2006) develop a model with incomplete transparency that predicts stock crashes. They argue that outside investors will force insiders to reduce their future cash flow capture if the firm lacks information transparency. The risk-shifting from outsider to insider will reduce the amount of firm-specific information absorbed by outsiders, increasing the market model's R-square. However, suppose the bad news accumulates to a level that managers are unwilling or unable to absorb. In that case, they will release the negative information to the public at once, thus, resulting in a stock price crash. Following Morck, Yeung, and Yu (2000), we define the firm's idiosyncratic risk using a logistic transformation of R-square, which can range from negative to positive infinity.

$$idio = \ln\left(\frac{1-\mathrm{R}^2}{\mathrm{R}^2}\right) \tag{11}$$

A high value for *idio* indicates a high level of idiosyncratic risk. Firms with more bad news hoarding tend to be more synchronous with the market and have a lower value of *idio*. If customer satisfaction decreases the stock crash risk through the bad news hoarding channel, we could expect a negative coefficient for *ACSI* on the idiosyncratic risk. Thus, we estimate the following Probit and OLS model to test this mechanism:

$$CRASH\_Risk_{i,t} = \alpha + \beta_1 * ACSI_{i,t-1} + \beta_2 * High\_idio_{i,t-1} + \beta_3 * ACSI_{i,t-1} * High\_idio_{i,t-1} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (12)$$

where firm is indexed by i and year by t. *CRASH_Risk* is one of the crash-risk variables. *High_idio* is a dummy variable equals one if the firm's idiosyncratic risk is greater than the sample's median, and zero otherwise.

Our main variable of interest, the interaction between *ACSI* and idiosyncratic risk dummy, is expected to have a significant negative coefficient (β_3), suggesting that higher *ACSI* will reduce the crash risk by increasing information transparency (lower bad news hoarding).

Table 10 shows that our results do not support the bad news hoarding hypothesis. Column 1 provides evidence that the relation between *ACSI* and idiosyncratic risk is not significant. Columns 2 presents the Probit model results for the *CRASH* dummy, providing weak evidence with a significant coefficient on the interaction term at the 10% level. Columns 3 and 4 show that the coefficient on *ACSI* is still significant for *NCSKEW* and *DUVOL,* whereas coefficients on interaction terms are insignificant. Overall, the results do not support that customer satisfaction reduces crash risk through the information transparency channel.

Table 10 Evidence of Idiosyncratic Risks

This table reports the regression results of testing the information transparency in triggering stock crash. *CRASH* is a dummy variable that equals one when a firm experiences one or more crash weeks in a given year, and zeroes otherwise. *NCSKEW*, is the negative conditional return skewness of the firm-specific weekly returns. *DUVOL* is the down-to-up volatility of firm-specific weekly returns. The primary independent variable is *ACSI,* which calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *Idio* is the firm idiosyncratic risk, which is a function of R-square from market model. A higher *idio* is associated with more information available to the market, and more information transparency (Hutton et al., 2009). *High_idio* is a dummy variable equal to one if the firm's *Idio* is greater than the sample median, and zero otherwise. The definitions of other control variables can be found in Appendix A. Year fixed effects and industry fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Idio* (1)	*CRASH* (2)	*NCSKEW* (3)	*DUVOL* (4)
ACSI	-0.123	-0.272	-1.988*	-0.230**
	(0.144)	(0.693)	(1.058)	(0.112)
High_idio		0.010	0.271*	0.014
		(0.078)	(0.145)	(0.013)
*ACSI*High_idio*		-1.684*	-1.843	-0.081
		(0.907)	(1.533)	(0.175)
Control Variables (t-1)				
DTURN	0.012**	-0.010	0.061	0.007
	(0.006)	(0.027)	(0.058)	(0.006)
RET	124.546***	38.810	-109.402	3.515
	(37.671)	(60.639)	(116.061)	(10.717)
SIGMA	12.825***	0.824	-17.058**	-0.379
	(2.447)	(3.632)	(8.681)	(0.869)
NCSKEW	0.006*	0.021	0.018	0.001
	(0.003)	(0.014)	(0.029)	(0.003)
SIZE	-0.012	-0.066***	-0.005	-0.003
	(0.010)	(0.021)	(0.038)	(0.004)
LEVERAGE	0.026	0.019	-0.132	-0.006
	(0.018)	(0.094)	(0.185)	(0.013)
ROA	0.269**	0.066	-0.408	-0.046
	(0.119)	(0.725)	(1.171)	(0.136)
MB	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.002)	(0.000)
Constant	0.326***	-0.971***	-0.437	-0.021
	(0.116)	(0.221)	(0.405)	(0.046)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num of Observations	3,500	3,500	3,500	3,500
R-square	0.398	0.042	0.057	0.035

5.3.3 Timeliness of Loss Recognition

In this section, we further test how timely do firms recognise profit and loss. We investigate the timeliness of loss recognition following Basu (1997). Basu (1997) argues that the accountant is prone to require a higher degree of verification when recognizing good news in financial statements than bad news. Thus, earnings reflect bad news more quickly than good news. They regress earnings on annual stock returns, negative return dummy, and the interaction between stock return and negative return dummy. The interaction term captures the difference in the sensitivity of earnings to positive and negative returns. A positive coefficient indicates that firms recognise losses timelier than gains. Specifically, we estimate the following OLS model to test this mechanism:

$$EPS_{i,t}/\mathrm{P}_{\mathrm{i,t-1}} = \alpha + \beta_1 * ACSI_{i,t} + \beta_2 * anret_{i,t} + \beta_3 * negd_{i,t} + \beta_4 * ACSI_{i,t} * anret_{i,t} + \beta_5 * ACSI_{i,t} * negd_{i,t} + \beta_6 * anret_{i,t} * negd_{i,t} + \beta_7 * ACSI_{i,t} * anret_{i,t} * negd_{i,t} + \lambda * Control_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \quad (12)$$

where firm is indexed by *i* and year by *t*. The dependent variable is earnings per share before extraordinary items scaled by fiscal year beginning stock price. *Anret* is the firm annual return beginning nine months prior to fiscal year end. *Negd* is a dummy variable equal to one if the firm's annual return is negative, and zero otherwise. Following Basu (1997), the regression is based on contemporaneous variables with both dependent and independent variable are measured in the same fiscal year. An interaction between *Anret* and *Negd* is to measure the incremental timeliness loss recognition in earnings relative to gains. Our main variable of interest is the interaction between *ACSI*, *Anret*, and *Negd*, which measures the role of *ACSI* in loss recognition. Year fixed effects and industry fixed effects are included in each regression.

The results in Table 11 shows that the interaction between annual return and negative return dummy is positive and significant. It is consistent with the literature (Basu, 1997) that firms are timelier in recognizing losses than gains. However, we do not observe a significant coefficient of the interaction between *ACSI*, *Anret*, and *Negd* (β_7) which indicates customer satisfaction does not have direct impact on the timeliness of loss recognition. Overall, the tests suggest that customer satisfaction reduces the stock price crash risk through volatility feedback channel and difference of opinion channel, but we do not find strong evidence of bad news hoarding channel.

Table 11 Timely Loss Recognition

This table reports the regression results of testing the timely loss recognition channel. The regression is based on contemporaneous variables with both dependent and independent variable are measured in the same fiscal year. The dependent variable is earnings per share before extraordinary items scaled by fiscal year beginning stock price. *ACSI* is calculated by scaling firm ACSI score with industry ACSI score in a given year. Both firm and industry-level ACSI scores are obtained from ACSI website. This index ranging ranges from 0 to 100, where 0 represents least satisfied and 100 represents most satisfied. *Anret* is the firm's annual return beginning nine months prior to fiscal year end. *Negd* is a dummy variable equal to one if the firm's annual return is negative, and zero otherwise. Following Basu (1997), an interaction between *Anret* and *Negd* is to measure the incremental timeliness loss recognition in earnings relative to gains. Our main variable of interest is the interaction between *ACSI*, *Anret*, and *Negd*, which measures the role of *ACSI* in loss recognition. Year fixed effects and industry fixed effects are included in each regression. Standard errors are shown in brackets and are adjusted for within-firm clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: $EPS_{i,t}/\mathrm{P}_{\mathrm{i,t-1}}$
Variables (t)	
ACSI	0.357
	(0.233)
Anret	-0.099
	(0.097)
Negd	0.339**
	(0.146)
*ACSI*Negd*	-3.770
	(3.447)
*Anret*Negd*	2.537**
	(1.171)
*ACSI*Anret*	-0.145
	(0.249)
*ACSI*Anret*Negd*	-27.648
	(24.395)

Table 11 Continued

Constant	0.162*
	(0.084)
Year FE	Yes
Industry FE	Yes
Num of Observations	3,435
R-square	0.101

6. Conclusion

Building on the literature that customer satisfaction plays an important role in firm's future performance and shareholders' value, this study seeks to understand how customer satisfaction affects firm crash risk. Using a large sample of the U.S. public firms with retail customer survey conducted by the American Customer satisfaction Index (*ACSI*) between 1994 and 2018, we find strong evidence that customer satisfaction is negatively associated with the firm-specific crash risk in the future. Our study employs three measures of crash risk, and the results are robust across varies tests to address endogeneity concerns including firm-fixed effects, instrumental variables, DiD analysis using as an exogenous shock, viz. the Gramm-Leach-Bliley Act removing barriers in the financial market and improving service to customers.

We further test possible channels that affect this relationship between customer satisfaction and stock crash risk. We find that this negative relationship is more prone in the group of stocks with high volatility and high difference of opinion, which is consistent with the volatility feedback hypothesis (Campbell & Hentschel, 1992; French et al., 1987; Hutton et al., 2009) and difference of opinion hypothesis (Hong & Stein, 2003). However, we do not find any evidence that the effect of customer satisfaction on the stock crash risk is through the bad news hoarding channel (Jin & Myers, 2006).

Appendix A: Variable Definitions

Variables	Acronym	Definitions	Source
Dependent Variables			
Negative Skewness	*NCSKEW*	The negative skewness of firm-specific weekly returns in a given year.	CRSP
Down-to-Up Volatility	*DUVOL*	The natural logarithm of the ratio of the standard deviation of down-week firm-specific weekly returns to the standard deviation of up-week firm-specific weekly returns in a given year. A firm-week is defined as a down (an up) week if the firm-specific weekly return is below (above) its annual mean.	CRSP
Crash dummy	*CRASH*	A dummy variable equals to one if a stock has a crash week in a given year. A firm-week is defined as a crash (jump) week if the firm-specific weekly return is 3.09 standard deviations below (above) its annual mean.	CRSP
Independent Variable			
ACSI	*ACSI*	An ACSI score is from an annual survey of customer on company product, ranges from 0 to 100, with 100 as the highest level of customer satisfaction. ACSI is the firm score over industry average minus one.	ACSI Website
Stock-related Controls			
Return	*RET*	The mean of firm-specific weekly returns in a given year.	CRSP
Standard Deviation	*SIGMA*	The standard deviation of firm-specific weekly returns in a given year.	CRSP
Detrend Turnover	*DTURN*	The average monthly share turnover over the current year minus the average monthly share turnover over the previous year, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding.	CRSP

Appendix A Continued

Variables	Acronym	Definitions	Source
Firm-related Controls			
Firm Size	*SIZE*	The natural logarithm of book value of assets.	Compustat (item 6)
Financial Leverage	*LEVERAGE*	The long-term debts scaled by book value of assets.	Compustat (item 9)
Market-to-Book	*MB*	Market value of equity scaled by book value of equity.	Compustat (item 235)
Return on Assets	*ROA*	Income before extraordinary items scaled by book value of assets.	Compustat (item 18&6)
Information Channel Variables			
Volatility Dummy	*High_sigma*	A dummy variable equal to one if the firm's Sigma is greater than the sample median, and zero otherwise	CRSP
Idiosyncratic Risk	*Idio*	A logistic transformation of one minus R square over R square. R square is from the model in calculating firm-specific return.	CRSP
Idiosyncratic Risk Dummy	*High_idio*	A dummy variable equal to one if the firm's idio is greater than the sample median, and zero otherwise.	CRSP
Difference of Opinion	*Doo*	The standard deviation of analyst earnings forecasts in a fiscal year	I/B/E/S
Difference of Opinion Dummy	*High_doo*	A dummy variable equal to one if the firm's Doo is greater than the sample median, and zero otherwise.	I/B/E/S
Financial Report Readability	*Fog*	0.4*words per sentence plus 0.4*percent of complex words in the financial report, where complex words are words with three syllables or more.	I/B/E/S
Financial Report Readability Dummy	*High_fog*	A dummy variable equals to one if fog is greater than the sample median, and zero otherwise.	I/B/E/S

Appendix A Continued

Variables	Acronym	Definitions	Source
Financial Report Readability	*Negflesch*	1.015* words per sentence plus 84.6*syllables per word minus 206.835	F. Li (2008)
Financial Report Readability Dummy	*High_negflesch*	A dummy variable equals to one if negflesch is greater than the sample median, and zero otherwise.	F. Li (2008)
Financial Report Readability	*Kincaid*	0.39*words per sentence plus 11.8*syllables per word minus 15.59	F. Li (2008)
Financial Report Readability Dummy	*High_kincaid*	A dummy variable equals to one if kincaid is greater than the sample median, and zero otherwise.	F. Li (2008)
Financial Report Readability	*Length*	The logarithm of the number of words in the annual report.	F. Li (2008)
Financial Report Readability Dummy	*High_length*	A dummy variable equals to one if length is greater than the sample median, and zero otherwise.	F. Li (2008)
EPS	*E/P*	Income per share before extraordinary items scaled by fiscal year beginning stock price.	Compustat (item 18)
Firm Annual Return	*Anret*	The firm annual return beginning nine months prior to fiscal year end	CRSP
Negative Annual Return Dummy	*Negd*	A dummy variable equal to one if the firm's annual return is negative, and zero otherwise.	CRSP

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