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Trust and stock price crash risk: Evidence from China[☆]

Xiaorong Li[a], Steven Shuye Wang[b], Xue Wang[b,*]

[a] School of Public Finance and Taxation, Central University of Finance and Economics, Beijing, China
[b] School of Business, Renmin University of China, China

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ABSTRACT

This paper examines the impact of social trust on stock price crash risk. Social trust measures the level of mutual trust among the members of a society. Using a large sample of Chinese listed firms for the 2001–2015 period, we find that firms headquartered in regions of high social trust tend to have smaller crash risks. This result is robust to a battery of sensitivity tests and is more prominent for State-Owned Enterprises (SOEs), for firms with weak monitoring, and for firms with higher risk-taking. Moreover, we observe that firms in regions of high social trust are associated with higher accounting conservatism and fewer financial restatements. Our study suggests that social trust is an important variable that is omitted in the literature investigating the predictors of stock price crashes.

1. Introduction

Stock price crash risk measures the asymmetry in risk, especially the downside risk, and is thus an important issue in portfolio analysis and asset pricing. Understanding crash risk is also essential for making investment decisions and managing risks. It is well accepted that stock returns have distributions with negative skewness, which means that large negative returns (stock price crashes) occur more frequently than large positive returns (e.g., Chen et al., 2001; Hong and Stein, 2003). Many studies[1] have suggested a prominent explanation for firm-specific crash risk: managers have incentives to withhold bad news from investors. When the bad news accumulates to a certain level, it comes out all at once and causes stock prices to crash.

Given the importance of crash risk for portfolio management and asset pricing, a large body of literature investigates its predictors. In terms of the possible factors that affect stock price crash risk, many firm-level characteristics and managerial incentives have been identified, including financial reporting opacity (Jin and Myers, 2006; Hutton et al., 2009), the maintenance of reputation (Ball, 2009), corporate tax avoidance (Kim et al., 2011a), equity incentives (Kim et al., 2011b), excess management perks (Xu et al., 2014), and accounting conservatism (Kim and Zhang, 2016). Previous studies also show that performance in corporate social responsibility (CSR) (Kim et al., 2014) and religion (Callen and Fang, 2015a) affect crash risk. However, no existing studies have systematically explored the impact of social trust on crash risk. This paper helps fill this gap and investigates the role of social trust in firm-specific crash risk. Specifically, we study the impact of social trust on managerial bad news hoarding behavior and on the resulting future stock price crash risk.

Social trust describes the mutual trust among the members of a society. Trust is an agent's subjective assessment of the probability that certain actions will be performed by another party (Gambetta, 1988). Trust is also viewed as the tendency of cooperation among people (Coleman, 1990; Putnam, 1993). Therefore, regions with a group of social norms that facilitate productive and cooperative actions are regions with high social trust

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* Corresponding author.
E-mail addresses: lixiaorongchina@163.com (X. Li), wangshuye@rbs.ruc.edu.cn (S.S. Wang), wangxue@rbs.ruc.edu.cn (X. Wang).

[1] For example, Jin and Myers (2006) and Hutton et al. (2009).

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(Coleman, 1988, 1990; Guisoet et al., 2004; Jha, 2013). Consistent with the notion that high regional social trust stimulates honest behaviors, we hypothesize that the managers of firms headquartered in those regions tend to withhold bad news in a less severe manner. According to Jin and Myers (2006) and Hutton et al. (2009), managers' bad news hoarding behavior leads to future stock price crashes when the bad news accumulates to a tipping point and then comes out all at once. Therefore, if our hypothesis is correct, social trust should reduce stock price crashes, a consequence of deterred managerial bad news hoarding behavior. In other words, the attending firm-specific crash risks are likely to be reduced for firms in regions of high social trust compared to those in regions where social trust is low.

We test this hypothesis by using regional social trust data from China. Chinese data are particularly useful for our study for several reasons. First, since social trust serves as an imperfect substitute for formal institutions[2] in investor protection, contract enforcement, and the information environment, the study of social trust's impact on crash risk requires not only uniform formal institutions but also a weak legal and governance system so that the substituting role of social trust can be disentangled. China's investor protection systems, government regulations, and information environment are still very weak and underdeveloped compared to the systems in the U.S. and the U.K. (Allen et al., 2005). Second, to investigate the impact of social trust on firm-specific crash risk, there must be large regional variations in social trust. China's vast social trust diversity originates from the existence of fifty-six ethnic groups within thirty-one provinces and more than eighty different native dialects, which are not comprehensible to non-native speakers. People across the thirty-one provinces of China differ in terms of ethnicity and native dialect as well as culture, history, and religion.[3] Third, an intra-country analysis allows the impact of social trust on crash risk to be identified without the contamination of different legal and tax systems, capital market regulations, and codes of corporate governance, among others, all of which can factor into cross-country studies. Therefore, China provides an excellent setting for this empirical study.

Following the previous literature on this subject, we use three social trust proxies in this study. The first proxy, *TRUST1*, is taken from a survey by the Chinese Enterprise Survey System across China in 2000; it measures the perceived provincial trustworthiness by companies located in the thirty-one provinces of China (e.g., Zhang and Ke, 2002; Wu et al., 2014; and Ang et al., 2015). The second proxy, *TRUST2*, is the province-level per capita blood donation rate following Wu et al., (2014) and Ang et al., (2015) since blood donation is voluntary and reflects one's social values, sympathy towards others and altruism, which form the basis of trust. *TRUST3*, the third measure of social trust, is the city-level trustworthiness among citizens, taken from the Annual Report on Urban Competitiveness from 2001 to 2010 (Ni, 2001; Ni, 2002–2010). Ang et al. (2015) also use this measure to proxy for social trust.[4] Since we examine the impact of social trust on managers' bad news hoarding behavior and firms' consequent crash risks, the first measure in the study, enterprise trustworthiness, suits our purpose better than the other two measures. Therefore, we use *TRUST1* as the main measure in our empirical tests and *TRUST2* and *TRUST3* as alternative measures in the robustness tests.

Following Chen et al. (2001), Hutton et al. (2009) and Kim et al. (2011a, b, 2016), we measure stock price crash risk using two proxies: the negative coefficient of skewness of firm-specific weekly returns (*NCSKEW*) and the crash likelihood measure of the Down-to-Up Volatility (*DUVOL*) of firm-specific weekly returns.

Using a large dataset of all Chinese listed firms for the 2001–2015 period, we find that firms headquartered in the regions of high social trust tend to experience smaller future stock price crash risks. This result is consistent with the hypothesis that high social trust hinders managers' hoarding of bad news and therefore reduces firm-level crash risk. The relationship between social trust and firm-specific future crash risk is statistically and economically significant and remains robust after controlling for the variables deemed to be potential predictors of crash risk. For example, we control for Chen et al., (2001) investor heterogeneity, measured by the detrended stock trading volume and past returns, in addition to firm accounting properties such as opacity, measured by discretionary accruals, following Hutton et al. (2009). We also control for corporate social responsibility (Kim et al., 2014), and regional religiosity (Callen and Fang, 2015a). Furthermore, the levels of social trust and economic development in a particular region are typically highly correlated (Knack and Keefer, 1997). Thus, to exclude the potential effect of regional factors on a firm's crash risk, we control for the regional Gross Domestic Product (GDP) growth, marketization level, population growth, percentage of population with at least a college education, and percentage of the female population in the province (Hilary and Hui, 2009; Ang et al., 2015; Hilary and Huang, 2015). We further control for other regional factors such as the number of distinct dialects and ethnic groups (Ang et al., 2015; Piotroski et al., 2015). Finally, industry- and year-fixed effects are included.

Moreover, whether a firm's CEO is trustworthy and discloses information in a timely manner may also be affected by his/her home region's social environment rather than by that in the firm's location. Therefore, we manually collect CEOs' hometown information for all sample firms from 2001 to 2014 and examine the impact of regional social trust in CEOs' hometown on firms' crash risk as the robustness test. This test addresses the causality concern since the firm's crash risk may impact social trust in firms' location but can hardly affect that in the CEO's home region.[5] We also use alternative measures of crash risk, controlling for both market and industry factors, when calculating firm-specific weekly returns. We further utilize Logit regression to check the robustness of our main findings. The association between social trust and firm-specific future crash risk remains negative and significant after all of these controls and robustness tests.

One critical condition to the notion of trust is uncertainty or ignorance about other agents' behaviors. If there is any impact of social trust on managers' bad news hoarding behavior and the resulting stock price crash risk, then this impact should most likely be affected by the ownership structure and monitoring (e.g., Callen and Fang, 2013). According to agency theory, strong corporate governance or effective external monitoring mitigates managers'

[2] The formal institutions include investor protection and tax regulations, managerial compensation contracts, and financial reporting requirements (Knack and Keefer, 1997). Pevzner et al. (2015) examine the impact of social trust on investors' responses to earnings announcements and find that the effect is more salient when a country's formal institutions are weaker, indicating a substituting role of trust for formal institutions.

[3] Ang et al. (2015) find that the social and cultural differences among provinces in China tend to be larger than the differences across the 13 Western European countries in their sample, suggesting significant regional heterogeneity in China. Hilary and Huang (2015) investigate the impact of social trust in the U.S. setting and document a much smaller standard deviation in their trust measure (the average trust is 1.832, with a standard deviation of 0.466) compared to the trust measures using Chinese data in our study (for example, Table 1 shows that *TRUST1* has an average of 0.7858 and a standard deviation of 0.6866).

[4] This trustworthiness of citizens is measured by evaluating people's response to the following question: "What is the degree of trustworthiness among the citizens in the city?" For a more detailed description of the measure, please see Ang et al. (2015).

[5] We would like to thank the anonymous referees for suggesting the method to address the potential reverse causality concern.

opportunistic behavior (Jensen and Meckling, 1976). If social trust tends to constrain managers' bad news hoarding behavior and therefore reduce firm-specific crash risk, then, ceteris paribus, one would expect that the negative impact of social trust on crash risk is more prominent for State-Owned Enterprises (SOEs) and for firms with weak governance or less effective external monitoring.

We find that the negative effect of social trust on crash risk is more salient for SOEs, which is consistent with the fact that SOEs are more likely to have opaque financial reporting and withhold bad news due to political incentives (Bushman et al., 2004; Bushman and Piotroski, 2006) and therefore tend to have higher crash risks. Moreover, we follow previous studies (e.g., Kim et al., 2011a; Xu et al., 2014; Yuan et al., 2016) and use the ratio of independent board directors to proxy for the strength of internal monitoring, an indicator variable for the B shares available to foreign investors or the H-share listings on the Hong Kong Stock Exchange and institutional holdings as measures of the strength of external monitoring. The results show that the negative relationship between social trust and crash risk is more prominent for firms with weak internal or external monitoring.

Kim et al. (2011b) suggest that managers of firms with more risk-taking activities are more likely to withhold bad news and therefore have higher stock price crash risks. Consistent with this argument, we also find that the negative effect of social trust on crash risk is more pronounced for firms with higher risk-taking behaviors.

Finally, we examine the economic mechanism under the negative relationship between social trust and firm-specific crash risk. Specifically, we provide evidence that firms in more trustworthy provinces present more accounting conservatism and are less likely to have financial restatements compared to firms in provinces with lower social trust. The evidence shows that social trust reduces firms' crash risk through curbing managerial bad news hoarding behavior, which is reflected by the increased accounting conservatism and reduced frequency of financial restatements.

This article contributes to the existing literature in several ways. First, this study extends research in the crash risk literature, being the first study to examine the impact of social trust on firm-specific crash risk. Existing studies have held that one of the important causes of crash risk is managers' incentive to withhold bad news until a tipping point, after which the bad news comes out all at once and leads to stock prices crash. These studies have mainly focused on the predictability of firm- or manager-specific characteristics in regard to future firm-specific crash risks. Apart from these studies, firms' corporate social responsibility performance (Kim et al., 2014) and county-level religiosity (Callen and Fang, 2015a) have been shown to impact crash risks. Our study is closely related to but different from Kim et al. (2014) since corporate social responsibility (CSR) is firm-specific rather than a measure of the regional social environment. This study is also different from Callen and Fang (2015a), who show the impact of county-level religiosity on firms' crash risk. Although religion is a component of the social environment, its role is not as important in China as it is in Western countries (e.g., Weber, 1951). We postulate that social trust is another component of the social environment and therefore may play a relatively more important role in managerial behaviors than religion does. Building on the current literature, this study provides new evidence that regional social trust has incremental predictability in regard to firm-specific crash risks over and above the predictors documented by existing studies. It enhances our understanding of the potential predictors of stock price crash risk and finds an important but neglected factor, social trust, in predicting crash risks.

Second, this study is among the few in the finance and accounting literature to investigate the role of social trust in managerial decisions. Garret et al. (2014) find that intra-organizational trust is positively associated with a given firm's financial reporting quality. Jha and Chen (2015) show that firms in regions of high social trust tend to pay less in auditing fees. Hilary and Huang (2015) find that firms in high-trust regions tend to have higher profitability and valuation and are less likely to fire their CEOs. We extend this literature and examine the impact of social trust on managers' bad news hoarding behaviors. Our study is also related to the literature that examines the impact of religion and values/culture on managerial behavior and decisions. For example, Hilary and Hui (2009) show that religiosity affects firms' risk exposures. Dyreng et al. (2010), Grullon et al. (2010), and McGuire et al. (2012) find that religion also has an impact on firms' financial reporting quality. Han et al., (2010) find that culture/values tends to affect earnings management behavior. Since social trust interconnects with religion, culture, and values (Guisoet et al., 2006; Pevzner et al., 2015), our study adds to this stream of literature and raises the potential question for future research of whether other firm/manager decisions may be affected by the regional social trust at the firm's headquarters location.

Third, our study contributes to the literature on the relationship between social trust and economic prosperity. La et al. (1997) document a positive association between the level of trust in a country and the number of large enterprises in that country. Knack and Keefer (1997) find that trust is positively correlated with a country's economic growth rate. Ever since these studies were conducted, a strand of literature has investigated the relationship between social trust and economic prosperity as well as the mechanisms driving it. Guisoet et al. (2004) examine the impact of social trust on financial development by studying the choices of a variety of households. This study contributes to the stream of the existing literature by examining the relationship between social trust and an important aspect of financial market development, specifically, stock price crash risk, i.e., the asymmetry in the distribution of returns. Crash risk is critical in making investment decisions for both individual investors and institutions. Thus, this study deepens our understanding of the impact of social trust on financial market development.

The rest of the paper is organized as follows: Section 2 reviews the related literature and develops hypotheses. Section 3 introduces the sample, variables, and empirical methodology. Section 4 presents the empirical results and robustness tests. Section 5 addresses the endogeneity concerns, and Section 6 discusses economic mechanisms. Section 7 concludes.

2. Literature review and hypothesis development

2.1. Related literature on social trust

Trust is viewed as an agent's subjective assessment of the probability that another party will perform a certain action (Gambetta, 1988) or the propensity of people to cooperate with others (Coleman, 1990; Putnam, 1993). Social trust is the general level of mutual trust among the members of a society. Regions of high social trust can be interpreted as regions with a set of social norms that facilitate productive and cooperative actions (Coleman, 1988, 1990). The norms channel holds that certain informal values or norms are imprinted on people in a region via education and that these norms cause the individuals in that region to feel obligated to behave accordingly (Fukuyama, 1997; Portes, 1998; Guisoet et al., 2004; Guisoet et al., 2008).

Many studies in different disciplines examine the positive impact of social trust on the behaviors of human beings and social organizations as well as the economic consequences. For example, studies in economics and finance suggest that social trust is negatively related to corruption and positively related to the performance of organizations (La et al., 1997), that it tends to decrease the transaction costs related to buying stocks and receiving loans (Guisoet et al., 2004), and that it encourages firms in regions of high social trust to use more trade credits (Wu et al., 2014). Several studies in accounting find that intra-organizational trust is positively associated with a given firm's financial reporting quality (Garret et al., 2014) and that firms in regions of high social trust tend to pay less in auditing fees (Jha and Chen, 2015).

In summary, the existing literature on social trust agrees that regions of high social trust entail a higher level of mutual trust and facilitate cooperative activities. Additionally, social trust impacts the behavior of individuals and the economic consequences. This study extends the social trust literature and examines the impact of social trust on managers' bad news withholding behavior and the resulting stock price crash risks.

2.2. Related literature on crash risk

Crash risk is an important characteristic of the distribution of returns, which measures the negative skewness. A stream of the existing literature attempts to explain the sources of crash risk through financial market mechanisms, from the leverage effect[6] (Black, 1976; Christie, 1982) to the volatility feedback effect[7] (Pindyck, 1984; French et al., 1987; Campbell and Hentschel, 1992) to the stochastic bubbles model[8] (Blanchard and Watson, 1982) .[9] Comparing the above three models in the representative-investor framework, Hong and Stein (2003) propose that investor heterogeneity and short-sale constraints represent key elements in stock price crashes. Specifically, they argue that, if investors have different beliefs and some face short-sale constraints, then the negative opinions are not fully incorporated into stock prices. Therefore, once the hidden bad news has accumulated to a tipping point and comes out all at once, stock prices crash.

Another stream of literature, composed of studies that have been conducted more recently, focuses on the agency theory framework. For example, Jin and Myers (2006) suggest that different levels of opacity, or incomplete transparency, across countries can predict crash risk. In their model, assuming a conflict of interest between managers and investors, managers tend to hide bad news and reveal good news due to job concerns. However, managers can withhold only a limited amount of bad news. When that amount is reached and managers give up, all of the firm-specific bad news comes out at once and results in crashes. In addition to job-specific concerns, managers have other incentives to delay the release of bad news to investors, including concerns related to equity incentives (Kim et al., 2011b), excess perks (Xu et al., 2014), and nonfinancial motivations such as reputation maintenance (Ball, 2009). When bad news withholding and accumulation reach a threshold level and all of the bad news suddenly becomes publicly accessible, the stock price crashes. Empirical evidence supports managers' bad news hoarding behavior as a source of high future crash risks. For example, Jin and Myers (2006) and Hutton et al. (2009) show that financial reporting opacity increases future firm-specific crash risk. Kim et al., (2011a, b) demonstrate that corporate tax avoidance and CFOs' equity incentives are also positively associated with future firm-specific crash risk. Kim and Zhang (2016) show that firms with more accounting conservatism tend to have smaller future crash risk. Non-financial reporting activities such as corporate social responsibility reports (Kim et al., 2014) and regional factors such as religiosity (Callen and Fang, 2015a) have also been shown to impact firm-specific crash risks.

2.3. The impact of social trust on stock prices' crash risks

An environment with high social trust facilitates honest behaviors through moral norms imprinted by education (Guisoet et al., 2004; Jha and Chen, 2015). Therefore, for the firms located in regions of high social trust, managers are influenced by moral norms and tend to disclose financial information in a timelier manner. Thus, we would expect the managers of firms headquartered in regions of high social trust to conceal bad news in a less severe manner than the managers of firms in regions of low social trust. The subsequent firm-specific crash risks are expected to decrease. We propose the following hypothesis.

Hypothesis 1. Firms headquartered in regions of high social trust have smaller future firm-specific crash risks, ceteris paribus.

Because the level of trust relies on one agent's ignorance or uncertainty about other agents' behaviors (Gambetta, 1988), we expect that the impact of social trust on crash risk will be affected by the ownership structure and the effectiveness of monitoring. Specifically, State-Owned Enterprises (SOEs) tend to have opaque reporting practices and suppress bad news due to political incentives (Bushman et al., 2004; Bushman and Piotroski, 2006) and therefore are associated with higher crash risks. We expect the negative association between social trust and crash risk will be more prominent for SOEs due to more severe agency problems.

Hypothesis 2. The negative association between social trust and crash risk is more prominent for State-Owned Enterprises, ceteris paribus.

Additionally, the agency tension between managers and shareholders, which motivates opportunistic behavior by managers and leads to future crash risk, can be mitigated by effective monitoring (Jensen and Meckling, 1976). For example, a board of directors with higher independence (Weisbach, 1988) and higher institutional ownership (Shleifer and Vishny, 1986, 1997) and firms that issue B shares to foreigners and cross-list their shares in overseas exchanges (Coffee, 2002; Gul et al., 2010), such as H shares on the Hong Kong Stock Exchange, can provide stronger monitoring of managers, deter managers' bad news hoarding behavior, and therefore reduce future crash risk. Employing the arguments above, we propose the following testable hypothesis.

Hypothesis 3. The negative association between social trust and crash risk is attenuated for firms with effective monitoring, ceteris paribus.

As suggested by numerous studies (e.g., Lambert, 1984; Dye, 1988; Trueman and Titman, 1988), managers tend to smooth firms' income to conceal their excessive risk-taking activities, as measured by earnings volatilities. Kim et al. (2011b) suggest that managers have incentives to hide excessive risk-taking behaviors to uphold the stock price since outside investors or the board of directors are likely to take actions to constrain managers' risk-taking activities once detected. Along these lines, managers of firms with more risk-taking will withhold bad news more extensively to manage investors' perceptions of the riskiness of the firm. As a result, firms with higher levels of risk-taking tend to have higher stock price crash risks. Therefore, we should expect the negative impact of social trust on firm-specific crash risk to be more pronounced

[6] The leverage effect suggests that price drops raise financial and operating leverage and that, therefore, the subsequent stock return volatility increases.

[7] The volatility feedback effect explains the asymmetry in stock returns as follows: whenever news comes, market volatility rises and the risk premium is higher. If the news is good, then the direct effect on the stock price is opposite to the risk premium effect. Conversely, if the news is bad, then the direct effect on the stock price and the risk premium effect are in the same direction. Overall, the stock returns show asymmetry.

[8] The stochastic bubbles model claims that the asymmetry in stock returns is due to the low probability that bubbles will lead to large negative stock returns.

[9] For a more detailed discussion on the earlier explanations of the crashes, please see Chen et al. (2001).

Table 1
Sample distribution.

Panel A: Full sample distribution across industry			Panel B: Full sample distribution by year		
Industry	N	%	Year	N	%
Agriculture	319	1.57	2001	964	4.76
Mining	699	3.45	2002	1041	5.14
Manufacturing	11,875	58.58	2003	1104	5.45
Electricity, gas, and water	1016	5.01	2004	1171	5.78
Building and construction	484	2.39	2005	1254	6.19
Commerce	1560	7.70	2006	1223	6.03
Transportation and logistics	810	4.00	2007	1257	6.2
Accommodation and restaurants	118	0.58	2008	1370	6.76
Information technology	704	3.47	2009	1465	7.23
Real estate	1575	7.77	2010	1611	7.95
Leasing and commercial services	224	1.10	2011	1963	9.68
Research and technical services	56	0.28	2012	1880	9.27
Environment and public facilities management	235	1.16	2013	2044	10.08
Education	11	0.05	2014	1925	9.5
Health and social work	23	0.11			
Culture, sports and entertainment	260	1.28			
Conglomerates	303	1.49			
Total	20,272	100.00	Total	20,272	100.00

Panels A and B of Table 1 show the distribution of the sample Chinese listed firms by industry and by year, respectively. Firms' industries are categorized based on the *Guidance on the Industry Category of Listed Companies* issued by the CSRC.

for high risk-taking firms. We propose the following testable hypothesis.

Hypothesis 4. The negative association between social trust and crash risk is more prominent in firms with higher risk-taking, ceteris paribus.

3. Sample and empirical methodology

3.1. Sample

To construct our sample, we start with all Chinese A share[10] listed companies during the 2001–2015 period, using the China Securities Market and Accounting Research (CSMAR) database. Please note that the sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. Then, we exclude (1) financial services firms,[11] (2) firms with fewer than thirty trading weeks of stock returns in a fiscal year,[12] and (3) firm-year observations with missing information for the control variables. Our final sample includes 20,272 firm-year observations representing 2408 individual firms. We also winsorize the continuous variables at the 1% and 99% levels to mitigate the effect of outliers. The data for the first proxy of social trust (*TRUST1*) are obtained from the survey in 2000 by Zhang and Ke (2002). Following Wu et al. (2014) and Ang et al. (2015), we use two alternative measures of social trust in the robustness tests; one is the level of voluntary blood donation (*TRUST2*) in 2000, available from the Chinese Society of Blood Transfusion, and the other is citizen's trustworthiness (*TRUST3*), obtained from Annual Report on Urban Competitiveness from 2001 to 2010[13] (Ni, 2001; Ni, 2002–2010).

Panels A and B of Table 1 show the sample firm-year distribution across industries and by year, respectively, with industries being categorized based on the Guidance on the Industry Category of Listed Companies issued by the China Security Regulatory Commission (CSRC). Panel A shows that the majority of our sample firms are from the manufacturing sector (58.58%), representing the industrial structure of Chinese A shares. Panel B reports the chronological distribution of our sample firms. The number of observations increases from 964 firm-year observations in 2001 to 1925 observations in 2014, representing the underlying growth in China's capital markets.

3.2. Measuring firm-specific crash risk

Following Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a, b), we measure firm-specific crash risk using two statistics: the negative coefficient of skewness of firm-specific weekly returns (*NCSKEW*) and the crash likelihood measure of the Down-to-Up Volatility (*DUVOL*) of firm-specific weekly returns. We first calculate the firm-specific weekly returns (*W*) as the natural logarithm of one plus the residual return from the expanded market model regression for each firm and year :[14]

$$R_{i,t} = \alpha_i + \beta_1 R_{m,t-2} + \beta_2 R_{m,t-1} + \beta_3 R_{m,t} + \beta_4 R_{m,t+1} + \beta_5 R_{m,t+2} + \varepsilon_{i,t} \tag{1}$$

The first measure, $NCSKEW_{i,t}$, is calculated by the third moment of the firm-specific weekly returns of firm *i* in year *t*, divided by the cubed standard deviation of firm-specific weekly returns, times negative one. Specifically, the equation is as follows:

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

where *n* is the number of trading weeks of firm *i* in year *t*. The negative sign in front of the standardized third moment gives us

[10] Most companies listed on Chinese exchanges offer two share classes: A shares and B shares. A-shares are quoted in Chinese Yuan and are generally only available for purchase by mainland citizens; foreign investment is only allowed through a tightly-regulated structure known as the Qualified Foreign Institutional Investor (QFII) system. B shares are quoted in foreign currencies (the U.S. dollar for Shanghai B shares and the Hong Kong dollar for Shenzhen B shares) and are open to both domestic and foreign investment.

[11] We drop financial services firms because the disclosure requirements and accounting rules are significantly different for this regulated industry.

[12] We require at least 30 trading weeks of stock returns within a fiscal year to ensure the calculation of firm-specific weekly returns.

[13] This trustworthiness of citizens is measured by evaluating people's response to the following question: "What is the degree of trustworthiness among the citizens in the city?" For a more detailed description of the measure, please see Ang et al. (2015).

[14] To check the robustness of our results, we also use an alternative model that adds the industry returns in calculating the firm-specific weekly returns. The results remain robust and are reported in Table 4.

a better interpretation of the measure, i.e., an increase in *NCSKEW* shows greater left skewness in the distribution of firm-specific excess returns and suggests that the firm is more likely to crash.

The second measure of crash risk, Down-to-Up Volatility (*DUVOL*), is calculated as the logarithm of the ratio of the standard deviation of firm-specific weekly returns in “down” weeks to the standard deviation of firm-specific weekly returns in “up” weeks. Down and up weeks are measured relative to the mean firm-specific weekly returns over year *t*. If a given firm’s specific weekly return is higher than the mean value over year *t*, then the week is considered “up” ; if the firm’s specific weekly return is below the mean, then the week is considered “down” . Specifically, the equation is as follows:

$$DUVOL_{i,t} = \log\left\{\left[(n_u-1)\sum_{DOWN} W_{i,t}^2\right] \Big/ \left[(n_d-1)\sum_{UP} W_{i,t}^2\right]\right\} \quad (3)$$

where n_u (n_d) is the number of weeks that firm *i*’s specific weekly returns are higher (lower) than the mean firm-specific weekly returns over year *t*. Firms with a higher level of *DUVOL* are interpreted as being more prone to crash.

In addition to the above two measures of crash risk, *NCSKEW* and *DUVOL*, following Hutton et al. (2009), in the robustness test, we also use an indicator variable, $CRASH_{i,t}$, to measure the likelihood of a crash for firm *i* over year *t*. Specifically, $CRASH_{i,t}$ is equal one if a firm experiences at least one crash week during year *t* and zero otherwise, where a crash week for a firm is a calendar week in which the firm-specific weekly return falls 3.09 or more standard deviations below the mean firm-specific weekly returns over year *t*.

3.3. Measuring social trust

Following the previous literature,[15] we measure social trust using a number of proxies to ensure robust conclusions. The first proxy for social trust, *TRUST1*, represents provincial-level enterprise trustworthiness, as taken from a survey across China in 2000; the same measure has been employed in works by Zhang and Ke (2002), Wu et al. (2014), and Ang et al. (2015).[16] This survey was conducted by the Chinese Enterprise Survey System for the purpose of collecting and examining data on the perceived provincial trustworthiness of companies located in the thirty-one Chinese provinces. The questionnaires were sent to over 15,000 managers of companies located in the 31 provinces, and more than 5000 valid responses were received. The main question related to trust is the following: “According to your experience, which five provinces have the most trustworthy enterprises? Please list them in order.” The raw scores of the ranking obtained from the survey are simply 5 for a number-one ranking, 4 for a number-two ranking, and so on. The trust score for each province is calculated by the weighted average of the rankings, where the weights are the percentages of managers who indicated that a province ranks number one, ranks number two, etc. (Zhang and Ke, 2002). For example, Beijing is ranked number one by 16.6% of the responding managers, number two by 11.3%, number three by 8.3%, number four by 5.5%, and number five by 4.9%. Therefore, the trust score of Beijing is calculated as 169% ($16.6\% \times 5 + 11.3\% \times 4 + 8.3\% \times 3 + 5.5\% \times 2 + 4.9\% \times 1$).[17] *TRUST1* is used as the main proxy of social trust for our study because it evaluates the trustworthiness among enterprises, which better serves our study on firm managers’ bad news hoarding behavior and future stock price crash risks.

Following Wu et al. (2014) and Ang et al. (2015), we also measure social trust by the province-level per capita voluntary blood donation rate (*TRUST2*). Blood donation reflects citizens’ willingness to help others, altruism, and trust in the social system. As suggested by Ang et al. (2015), we take the third measure of social trust (*TRUST3*) as the survey value of citizens’ trustworthiness from the Annual Report on Urban Competitiveness from 2001 to 2010 (Ni, 2001; Ni, 2002–2010). This survey evaluates citizens’ trustworthiness by assessing people’s response to the following question: “What is the degree of trustworthiness among the citizens in your local city?”[18] The two citizens’ trustworthiness measures above (*TRUST2* and *TRUST3*) are at the province level and the city level, respectively, and they are used to gauge the robustness of our main findings.

Among the three proxies of social trust, *TRUST1* and *TRUST2* are only available in 2000, whereas *TRUST3* is measured from 2001 to 2010. Since the previous literature has shown that regional social trust does not have much time series variation (Putnam, 1993; Uslaner, 2002; Bjørnskov, 2006), in our analysis, it is reasonable to use the same value of *TRUST1* and *TRUST2* through our sample period from 2001 to 2014 and to extend the 2010 value of *TRUST3* to 2014.[19]

3.4. Empirical models

To investigate the impact of social trust on firm-specific future stock price crash risk, we estimate the following model:

$$\begin{aligned} CrashRisk_{t+1} &= \beta_0 + \beta_1 SocialTrust_t + \gamma' Controls_t \\ &\quad + Industry\_dummies + Year\_dummies + \varepsilon_t \end{aligned} \quad (4)$$

where the dependent variable, $CrashRisk_{t+1}$, is measured by *NCSKEW* or *DUVOL* and the primary independent variable, $SocialTrust_t$ is proxied by *TRUST1* in our main test and by *TRUST2* and *TRUST3* in our robustness tests. We measure all independent variables in year *t*, which is a one-year lag from the dependent variable, thus allowing us to examine whether social trust in year *t* can predict the crash risk in year $t+1$.

The control variables (*Controls*) are the potential factors that have been shown in the literature to predict future crash risk. First, we include the lagged variable of crash risk ($NCSKEW_t$ or $DUVOL_t$) to control for potential serial correlation. Second, we include nine firm-level control variables in the model. Hong and Stein (2003) document that investor opinion heterogeneity is a predictor of stock price crash risk. Therefore, we control for the detrended stock trading volume (*DTURN*), which is a proxy for investor opinion heterogeneity (Chen et al., 2001). Chen et al. (2001) suggest that, in addition to trading volume, past returns are related to future crash risk because the bubble built up by past returns is typically followed by a sudden drop in prices. For this reason, we include past returns (*RET*), firm size (*SIZE*), and the market-to-book ratio (*MB*) in our regression. We also include stock volatility (*SIGMA*) since stocks that are more volatile are more likely to undergo a future price crash. Additional firm-level control variables

[15] For example, Zhang and Ke (2002), Wu et al. (2014), and Ang et al. (2015).

[16] Zhang and Ke (2002) use this score to examine the determinants of social trust. Ang et al. (2015) also use this measure to investigate the impact of regional social trust on foreign investment decisions.

[17] One concern is that the trust score may be affected by local bias, i.e., the responding managers may have been biased towards the trustworthiness of the companies located in their own province. To address this concern, Zhang and Ke (2002) alternatively calculate the score by excluding the managers who ranked their own province as No. 1. Using a two-tailed t-test, they show that the two scores are not significantly different.

[18] For a more detailed description of the citizens’ trustworthiness measure, please see Ang et al. (2015).

[19] Wu et al. (2014) and Ang et al. (2015) also use the one-year data of enterprise trustworthiness (*TRUST1*) and citizen trustworthiness (*TRUST3*) for their entire sample periods.

are financial leverage (*LEV*), profitability (*ROA*) and the absolute value of abnormal accruals (*ABACC*), which is a proxy for earnings management (Hutton et al., 2009; Kim et al., 2011a, b; Kim and Zhang, 2016). Kim et al. (2014) suggest that firms with high corporate social responsibility (CSR) performance tend to have smaller crash risks. Therefore, we include *CSR*, an indicator variable that equals one if the firm has issued a stand-alone *CSR* report in year *t* and zero otherwise, to control for the impact of CSR.

Further, it cannot be neglected that the negative relationship between social trust and crash risk can also be driven by other regional factors. Because some regional characteristics may be different between firms in regions of high social trust and those in regions of low social trust, we include eight province-level variables in the analysis, thus ensuring that our results are not driven simply by these factors. Following Hilary and Hui (2009) and Ang et al. (2015), we control for the annual province-level GDP growth rate (*GDP%*),[20] which measures provincial economic development, the annual provincial population growth rate (*POPG*),[21] and the annual province-level marketization index (*HIGHNERI*), which measures the annual progress of institutional transformation in every Chinese province and indicates the differences in institutions and economic policies across provinces (Fan et al., 2011). Following Hilary and Huang (2015), we further include the percentage of the population with at least a college education (*EDU*), and the percentage of the female population in the province (*FEMALEP*)[22] in our test. We also control for other regional factors that have been shown to be predictors of crash risk or correlated with social trust (Callen and Fang, 2015a; Ang et al., 2015; Bushman and Piotroski, 2006), such as regional religiosity (*RELIGION*) and the number of distinct dialects (*DIALECT*) and ethnic groups (*ETHGR*).

All of the above variables are defined in Appendix A. Industry and year fixed effects (*INDUSTRY*[23] and *YEAR* dummies) are included in our regressions as well. Further, we cluster the standard errors at the firm and time level (Petersen, 2009).

4. Empirical tests and results

4.1. Descriptive statistics

Panel A of Table 2 reports the summary statistics on the variables used in our analysis that are defined in the section above and described in detail in Appendix A. The two measures of future crash risk, $NCSKEW_{t+1}$ and DUVOL_{t+1}, are similar in both magnitude and distribution. The mean and median values of $NCSKEW_{t+1}$ are −0.2053 and −0.1850, respectively, whereas the mean and median of $DUVOL_{t+1}$ are −0.1653 and −0.1636, respectively. The mean and standard deviation of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are comparable to the estimates by Xu et al. (2013); they use weekly market-adjusted returns for Chinese A-listed firms with analyst coverage from 2004 to 2012, though we have a longer and newer sample period.

The measures of social trust present large cross-sectional variations among provinces and cities in China, which facilitates our empirical tests. The mean value of the first proxy of social trust, provincial enterprise trustworthiness (*TRUST1*), is 78.58%, with a standard deviation of 68.66%. The average level of provincial blood donation (*TRUST2*) is approximately 1.4029 mL per capita, with a standard deviation of 1.0052. The proxy of city-level citizen trustworthiness (*TRUST3*) has a mean value of 0.8283, with a standard deviation of 0.0819. The mean and standard deviation of the three measures of social trust are also similar to the statistics reported in prior studies (Zhang and Ke, 2002; Wu et al., 2014; Ang et al., 2015).

Panel B of Table 2 presents the Pearson correlation matrix for the variables used in our main regression models. The future firm-specific stock price crash risk variables, $NCSKEW_{t+1}$ and DUVOL_{t+1}, are highly correlated, with a significant correlation of 0.88. This result suggests that they tend to pick up the same information with respect to firm-specific crash risk. The three social trust measures, *TRUST1, TRUST2*, and *TRUST3*, are also positively correlated and significant at the 5% level. This result indicates that, although the three measures capture different dimensions of provincial or city trustworthiness among enterprises or citizens, they additionally share some fundamental components underlying social trust.

The correlation coefficients reported in panel B of Table 2 are consistent with Hypothesis 1: $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are negatively associated with the three social trust measures. The two crash risk measures, $NCSKEW_{t+1}$ and DUVOL_{t+1}, are also negatively associated with $SIZE_t$, LEV_t, $POPG_t$, EDU_t, and CSR_t but positively associated with $DTURN_t$, MB_t, $ABACC_t$, and $FEMALEP_t$, which is largely consistent with previous studies (Xu et al., 2013; Piotroski et al., 2015). Among the control variables, $SIZE_t$, ROA_t, $ABACC_t$, $POPG_t$, $HIGHNERI_t$, CSR_t and EDU_t are positively associated with the social trust measures, whereas $GDP\%_t$, $FEMALEP_t$, $RELIGION_t$, $DIALECT_t$, and $ETHGR_t$ are negatively associated with the same measures. These correlation coefficients are all significant at the 5% level and indicate that there are different firm-level and regional characteristics that affect firms' future crash risks as well as the social trust in the region. Therefore, it is important to analyze the impact of social trust on future firm-specific crash risk within a multivariate framework.

4.2. Main regression analysis

Table 3 reports the estimates of the main regression model (4). The t-statistics in parentheses are based on standard errors corrected for firm and time clustering (Petersen, 2009). Columns (1), (3) and (5) suggest that $NCSKEW_{t+1}$ is significantly and negatively associated with social trust as measured by $TRUST1_t$ after controlling for the possible firm-level and province-level predictors of crash risk. Similarly, the results in columns (2), (4) and (6) using $DUVOL_{t+1}$ as the proxy for crash risk also show a negatively significant relationship between social trust and future crash risk.

This negative relationship between crash risk and social trust is both statistically and economically significant. For example, the coefficient of $TRUST1_t$ (column 1) is −0.0193, which means that a one-standard-deviation increase in the social trust of a firm location is associated with a decrease of 1.94% (=0.0193 × 0.6866/0.6843) of a standard deviation in future crash risk as measured by *NCSKEW*, ceteris paribus.

One method of hoarding bad news is through abnormal accruals (Hutton et al., 2009; McGuire et al., 2012; Callen and Fang, 2015a). Therefore, firms with high abnormal accruals may have higher crash risks in the future. In addition, Kim et al. (2014) show a negative impact of firms' corporate social responsibility (CSR) reporting on crash risk. Hence, we run the regression controlling for abnormal accruals (*ABACC*) and *CSR* to ensure that the relationship between social trust and crash risk is not due to earnings management through accruals or *CSR* reporting. The results in Table 3 indicate that firm-level financial and non-financial reporting activities impact crash risk, with the coefficients of *ABACC*

[20] The provincial GDP growth rate data are from the National Bureau of Statistics of China (NBS).

[21] The annual provincial population growth rates are from the National Bureau of Statistics of China (NBS).

[22] The percentage of the population with at least a college degree and the percentage of the female population in the province are also obtained from the National Bureau of Statistics of China (NBS).

[23] According to the industry categories from the China Securities Regulatory Commission (CSRC), we further classify the stocks from the manufacture industry into more detailed industry categories using the 2-digit code and have a total of 21 industries.

Table 2
Descriptive statistics.

Panel A: Sample statistics

Variable	N	Mean	25th Pctl.	Median	75th Pctl.	Std. Dev.
$NCSKEW_{t+1}$	20,272	−0.2053	−0.5947	−0.1850	0.2017	0.6843
$DUVOL_{t+1}$	20,272	−0.1653	−0.4890	−0.1636	0.1523	0.4805
$TRUST1_t$	20,272	0.7858	0.1440	0.7770	1.1870	0.6866
$TRUST2_t$	19,938	1.4029	0.7032	1.2591	1.4277	1.0052
$TRUST3_t$	13,904	0.8283	0.7750	0.8130	0.8870	0.0819
$NCSKEW_t$	20,272	−0.2011	−0.5955	−0.1820	0.2075	0.6909
$DUVOL_t$	20,272	−0.1522	−0.4782	−0.1488	0.1693	0.4832
Firm-level Controls						
$DTURN_t$	20,272	0.0099	−0.077	0.0033	0.0978	0.1852
RET_t	20,272	−0.1167	−0.1517	−0.0923	−0.0527	0.0908
$SIZE_t$	20,272	21.6293	20.8002	21.4861	22.2837	1.1964
MB_t	20,272	1.8155	1.1152	1.4201	2.0473	1.1627
$SIGMA_t$	20,272	4.5481	3.2762	4.3338	5.5490	1.7177
LEV_t	20,272	0.4823	0.3241	0.4859	0.6294	0.2195
ROA_t	20,272	0.0507	0.0281	0.0507	0.0800	0.0675
CSR_t	20,272	0.1603	0.0000	0.0000	0.0000	0.3669
$ABACC_t$	20,272	0.0657	0.0205	0.0450	0.0879	0.0660
Province-level Controls						
$GDP\%_t$	20,272	0.1333	0.0895	0.1307	0.1739	0.0555
$POPG_t$	20,272	0.0113	0.0029	0.0064	0.0142	0.0271
$HIGHNERI_t$	20,272	0.5574	0.0000	1.0000	1.0000	0.4967
EDU_t	20,272	0.0937	0.0507	0.0680	0.1057	0.0698
$FEMALEP_t$	20,272	0.4554	0.4471	0.4817	0.4932	0.0791
$RELIGION_t$	20,272	21.7724	5.0000	15.0000	27.0000	19.4570
$DIALECT_t$	20,272	5.1087	2.0000	4.0000	9.0000	4.2145
$ETHGR_t$	20,272	3.2015	1.0000	2.0000	3.0000	3.4214

Panel B: Pearson correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. $NCSKEW_{t+1}$	1.00																							
2. $DUVOL_{t+1}$	**0.88**	1.00																						
3. $TRUST1_t$	**−0.02**	**−0.02**	1.00																					
4. $TRUST2_t$	**−0.03**	**−0.03**	**0.89**	1.00																				
5. $TRUST3_t$	**−0.04**	**−0.05**	**0.27**	**0.16**	1.00																			
6. $NCSKEW_t$	**0.04**	**0.04**	**−0.02**	**−0.03**	**−0.06**	1.00																		
7. *DUVOLt*	**0.04**	**0.05**	**−0.02**	**−0.02**	**−0.07**	**0.89**	1.00																	
8. $DTURN_t$	**0.06**	**0.06**	−0.01	0.00	0.00	**−0.13**	**−0.14**	1.00																
9. RET_t	0.00	0.01	0.00	−0.01	**−0.03**	**0.12**	**0.11**	**−0.33**	1.00															
10. $SIZE_t$	**−0.10**	**−0.13**	**0.08**	**0.11**	**0.03**	**−0.10**	**−0.12**	0.00	**0.14**	1.00														
11. MB_t	**0.08**	**0.07**	0.01	0.01	**0.06**	−0.01	**−0.03**	**0.11**	**−0.31**	**−0.32**	1.00													
12. $SIGMA_t$	0.00	−0.01	0.00	0.00	**0.04**	**−0.10**	**−0.09**	**0.33**	**−0.97**	**−0.15**	**0.33**	1.00												
13. LEV_t	**−0.02**	**−0.03**	**−0.06**	**−0.03**	**−0.02**	**−0.02**	**−0.02**	**0.03**	**−0.07**	**0.24**	**−0.19**	**0.07**	1.00											
14. ROA_t	0.00	−0.01	**0.05**	**0.04**	**0.05**	**−0.03**	**−0.05**	**−0.02**	**0.03**	**0.17**	**0.14**	**−0.03**	**−0.32**	1.00										
15. CSR_t	**−0.08**	**−0.09**	**0.02**	**0.06**	0.00	**−0.06**	**−0.07**	**−0.02**	**0.07**	**0.42**	0.01	**−0.06**	**0.03**	**0.11**	1.00									
16. $ABACC_t$	**0.03**	**0.02**	**0.02**	**0.02**	−0.01	**0.02**	**0.02**	−0.01	**−0.12**	**−0.07**	**0.09**	**0.13**	**0.15**	**−0.07**	**−0.05**	1.00								
17. $GDP\%_t$	−0.01	**0.02**	**−0.32**	**−0.33**	**−0.15**	**0.09**	**0.10**	**−0.16**	**−0.09**	**−0.13**	**−0.14**	**0.10**	**0.08**	−0.01	**−0.16**	**0.04**	1.00							
18. $POPG_t$	**−0.02**	−0.01	**0.34**	**0.35**	0.00	**0.01**	**0.02**	**−0.04**	**−0.05**	**0.06**	**0.05**	**0.06**	0.00	**0.05**	**0.07**	**0.03**	**−0.18**	1.00						
19. *HIGHNERIt*	0.00	−0.01	**0.76**	**0.60**	**0.23**	−0.01	0.00	0.01	**0.02**	**0.06**	0.01	**−0.02**	**−0.07**	**0.06**	**0.06**	0.01	**−0.31**	**0.26**	1.00					
20. EDU_t	**−0.02**	**−0.06**	**0.26**	**0.32**	0.01	**−0.05**	**−0.05**	**0.07**	−0.01	**0.19**	**0.19**	**0.02**	**−0.09**	**0.03**	**0.20**	**−0.05**	**−0.43**	0.01	**0.25**	1.00				
21. $FEMALEP_t$	**0.02**	**0.02**	**−0.46**	**−0.51**	**−0.11**	**0.04**	**0.03**	**−0.01**	−0.01	**−0.11**	**−0.04**	0.01	**0.05**	**−0.04**	**−0.10**	0.01	**0.29**	**−0.12**	**−0.29**	**−0.41**	1.00			
22. $RELIGION_t$	0.01	0.01	**−0.32**	**−0.37**	**0.16**	0.01	0.01	0.00	−0.01	**−0.04**	**−0.02**	**0.02**	0.00	**0.02**	0.01	**−0.02**	**0.04**	**−0.12**	**−0.06**	**−0.10**	**0.16**	1.00		
23. $DIALECT_t$	0.01	0.01	**−0.36**	**−0.53**	**−0.17**	0.01	0.01	−0.01	−0.01	**−0.08**	0.01	0.01	0.00	**−0.02**	**−0.03**	0.00	**0.14**	**−0.12**	**−0.28**	**−0.18**	**0.25**	0.00	1.00	
24. $ETHGR_t$	0.00	0.00	**−0.42**	**−0.39**	**−0.19**	−0.01	−0.01	0.00	−0.01	**−0.03**	0.00	0.00	**0.04**	**−0.04**	−0.01	0.01	**0.11**	**−0.12**	**−0.51**	**−0.08**	**0.21**	**0.11**	**0.56**	1.00

This table reports the descriptive statistics for the stock price crash risk measures, social trust measures, and control variables. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. Panels A and B report the basic statistics and a Pearson correlation matrix, respectively. Bold values indicate statistical significance at the 5% or 1% level. All variables are defined in Appendix A.

Table 3
Social trust and stock price crash risk.

	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $NCSKEW_{t+1}$	(4) $DUVOL_{t+1}$	(5) $NCSKEW_{t+1}$	(6) $DUVOL_{t+1}$
$TRUST1_t$	−0.0193**	−0.0109**	−0.0198***	−0.0111**	−0.0569***	−0.0358***
	(−2.58)	(−2.10)	(−2.65)	(−2.14)	(−2.93)	(−3.08)
$NCSKEW_t$	0.0313***		0.0309***		0.0302**	
	(4.25)		(4.20)		(2.45)	
$DUVOL_t$		0.0336***		0.0335***		0.0327**
		(4.55)		(4.54)		(2.58)
$DTURN_t$	−0.0128	0.0072	−0.0054	0.0104	−0.0057	0.0102
	(−0.38)	(0.31)	(−0.16)	(0.45)	(−0.15)	(0.38)
RET_t	1.1207***	0.7962***	1.0954***	0.7847***	1.0777**	0.7717***
	(4.37)	(4.51)	(4.27)	(4.44)	(2.50)	(2.79)
$SIZE_t$	−0.0224***	−0.0212***	−0.0160***	−0.0184***	−0.0142	−0.0171
	(−4.22)	(−5.70)	(−2.89)	(−4.70)	(−1.01)	(−1.41)
MB_t	0.0335***	0.0211***	0.0339***	0.0213***	0.0352***	0.0223**
	(5.69)	(5.18)	(5.74)	(5.20)	(2.72)	(2.51)
$SIGMA_t$	0.0759***	0.0519***	0.0729***	0.0506***	0.0719**	0.0499***
	(5.19)	(5.21)	(4.98)	(5.07)	(2.46)	(2.65)
LEV_t	−0.0014	−0.0225	−0.0098	−0.0260	−0.0087	−0.0255
	(−0.06)	(−1.29)	(−0.39)	(−1.48)	(−0.21)	(−0.79)
ROA_t	0.0809	−0.0038	0.0848	−0.0021	0.0665	−0.0159
	(1.02)	(−0.07)	(1.06)	(−0.04)	(0.53)	(−0.16)
CSR_t			−0.0532***	−0.0234**	−0.0579**	−0.0267
			(−3.44)	(−2.21)	(−2.32)	(−1.36)
$ABACC_t$			0.1682**	0.0703	0.1674	0.0709
			(2.25)	(1.37)	(1.28)	(0.99)
$GDP\%_t$					−0.0873	−0.0221
					(−0.61)	(−0.20)
$POPG_t$					−0.1228	−0.0041
					(−0.45)	(−0.02)
$HIGHNERI_t$					0.0549***	0.0323***
					(3.75)	(3.14)
EDU_t					0.0022	0.0013
					(1.32)	(1.47)
$FEMALEP_t$					−0.0073	−0.0420
					(−0.09)	(−0.81)
$RELIGION_t$					0.0001	0.0002
					(0.47)	(0.85)
$DIALECT_t$					0.0004	0.0006
					(0.31)	(0.75)
$ETHGR_t$					−0.0020	−0.0023
					(−1.03)	(−1.51)
INDUSTRY	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES
CONSTANT	0.0780	0.2263**	−0.0582	0.1667*	−0.0643	0.1743
	(0.58)	(2.41)	(−0.42)	(1.73)	(−0.21)	(0.67)
N	20,272	20,272	20,272	20,272	20,272	20,272
R^2	0.0551	0.0702	0.0560	0.0705	0.0569	0.0714

This table presents the regression results of the impact of social trust on firm-level stock price crash risk. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

and *CSR* having the expected signs, consistent with previous studies. The coefficients of *TRUST1* remain negative and significant after controlling for *ABACC* and *CSR*, suggesting that social trust has incremental predictability in regard to future crash risk over and above the firm's financial and non-financial reporting activities and other predictors documented in the previous literature. The coefficients of other firm-level control variables are mostly consistent with previous studies (e.g., Chen et al., 2001; Kim et al., 2011a, b). Firms that have a higher past return, a higher return volatility, and a higher market-to-book ratio tend to have higher risks of a future crash.

Following the previous studies noted above, to rule out the possible explanation that other regional factors drive the relationship between social trust and crash risk, we include eight province-level variables in the analysis: the annual province-level GDP growth rate (*GDP%*), the annual provincial population growth rate (*POPG*), the annual province-level marketization index (*HIGHNERI*), the percentage of the population with at least a college education (*EDU*), the percentage of the female population (*FEMALEP*), the number of religious places (*RELIGION*), the number of distinct dialects (*DIALECT*), and the number of ethnic groups (*ETHGR*). The definitions of all of these regional variables are detailed in Appendix A. As shown in Table 3, none of the regional factors except for *HIGHNERI* has a significant impact on firms' crash risks. The regional marketization index measures the levels of and differences in institutional transformation and economic policies across provinces (Fan et al., 2011). A high regional marketization index indicates further progress towards a market economy relative to other regions and is therefore typically accompanied by higher competition among firms in the region. One possible explanation for the significantly positive relationship between crash risk and *HIGHNERI* is that high competition tends to lower cooperation (trust) in the region (Gambetta, 1988) and induces the managers to withhold bad news from the general public, including competitors.

In summary, consistent with Hypothesis 1, the results in Table 3 suggest that firms in regions of high social trust tend to have a lower risk of a future crash after ruling out alternative explanations at both the firm level and the regional level.

4.3. Robustness tests: alternative measures of social trust and crash risk

In this subsection, we run several robustness tests. First, we use citizens' trustworthiness (*TRUST2* and *TRUST3*) to replace the enterprise trustworthiness measure (*TRUST1*) in Model (4) and test the effect of social trust on stock price crash risks. Consistent with the evidence shown in Table 3, the coefficients of the two alternative social trust measures (*TRUST2* and *TRUST3*) in Panel A of Table 4 are negative and significant, supporting Hypothesis 1, i.e., firms in regions of high social trust tend to have smaller future stock price crash risks.

Second, following Hutton et al. (2009), we further measure the firm-specific weekly returns (*W*) as the natural logarithm of one plus the residual return from the model below, adjusting for not only market returns but also industry returns.

$$R_{i,t} = \alpha_i + \beta_1 R_{m,t-1} + \beta_2 R_{I,t-1} + \beta_3 R_{m,t} + \beta_4 R_{I,t} + \beta_5 R_{m,t+1} + \beta_6 R_{I,t+1} + \varepsilon_{i,t} \quad (5)$$

where $R_{i,t}$ is the weekly return for stock i in week t, and $R_{m,t}$ and $R_{I,t}$ are the value-weighted average weekly market return and industry I return, respectively. We include the lag and lead terms of the market returns and industry returns to mitigate the nonsynchronized trading problem (Dimson, 1979). We then use the same models, (2) and (3), to calculate the two measures of firm-specific future crash risk, *NCSKEW* and *DUVOL*, respectively.

Columns (1) and (2) of Panel B in Table 4 present the regression results of model (4) using the alternative measures of crash risk, adjusted by the market and industry returns. Consistent with Table 3, the association between social trust and crash risk remains negative and significant. The coefficients of nearly all of the control variables are similar to those listed in Table 3.

Additionally, following Hutton et al. (2009) and Kim et al. (2011b), we also use an indicator variable, *CRASH*, defined in detail in Section 3.2, to measure the crash likelihood for each firm and year. When crash risk is measured by *CRASH*, a logit regression of model (4) is used, and the regression results are shown in column (3) of Panel B in Table 4. We can observe that the coefficient of *TRUST1* remains significantly negative when the alternative crash risk proxy (*CRASH*) is used in the logit model specification.[24]

In conclusion, our main results are robust to the three alternative measures of crash risk and remain significant after controlling for past crash history, lending support to Hypothesis 1.

4.4. The effect of state-owned enterprises (SOEs)

Piotroski et al. (2015) suggest that firms' crash risk may be affected by the ownership type. For example, State-Owned Enterprises (SOEs) typically have opaque financial reporting practices (Bushman et al., 2004), are more likely to withhold bad news due to political incentives (Bushman and Piotroski, 2006) and therefore tend to have higher crash risks. Therefore, the negative impact of social trust on firms' crash risk is expected to be more prominent

[24] We further use a Cox proportional hazard model (Cox, 1972) to examine the determinants of crash risks controlling for past crash history (Jin and Myers, 2006; Kim et al., 2011a). The unreported results from the Cox proportional hazard model are generally consistent with the logistic regression results shown in column (3), though with smaller magnitude in the coefficient of *TRUST1*. The results of the Cox proportional hazard model are available upon request. It should be noted that the Cox proportional hazard model uses only firms with at least one crash; therefore, the sample size has been dramatically reduced, lowering the statistical power of the test.

Table 4
Robustness tests.

Panel A: Alternative measures of social trust

	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $NCSKEW_{t+1}$	(4) $DUVOL_{t+1}$
$TRUST2_t$	−0.0464***	−0.0299***		
	(−5.75)	(−5.17)		
$TRUST3_t$			−0.1485**	−0.1509***
			(−2.37)	(−3.28)
$NCSKEW_t$	0.0306**		0.0329***	
	(2.41)		(2.71)	
$DUVOL_t$		0.0327**		0.0353***
		(2.48)		(2.90)
$DTURN_t$	−0.0056	0.0097	0.0280	0.0287
	(−0.15)	(0.36)	(0.77)	(1.08)
RET_t	1.0350**	0.7300**	1.2223***	0.8120***
	(2.35)	(2.59)	(2.65)	(2.73)
$SIZE_t$	−0.0144	−0.0171	−0.0161	−0.0167
	(−1.02)	(−1.42)	(−1.20)	(−1.39)
MB_t	0.0359***	0.0230***	0.0340***	0.0228***
	(2.80)	(2.62)	(2.93)	(3.04)
$SIGMA_t$	0.0704**	0.0480**	0.0828***	0.0550***
	(2.36)	(2.52)	(2.68)	(2.79)
LEV_t	−0.0065	−0.0241	−0.0045	−0.0224
	(−0.14)	(−0.71)	(−0.08)	(−0.55)
ROA_t	0.0629	−0.0238	0.2100*	0.0716
	(0.52)	(−0.26)	(1.78)	(0.76)
CSR_t	−0.0555**	−0.0250	−0.0473*	−0.0221
	(−2.18)	(−1.29)	(−1.75)	(−1.15)
$ABACC_t$	0.1651	0.0696	0.2000	0.0937
	(1.26)	(0.97)	(1.28)	(1.09)
$GDP\%_t$	−0.2103	−0.1150	−0.0929	−0.0493
	(−1.52)	(−1.11)	(−0.47)	(−0.30)
$POPG_t$	−0.1010	0.0021	−0.3184	−0.1487
	(−0.40)	(0.01)	(−0.85)	(−0.54)
$HIGHNERI_t$	0.0404***	0.0242***	0.0123	0.0076
	(5.05)	(3.38)	(0.92)	(0.68)
EDU_t	0.0032**	0.0020**	0.0004	0.0005
	(2.06)	(2.30)	(0.39)	(0.81)
$FEMALEP_t$	−0.0311	−0.0583	0.1512***	0.0611*
	(−0.36)	(−1.09)	(3.20)	(1.85)
$RELIGION_t$	−0.0001	0.0000	0.0005	0.0006
	(−0.20)	(0.10)	(0.93)	(1.31)
$DIALECT_t$	−0.0026**	−0.0012	0.0019	0.0015
	(−2.17)	(−1.28)	(0.96)	(1.13)
$ETHGR_t$	−0.0010	−0.0016	−0.0027	−0.0023
	(−0.53)	(−1.08)	(−0.91)	(−1.12)
INDUSTRY	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
CONSTANT	0.0167	0.230	−0.0596	0.1747
	(0.05)	(0.89)	(−0.21)	(0.71)
N	19,938	19,938	13,904	13,904
R^2	0.0574	0.0719	0.0619	0.0770

Panel B: Alternative measures of crash risk

	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $CRASH_{t+1}$
$TRUST1_t$	−0.0888**	−0.0563**	−0.1419**
	(−2.27)	(−2.25)	(−2.06)
$NCSKEW_t$	0.0193		−0.0256
	(1.27)		(−0.75)
$DUVOL_t$		0.0353**	
		(2.21)	
$DTURN_t$	0.1658	0.1429	−0.2109
	(1.08)	(1.14)	(−1.17)
RET_t	0.9855	0.3941	1.6988
	(0.96)	(0.77)	(1.21)
$SIZE_t$	−0.0380**	−0.0284**	−0.0886***
	(−2.50)	(−2.58)	(−3.22)
MB_t	−0.0106	0.0024	0.0393
	(−0.56)	(0.17)	(1.34)
$SIGMA_t$	0.0486	0.0063	0.0582
	(0.74)	(0.17)	(0.80)
LEV_t	−0.0696	−0.0574	−0.4644***
	(−0.68)	(−1.10)	(−4.04)
ROA_t	−0.3697	−0.1785	−0.3759

(*continued on next page*)

Table 4 (*continued*)

	(−1.51)	(−1.43)	(−1.02)
CSR_t	−0.0014	−0.0174	−0.1972**
	(−0.05)	(−0.96)	(−2.46)
$ABACC_t$	0.0227	0.0250	0.4917
	(0.13)	(0.25)	(1.34)
$GDP\%_t$	−0.3429	−0.0549	−0.8808
	(−0.91)	(−0.21)	(−1.33)
$POPG_t$	−0.2852	−0.0459	−2.5595**
	(−0.56)	(−0.17)	(−2.54)
$HIGHNERI_t$	−0.0023	0.0096	0.1163
	(−0.06)	(0.44)	(1.32)
EDU_t	0.0123***	0.0054**	0.0037
	(4.26)	(2.52)	(0.29)
$FEMALEP_t$	−0.1379	−0.0507	−0.0187
	(−1.03)	(−0.64)	(−0.04)
$RELIGION_t$	0.0008**	0.0005*	−0.0014
	(2.03)	(1.83)	(−1.07)
$DIALECT_t$	−0.0023	−0.0025*	0.0036
	(−0.85)	(−1.74)	(0.51)
$ETHGR_t$	0.0016	0.0019	−0.0128
	(0.48)	(1.04)	(−1.33)
INDUSTRY	YES	YES	YES
YEAR	YES	YES	YES
CONSTANT	1.3289***	0.9601***	0.0705
	(3.22)	(4.04)	(0.10)
N	20,272	20,272	20,272
R^2	0.0083	0.0117	
Pseudo R^2			0.5153

Panel A presents the analysis using two alternative measures of social trust, i.e., citizens' trustworthiness (*TRUST2* and *TRUST3*). Columns (1) and (2) of Panel B present the analysis using alternative measures of crash risk, which adjust for both market and industry returns. Column (3) of Panel B shows the logit regression results using an indicator variable, *CRASH*, to measure the crash likelihood for each firm and year. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

for SOEs than for non-SOEs. We test Hypothesis 2 by including *SOE*, an indicator variable for SOEs, as well as the interaction between *SOE* and social trust (*TRUST1*), to examine the impact of ownership type on the relationship between social trust and crash risk. Specifically, we test the following model in this subsection:

$$CrashRisk_{t+1} = \beta_0 + \beta_1 SocialTrust_t + \beta_2 SocialTrust_t \times SOE_t + \beta_3 SOE_t + \gamma Controls_t + Industry\_dummies + Year\_dummies + \varepsilon_t \quad (6)$$

where all of the variables are the same as those in model (4) except for SOE_t, which is an indicator variable discussed above. The coefficients of interest are β_1 and β_2. Hypothesis 1 predicts a negative coefficient for $SocialTrust_t$ (β_1), suggesting that firms located in regions of high social trust tend to have a smaller risk of a future crash than firms in regions of low social trust. On the other hand, Hypothesis 2 suggests a negative coefficient for the interaction term between $SocialTrust_t$ and SOE_t (β_2), indicating that the negative association between social trust and future crash risk is more prominent for SOEs.

Columns (1) and (2) in Table 5 report the empirical results of model (6). They show a negative and significant relationship (β_1) between social trust and future crash risk, regardless of which measure for crash risk is used. The coefficients (β_2) of the interaction between *SocialTrust* and *SOE* are positive and significant at the 5% level when crash risk is proxied by either *DUVOL* or *NCSKEW*. The coefficients of all of the control variables are similar to those reported in Table 3. The results are consistent with Hypothesis 2, suggesting that the negative association between social trust and crash risk is more prominent for SOEs.

Table 5
The effect of state-owned enterprises.

	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$
$TRUST1_t$	−0.0384**	−0.0195**
	(−2.19)	(−2.06)
$TRUST1_t{}^*SOE_t$	−0.0280*	−0.0249**
	(−1.93)	(−2.13)
SOE_t	−0.0057	0.0020
	(−0.27)	(0.14)
$NCSKEW_t$	0.0294**	
	(2.40)	
$DUVOL_t$		0.0319**
		(2.52)
$DTURN_t$	−0.0055	0.0104
	(−0.15)	(0.39)
RET_t	1.0752**	0.7713***
	(2.53)	(2.83)
$SIZE_t$	−0.0108	−0.0148
	(−0.74)	(−1.19)
MB_t	0.0355**	0.0225**
	(2.74)	(2.54)
$SIGMA_t$	0.0715**	0.0497***
	(2.48)	(2.68)
LEV_t	−0.0063	−0.0240
	(−0.15)	(−0.76)
ROA_t	0.0518	−0.0259
	(0.41)	(−0.27)
CSR_t	−0.0553**	−0.0248
	(−2.19)	(−1.25)
$ABACC_t$	0.1566	0.0640
	(1.22)	(0.90)
$GDP\%_t$	−0.0721	−0.0113
	(−0.51)	(−0.10)
$POPG_t$	−0.1007	0.0102
	(−0.37)	(0.05)
$HIGHNERI_t$	0.0515***	0.0302***
	(3.71)	(3.04)
EDU_t	0.0020	0.0011
	(1.23)	(1.36)
$FEMALEP_t$	−0.0186	−0.0505
	(−0.23)	(−0.98)
$RELIGION_t$	0.0001	0.0001
	(0.29)	(0.64)
$DIALECT_t$	0.0001	0.0004
	(0.11)	(0.53)
$ETHGR_t$	−0.0016	−0.0020
	(−0.84)	(−1.31)
INDUSTRY	YES	YES
YEAR	YES	YES
CONSTANT	−0.1282	0.1285
	(−0.41)	(0.48)
N	20,272	20,272
R^2	0.0574	0.0720

Table 5 presents the regression results of the impact of State-Owned Enterprises on the relationship between social trust and stock price crash risk. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

4.5. The effect of monitoring

Because the negative association between social trust and future firm-specific crash risk shown in Table 3 is based on the explanation by agency theory of crash risk (Jin and Myers, 2006; Hutton et al., 2009), one would expect that the impact of social trust on crash risk will be alleviated for firms that are better monitored (Callen and Fang, 2013). Following Klein (1998) and Hermalin and Weisbach (1988), we measure internal monitoring by board independence (*HIGHINDE*), which is a dummy variable that equals one if the percentage of outstanding shares held by the institutional shareholders of a firm is above the median of institutional ownership of all sample firms and zero otherwise.

We proxy external monitoring by two measures, institutional holdings (*HIGNINST*) and foreign B or H shares issuance (*BH*). *HIGNINST* is a dummy variable that equals one if the ratio of the number of independent directors to the total number of directors on a firm's board is above the median of all sample firms and zero otherwise. Numerous studies (e.g., Hartzell and Starks, 2003; Kim et al., 2011a) state that high institutional ownership indicates effective external monitoring. *BH* is a dummy variable that equals one if an A share-issuing firm also issues foreign shares (B shares in the Shanghai or Shenzhen Stock Exchange or H shares in the Hong Kong Stock Exchange) and zero otherwise. Foreign investors in the B share market are typically sophisticated institutional investors and therefore may have better resources and expertise to process information and provide better external monitoring overt the firm (Gul et al., 2010). Similarly, cross-listing in the Hong Kong Stock Exchange, which has a better legal and institutional environment than that in mainland China, may improve investor protection and enhance external monitoring (Xu et al., 2014).

Specifically, we test the following model in this subsection:

$$\begin{aligned} CrashRisk_{t+1} = {} & \beta_0 + \beta_1 SocialTrust_t + \beta_2 SocialTrust_t \\ & \times Monitor_t + \beta_3 Monitor_t + \gamma Controls_t \\ & + Industry\_dummies + Year\_dummies + \varepsilon_t \end{aligned} \tag{7}$$

where all of the variables are the same as those in model (4) except for $Monitor_t$, which is the three internal and external monitoring variables discussed above (*HIGHINDE, HIGHINST*, or *BH*).

Columns (1)–(6) in Table 6 report the empirical results of model (7), where *Monitor* is measured by either the internal monitoring proxy (*HIGHINDE*) or the two external monitoring proxies (*HIGHINST* and *BH*). Consistent with Hypothesis 1, the estimated coefficient of β_1 is significantly negative at the 1% or 5% level in all columns, regardless of which measure for crash risk is used. Consistent with Hypothesis 3, the estimated coefficient β_2 of the interaction between social trust and monitoring is significantly positive at the 1% level, regardless of which monitoring proxy measure is used. The coefficients of all of the control variables are similar to those listed in Table 3. In short, the evidence presented in Table 6 clearly indicates a negative association between social trust and crash risk as well as an attenuated negative association for firms with a better internal or external monitoring mechanism.

4.6. The effect of risk-taking

To strengthen our understanding of the negative association between social trust and future crash risk, as well as the agency theory underling the association, we examine the effect of firms' incentives to conceal risk-taking activities on the relationship between social trust and future crash risk in the following model.

$$\begin{aligned} CrashRisk_{t+1} = {} & \beta_0 + \beta_1 SocialTrust_t + \beta_2 SocialTrust_t \times HIGHRISK_t \\ & + \beta_3 HIGHRISK_t + \gamma Controls_t \\ & + Industry\_dummies + Year\_dummies + \varepsilon_t \end{aligned} \tag{8}$$

where all of the variables are the same as those in model (4) except for $HIGHRISK_t$, which is measured by the variation in firms' profitability (*HIGHSTDROA*) and Altman's *Z-SCORE* (*LOWZSCORE*, Altman et al., 2007). Callen and Fang (2015b) and Kim et al. (2011b) suggest that the variation in firms' profitability and Altman's *Z-SCORE* serve as proxies for managers' incentives to hide risk-taking activities since higher profitability variations and a lower *Z-SCORE* will attract investors' attention to managers' abnormal risk-taking behaviors. Detailed definitions of the variables can be found in Appendix A.

If Hypothesis 4 is true, then the negative impact of social trust on firm-specific crash risk should be more pronounced for firms with higher incentives to hide risk-taking behaviors. Thus, we expect that the coefficient of the interaction between social trust and *HIGHRISK* (β_2) will be negative and significant.

Table 7 reports the estimation results of model (8). As predicted, the coefficients of the interaction between social trust and *HIGHSTDROA* (Columns (1) and (2)) are negative and significant at the 5% level if *NCSKEW* is used to proxy for crash risk. Columns (3) and (4) also show negative and significant coefficients of the interaction between social trust and *LOWZSCORE*, though they are only significant at the 10% level, suggesting a more salient impact of trust on crash risk when firms' financial risk is higher (a *Z-SCORE* lower than the median). Consistent with Hypothesis 4, this evidence further corroborates the explanation by agency theory of the negative association between social trust and firm-specific crash risk.

5. Endogeneity correction

The analysis in the previous sections identifies a significantly negative association between crash risk and social trust. However, although we use crash risk measures in year $t+1$ and social trust measures in year t to alleviate the potential reverse causality problem, endogeneity concerns persist. For example, the negative association between social trust and firms' crash risk may due to some unobservable regional factors related to social trust[25] or because firms with smaller crash risks self-select being located in regions of high social trust.

To address the endogeneity concern, we manually collect firms' CEOs' hometown information and denote the province-level enterprise trustworthiness score (*TRUST1*) of the CEO's hometown as *CEOTRUST1* and use it as an additional measure of the firm's social trust. The reasoning is that a firm's CEO may determine a large proportion of the firm's bad news hoarding behavior and, therefore, his hometown's social trust is likely to be related to the firm's crash risk as well. Moreover, the crash risks of firms located in a specific region can hardly affect the social trust of their CEOs' hometowns, which addresses the endogeneity problem. Columns (1) and (2) of Table 8 present the estimation results of model (4) using *CEOTRUST1* as the measure of social trust in the CEO's hometown. The coefficients of *CEOTRUST1* are significantly negative for both crash risk measures, which supports our main finding that social trust leads to more honest behaviors and smaller crash risks.

We further employ a difference-in-differences (DID) analysis to address the potential endogeneity issue. Specifically, we examine sample firms with CEO transitions during the 2001–2015 period and compare the changes in a firm's crash risk for the four years around the CEO transition (two years before and two years after) when the new CEO is from a region of higher social trust (low-to-high, treatment group) with those when the new CEO is from a region of lower social trust (high-to-low, control group). This DID empirical framework mitigates the impact of time-invariant unobservable regional factors on both social trust and crash risk and helps address the endogeneity issue.[26]

The model is as follows:

$$\begin{aligned} CrashRisk_{t+1} = {} & \beta_0 + \beta_1 HIGHTRUST_t + \beta_2 POST_t \\ & + \beta_3 POST_t \times HIGHTRUST_t + \gamma Controls_t \\ & + Industry\_dummies + Year\_dummies + \varepsilon_t \end{aligned} \tag{9}$$

[25] Specifically, Han and Yang (2013) show the importance of endogenous information acquisition in examining the implications of social networks for financial markets.

[26] This DID framework differs from typical DID tests in that our observations are not entirely concentrated around a particular date. We control for the year effect in all of the tests to address this difference.

Table 6
The effect of monitoring.

	MONITOR					
	HIGHINDE		HIGHINST		BH	
	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $NCSKEW_{t+1}$	(4) $DUVOL_{t+1}$	(5) $NCSKEW_{t+1}$	(6) $DUVOL_{t+1}$
$TRUST1_t$	−0.0860***	−0.0518***	−0.0779***	−0.0489***	−0.0613**	−0.0382***
	(−4.50)	(−4.34)	(−3.58)	(−3.62)	(−3.22)	(−3.36)
$TRUST1_t{*}MONITOR_t$	−0.0860***	−0.0518***	−0.0779***	−0.0489***	−0.0613***	−0.0382***
	(−4.50)	(−4.34)	(−3.58)	(−3.62)	(−3.22)	(−3.36)
$MONITOR_t$	0.0649***	0.0357***	0.0400***	0.0251**	0.0933***	0.0540**
	(3.58)	(2.90)	(2.70)	(2.55)	(3.19)	(2.56)
$NCSKEW_t$	0.0296**		0.0274*		0.0300*	
	(2.43)		(2.33)		(2.44)	
$DUVOL_t$		0.0322**		0.0304**		0.0325**
		(2.57)		(2.52)		(2.57)
$DTURN_t$	−0.0049	0.0107	0.0013	0.0148	−0.0057	0.0101
	(−0.13)	(0.40)	(0.03)	(0.56)	(−0.15)	(0.38)
RET_t	1.0880**	0.7770***	1.0361**	0.7446***	1.0765**	0.7706***
	(2.52)	(2.81)	(2.50)	(2.75)	(2.49)	(2.78)
$SIZE_t$	−0.0139	−0.0170	−0.0184	−0.0197	−0.0129	−0.0161
	(−1.00)	(−1.41)	(−1.31)	(−1.64)	(−0.97)	(−1.41)
MB_t	0.0359***	0.0226**	0.0315**	0.0199**	0.0357***	0.0226***
	(2.78)	(2.56)	(2.53)	(2.34)	(2.80)	(2.60)
$SIGMA_t$	0.0724**	0.0501***	0.0682**	0.0475**	0.0718**	0.0498***
	(2.48)	(2.67)	(2.40)	(2.58)	(2.45)	(2.65)
LEV_t	−0.0082	−0.0253	−0.0105	−0.0270	−0.0102	−0.0264
	(−0.19)	(−0.78)	(−0.25)	(−0.83)	(−0.24)	(−0.81)
ROA_t	0.0676	−0.0148	0.0242	−0.0426	0.0690	−0.0153
	(0.53)	(−0.15)	(0.21)	(−0.48)	(0.54)	(−0.16)
CSR_t	−0.0575**	−0.0265	−0.0618***	−0.0291	−0.0568**	−0.0258
	(−2.32)	(−1.36)	(−2.64)	(−1.56)	(−2.33)	(−1.34)
$ABACC_t$	0.1668	0.0704	0.1641	0.0688	0.1693	0.0718
	(1.27)	(0.98)	(1.26)	(0.97)	(1.29)	(1.00)
$GDP\%_t$	−0.0281	0.0101	−0.0430	0.0057	−0.0822	−0.0194
	(−0.23)	(0.10)	(−0.30)	(0.05)	(−0.59)	(−0.18)
$POPG_t$	−0.0834	0.0172	−0.1044	0.0059	−0.1164	−0.0005
	(−0.34)	(0.08)	(−0.39)	(0.03)	(−0.43)	(−0.00)
$HIGHNERI_t$	0.0576***	0.0337***	0.0546***	0.0320**	0.0565***	0.0331***
	(4.04)	(3.34)	(3.88)	(3.16)	(3.92)	(3.29)
EDU_t	−0.0007	−0.0003	0.0019	0.0011	0.0020	0.0012
	(−0.45)	(−0.33)	(1.12)	(1.23)	(1.18)	(1.34)
$FEMALEP_t$	−0.0243	−0.0514	−0.0021	−0.0388	−0.0122	−0.0453
	(−0.29)	(−0.95)	(−0.02)	(−0.73)	(−0.14)	(−0.84)
$RELIGION_t$	0.0001	0.0001	0.0001	0.0002	0.0001	0.0002
	(0.35)	(0.74)	(0.51)	(0.89)	(0.47)	(0.85)
$DIALECT_t$	−0.0001	0.0004	−0.0000	0.0004	0.0005	0.0007
	(−0.08)	(0.45)	(−0.00)	(0.49)	(0.42)	(0.85)
$ETHGR_t$	−0.0014	−0.0019	−0.0019	−0.0022	−0.0021	−0.0023
	(−0.74)	(−1.34)	(−1.00)	(−1.48)	(−1.09)	(−1.56)
INDUSTRY	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES
CONSTANT	−0.1393	−0.0249	0.0584	0.2180	−0.0903	0.1537
	(−0.43)	(−0.09)	(0.20)	(0.85)	(−0.31)	(0.63)
N	20,272	20,272	20,266	20,266	20,272	20,272
R^2	0.0578	0.0720	0.0594	0.0734	0.0573	0.0718

This table presents the regression results of the impact of monitoring on the relationship between social trust and firm-level stock price crash risk. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

where all of the variables are defined similarly to those in model (4) except for $HIGHTRUST_t$, which equals one if the new CEO is from a region of higher social trust and zero otherwise, and $POST_t$, which is an indicator variable for whether year t is after the CEO transition.

If Hypothesis 1 is valid, i.e., high social trust leads to lower firm-specific crash risks, then we will observe a significantly negative coefficient of the interaction term, $POST_t{*}HIGHTRUST_t$, suggesting a reduction in the firm's crash risk after a low-to-high social trust CEO transition. Columns (3) and (4) of Table 8 present the estimation results of the difference-in-differences test. Consistent with Hypothesis 1, the coefficient estimates of $POST_t{*}HIGHTRUST_t$ are negatively significant for both crash risk measures. Overall, the evidence of this section indicates that our main results are robust after correcting for potential reverse causality and the endogeneity concern and lend support to Hypothesis 1, which states that regional social trust tends to reduce the firm-specific stock price crash risk.

6. Economic mechanisms

Hitherto, our analysis indicates that firms in regions of high social trust tend to have a lower future firm-specific stock price crash risk. In this section, we explore the economic mechanisms through

Table 7
The effect of risk-taking.

	HIGHRISK			
	HIGHSTDROA		LOWZSCORE	
	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $NCSKEW_{t+1}$	(4) $DUVOL_{t+1}$
$TRUST1_t$	−0.0441***	−0.0313***	−0.0430***	−0.0176*
	(−2.73)	(−2.88)	(−3.07)	(−1.79)
$TRUST1_t{}^*HIGHRISK_t$	−0.0294**	−0.0115	−0.0262*	−0.0195*
	(−2.26)	(−1.29)	(−1.71)	(−1.82)
$HIGHRISK_t$	0.0483***	0.0195*	0.0451***	0.0501***
	(3.53)	(1.67)	(2.67)	(4.07)
$NCSKEW_t$	0.0287**		0.0343***	
	(2.12)		(4.85)	
$DUVOL_t$		0.0329**		0.0376***
		(2.29)		(5.31)
$DTURN_t$	0.0223	0.0327	0.2654***	0.2213***
	(0.36)	(0.78)	(9.42)	(11.21)
RET_t	1.0909**	0.7620**	−0.4264*	−0.4864***
	(2.30)	(2.48)	(−1.82)	(−2.98)
$SIZE_t$	−0.0129	−0.0160	−0.0249***	−0.0315***
	(−0.86)	(−1.27)	(−4.84)	(−8.48)
MB_t	0.0398**	0.0257**	0.0469***	0.0270***
	(2.58)	(2.51)	(9.35)	(7.70)
$SIGMA_t$	0.0690**	0.0464**	−0.0440***	−0.0455***
	(2.24)	(2.40)	(−3.54)	(−5.23)
LEV_t	0.0287	0.0021	−0.0058	0.0368*
	(0.85)	(0.08)	(−0.75)	(1.87)
ROA_t	0.1004	0.0068	−0.0120	−0.0209
	(0.78)	(0.07)	(−0.15)	(−0.36)
CSR_t	−0.0459	−0.0184	−0.0996***	−0.0586***
	(−1.45)	(−0.85)	(−6.78)	(−5.70)
$ABACC_t$	0.1680	0.0761	0.2312***	0.1021*
	(1.30)	(1.01)	(3.07)	(1.92)
$GDP\%_t$	−0.0860	−0.0179	−0.1940*	0.0399
	(−0.56)	(−0.16)	(−1.84)	(0.54)
$POPG_t$	−0.1683	0.0034	−0.1257	0.1312
	(−0.46)	(0.01)	(−0.65)	(0.97)
$HIGHNERI_t$	0.0526***	0.0303***	0.0544***	0.0266**
	(3.77)	(2.88)	(3.16)	(2.21)
EDU_t	0.0030	0.0019*	−0.0033***	−0.0038***
	(1.37)	(1.88)	(−2.61)	(−4.32)
$FEMALEP_t$	0.0374	−0.0147	−0.0432	−0.0687
	(0.38)	(−0.23)	(−0.59)	(−1.33)
$RELIGION_t$	0.0003	0.0003	−0.0001	0.0000
	(0.99)	(1.30)	(−0.18)	(0.12)
$DIALECT_t$	−0.0003	0.0003	−0.0009	−0.0005
	(−0.24)	(0.30)	(−0.59)	(−0.44)
$ETHGR_t$	−0.0013	−0.0018	−0.0006	−0.0012
	(−0.62)	(−1.24)	(−0.30)	(−0.87)
INDUSTRY	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
CONSTANT	−0.1151	0.1340	0.4333***	0.6275***
	(−0.35)	(0.48)	(3.34)	(6.86)
N	17,657	17,657	20,263	20,263
R^2	0.0641	0.0795	0.0270	0.0341

This table presents the regression results of the impact of risk-taking on the relationship between social trust and firm-level stock price crash risk. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Table 8
Endogeneity correction.

	(1) $NCSKEW_{t+1}$	(2) $DUVOL_{t+1}$	(3) $NCSKEW_{t+1}$	(4) $DUVOL_{t+1}$
$CEOTRUST1_t$	−0.0207*	−0.0205***		
	(−1.66)	(−2.75)		
$POST_t{}^*HIGHTRUST_t$			−0.4058*	−0.6696***
			(−1.66)	(−2.98)
$POST_t$			−0.0473	0.0126
			(−0.97)	(0.34)
$HIGHTRUST_t$			−0.1633	−0.0834
			(−0.97)	(−0.89)
$NCSKEW_t$	0.0101	0.0265	−0.0072	
	(0.49)	(1.46)	(−0.15)	
$DUVOL_t$	−0.0112	−0.0057		0.0331
	(−0.20)	(−0.14)		(1.06)
$DTURN_t$	0.0597	0.0460*	0.1123	0.0324
	(1.57)	(1.80)	(0.71)	(0.31)
RET_t	−0.0136	−0.0146	−3.1003***	−1.5495*
	(−1.10)	(−1.13)	(−3.11)	(−1.74)
$SIZE_t$	0.0400***	0.0226**	−0.0420	−0.0248
	(3.20)	(2.45)	(−1.49)	(−1.08)
MB_t	0.0028	−0.0122	0.1007***	0.0525***
	(0.46)	(−0.33)	(3.00)	(2.76)
$SIGMA_t$	1.0100	0.7879*	−0.1963***	−0.0906
	(1.64)	(1.94)	(−3.14)	(−1.55)
LEV_t	0.3256**	0.1347	0.1138	0.1620*
	(2.42)	(1.19)	(0.66)	(1.65)
ROA_t	0.1508	0.1100	0.6409*	0.2873
	(1.12)	(1.25)	(1.70)	(0.88)
CSR_t	0.1974	0.0967	0.0297	0.0078
	(1.05)	(0.62)	(0.48)	(0.16)
$ABACC_t$	−0.0503*	−0.0277	0.6545***	0.3955*
	(−1.86)	(−1.23)	(2.93)	(1.82)
$GDP\%_t$	−0.3535	−0.2291	−0.6830	−0.2119
	(−1.32)	(−1.17)	(−0.73)	(−0.36)
$POPG_t$	0.0257	0.0176	−0.7401	0.0242
	(1.33)	(1.41)	(−0.79)	(0.03)
$HIGHNERI_t$	0.0035	0.0028	−0.0905	−0.0263
	(1.09)	(1.44)	(−1.16)	(−0.64)
EDU_t	0.1094	0.0147	0.0023	−0.0015
	(1.27)	(0.25)	(0.33)	(−0.35)
$FEMALEP_t$	−0.0002	−0.0000	0.8310**	0.3988
	(−0.60)	(−0.16)	(1.98)	(1.43)
$RELIGION_t$	0.0006	0.0011	−0.0023	−0.0009
	(0.27)	(0.73)	(−0.87)	(−0.72)
$DIALECT_t$	−0.0031	−0.0026	−0.0117***	−0.0062*
	(−1.45)	(−1.38)	(−2.88)	(−1.74)
$ETHGR_t$	0.0101	0.0265	−0.0002	−0.0012
	(0.49)	(1.46)	(−0.02)	(−0.22)
INDUSTRY	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
CONSTANT	−0.0469	0.1258	0.5237	−0.0845
	(−0.18)	(0.45)	(1.07)	(−0.18)
N	7944	7944	590	590
R^2	0.0608	0.0751	0.1615	0.1739

Columns (1) and (2) of this table present the estimation results of model (4) with the social trust of the CEO's home town measuring the firm's regional social trust. Columns (3) and (4) report the estimation results for the sample firms with CEO transitions using a difference-in-differences (DID) framework. The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

which social trust affects crash risk. Kim and Zhang (2016) suggest that firms' accounting conservatism improves firms' financial reporting quality and has a significantly negative impact on crash risk. Previous studies also show that firms with higher financial opacity are more likely to crash (Jin and Myers, 2006; Hutton et al., 2009). Therefore, we examine two potential economic mechanisms by which social trust may affect crash risk: (1) whether firms in regions of high social trust are more likely to be conservative in their financial reporting, which leads to a smaller crash risk; and (2) whether social trust reduces financial opacity, resulting in fewer crashes.

Following Khan and Watts (2009), we measure firm-year conditional conservatism by *CSCORE*, which is detailed in Appendix B. Due to missing accounting information in calculating *CSCORE*, we are left with 19,540 firm-year observations to examine the impact of social trust on conservatism. We measure financial opacity by the likelihood of financial restatements (Hutton et al., 2009; Kim and Zhang, 2014). The financial restatement announcements are

Table 9
Mechanisms: Social trust and bad news hoarding.

	(1) $CSCORE_t$	(2) $RESTATE_t$
$TRUST1_t$	0.0403***	−0.1369***
	(3.65)	(−3.36)
$SIZE_t$	0.0705***	−0.0457***
	(19.40)	(−2.77)
MB_t	0.0396***	0.0025
	(4.37)	(0.18)
LEV_t	0.0946***	0.2394***
	(3.77)	(3.54)
ROA_t	−0.3016***	−1.4150***
	(−2.74)	(−6.82)
SOE_t	−0.0254***	−0.1052***
	(−4.05)	(−3.36)
$GDP\%_t$	0.0163	−1.3784***
	(0.13)	(−3.23)
$POPG_t$	−1.2778***	−0.1210
	(−4.84)	(−0.19)
$HIGHNERI_t$	0.0059	−0.0418
	(0.55)	(−0.89)
EDU_t	−0.0001	−0.0044
	(−0.14)	(−1.09)
$FEMALEP_t$	−0.0446	0.4546**
	(−1.74)	(2.18)
CSR_t	0.0015	−0.0082
	(0.26)	(−0.20)
$RELIGION_t$	0.0001	−0.0010
	(0.35)	(−1.29)
$DIALECT_t$	0.0007	−0.0040
	(0.93)	(−1.01)
$ETHGR_t$	0.0002	0.0048
	(0.32)	(0.90)
INDUSTRY	YES	YES
YEAR	YES	YES
CONSTANT	−0.9918***	0.2976
	(−11.57)	(0.80)
N	19,540	16,554
R^2	0.3593	
Pseudo R^2		0.0485

Table 9 presents the estimation results of the impacts of social trust on firms' accounting conservatism (*CSCORE*) in column (1) and on the probability of financial restatements (*RESTATE*) in column (2). The sample period is from 2001 to 2014 for the social trust measures and control variables and from 2002 to 2015 for the crash risk measures. The *t*-statistics reported in parentheses are based on standard errors clustered by both firm and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

from the Wind database. The data on financial restatements are only available from 2004, and therefore, in estimating the relationship between social trust and the frequency of financial restatements, the number of observations further decreases to 16,554. A probit model is used in this estimation, where *RESTATE* is an indicator variable that equals one if a firm announces a financial restatement and zero otherwise.

The empirical estimations are reported in Table 9, with Column (1) presenting the results for *CSCORE* and Column (2) for *RESTATE*. The coefficient estimates of *TRUST1* are positively significant (Column 1) and negatively significant (Column 2), which suggests that social trust tends to improve firms' accounting conservatism and reduces the likelihood of financial restatements. Combined with our main finding that social trust reduces firms' crash risk, this evidence indicates that accounting conservatism and financial opacity are viable economic mechanisms by which social trust can have a negative impact on crash risks.

7. Conclusions

This study investigates the impact of regional social trust on future firm-specific stock price crash risk. Previous studies suggest that regions of high social trust are considered to have a "good culture" and a greater amount of mutually beneficial cooperation. Using a sample of Chinese A share listed firms over the 2001–2015 period, we find that firms in provinces of high social trust tend to have a smaller firm-specific stock price crash risk.

This negative association between social trust and crash risk remains robust after controlling for various firm- and regional-level characteristics that may have predictive power for crash risk. Such characteristics include investor heterogeneity, information opacity, firm-specific characteristics, corporate social responsibility reporting, regional GDP growth, population growth, the marketization level, the educational level, the percentage of the female population, the number of religious groups, dialects, and ethnic groups in the region, and industry and year fixed effects. Using alternative measures of social trust and crash risk, we find that the negative relationship between social trust and crash risk remains significant. Moreover, we find that this negative and significant association between social trust and crash risk is diminished in firms with effective internal or external monitoring and is more prominent for SOEs and firms with higher incentives to hide risk-taking activities. We also manually collect CEOs' home town information and proxy a firm's social trust by its CEO's home town's social trust to address endogeneity concerns. This specification and a difference-in-differences framework confirm our main findings.

Furthermore, we explore the potential economic mechanisms through which social trust can impact crash risks. The evidence shows that social trust is positively related to accounting conservatism and negatively related to the likelihood of financial restatements, which leads to fewer firm-specific crash risks in the future. The results are consistent with the explanation by agency theory of crash risk, which holds that managers are incentivized and able to withhold bad news to a certain point, after which the accumulated bad news comes out at once and leads to a stock price crash. Because social trust encourages honest behavior, the managers of firms located in regions of high social trust are less likely to hoard bad news. The resulting crash risk is therefore reduced for firms in regions of high social trust relative to those in regions of low social trust.

This study has important implications for the literature focused on crash risk. Existing studies investigate the predictors of crash risk based on manager- and firm-specific characteristics and religiosity. We go beyond the current literature by examining the impact of regional social trust on future firm-specific crash risks. Our findings imply that regional social trust is an important factor, albeit one that is omitted from previous studies. It deters managers' bad news hoarding behavior and lowers the future crash risk. However, our findings should be interpreted with caution. For example, countries with high levels of social trust on average may still exhibit bad news hoarding and crash risks in specific firms in regions of relatively low social trust. Moreover, this evidence poses potential questions for future research regarding other managerial behaviors and whether they are affected by regional social trust.

Appendix A. Variable definitions

Crash risk variables	
NCSKEW	The negative coefficient of skewness, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. See Eq. (3) for details.
DUVOL	The down-to-up volatility. For any stock *i* in year *t*, we separate all of the weeks with firm-specific weekly returns below the annual mean (down weeks) from those with firm-specific weekly returns above the annual mean (up weeks) and compute the standard deviation for each of these subsamples separately. We then take the natural logarithm of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks. See Eq. (4) for details.
CRASH	A dummy variable that equals 1 if a firm experiences at least one crash week during year t and zero otherwise, where a crash week for a firm is a calendar week in which the firm-specific weekly return falls 3.09 or more standard deviations below the mean firm-specific weekly returns over year t.
Social Trust variables	
TRUST1	Enterprise trustworthiness at the provincial level, from a survey conducted by the "Chinese Enterprise Survey System" in 2000 that measures the trustworthiness of enterprises in China, where a higher index value suggests a more trustworthy enterprise business community in the province.
TRUST2	Citizen trustworthiness at the provincial level, which is the milliliters of blood donated on a purely voluntary basis in 2000 in a province divided by the population in the province. The data are available from the Chinese Society of Blood Transfusion.
TRUST3	Citizen trustworthiness at the city level, which is from the Annual Report on Urban Competitiveness in 2001–2010 (Ni, 2001; Ni, 2002–2010). We use the 2010 index for 2011–2014 as well.
Firm-level control variables	
DTURN	The detrended stock trading volume, calculated as the average monthly share turnover for the current fiscal year minus the average monthly share turnover for the previous fiscal year, where the monthly share turnover is the monthly trading volume divided by the total number of floating shares on the market that month.
RET	The mean of firm-specific weekly returns over the fiscal year.
SIZE	The natural logarithm of the book value of total assets at the end of the fiscal year.
MB	The market-to-book ratio of firm *i* in year *t*, i.e., (market price at the end of fiscal year × number of shares outstanding + net asset value per share × number of non-tradable outstanding shares)/book value of equity.
SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year.
LEV	Firm financial leverage, calculated as total liabilities divided by total assets.
ROA	Firm profitability, calculated as income before extraordinary items divided by total assets.
ABACC	The absolute value of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (Dechow et al., 1995).
CSR	A dummy variable that equals 1 if the firm has issued a stand-alone CSR report in year *t* and 0 otherwise.
Province-level control variables	
GDP%	The annual province-level GDP growth rate. We obtain the data from the National Bureau of Statistics of China (NBS).
POPG	The annual provincial population growth rate, which is obtained from the National Bureau of Statistics of China (NBS).
HIGHNERI	A dummy variable that equals 1 if the marketization index is above the median and 0 otherwise. The marketization indices of China's 31 provinces in various years, measuring the quality of market-supporting institutions at the provincial level, are obtained from the National Economic Research Institute (NERI), with a higher index indicating a higher quality of institutions. The NERI's index project was sponsored in conjunction with the China Reform Foundation and conducted by Fan et al. (2011). We use the 2009 index for 2010–2014 as well.
EDU	The ratio of the population with a college degree and above to the population over 6 years old at the province level. We obtain the data from the National Bureau of Statistics of China (NBS).
FEMALEP	The percentage of the female population in the province, which is obtained from the National Bureau of Statistics of China (NBS).
RELIGION	The number of religious places in the province, which is obtained from a 2010 article on the State Administration for Religious Affairs of People's Republic of China's website (http://www.sara.gov.cn/xwzx/gsgg/6764.htm).
DIALECT	The number of distinct dialects in the province, obtained from the Chinese Academy of Social Sciences (1987, 1990).
ETHGR	The number of ethnic groups in the province, obtained from the National Bureau of Statistics of China (NBS).
Other Variables of Interest	
SOE	A dummy variable that equals 1 if the firm is a State-Owned Enterprise (SOE) and 0 otherwise.
HIGHINDE	A dummy variable that equals 1 if the ratio of the number of independent directors over the total number of directors on the board is above the median and 0 otherwise.
HIGHINST	A dummy variable that equals 1 if the percentage of outstanding shares held by institutional shareholders is above the median of institutional ownership of all sample firms and 0 otherwise.
BH	A dummy variable that equals 1 if an A share-issuing firm also issues foreign shares (B shares in the Shanghai or Shenzhen Stock Exchange or H shares in the Hong Kong Stock Exchange) and 0 otherwise.
HIGHSTDROA	A dummy variable that equals 1 if the earnings volatility is above the median and 0 otherwise. Earnings volatility is measured by the standard deviation of earnings excluding extraordinary items and discontinued operations deflated by total assets over the current year and prior 2 years.
LOWZSCORE	A dummy variable that equals 1 if the Z-Score of Altman et al. (2007) is below the median and 0 otherwise. Z-Score$_t$ = 0.517 – 0.44 × Total Liabilities$_t$/Total Assets$_t$ + 0.932 × Net Profit$_t$/Average Total Assets$_t$ × 0.388 × Working Capital$_t$/Total Assets$_t$ + 1.158 × Retained Earnings$_t$/Total Assets$_t$.
CSCORE	The conservatism score estimated following Khan and Watts (2009). See Appendix B for a more detailed explanation.
RESTATE	A dummy variable that equals 1 if a firm announces a financial restatement and 0 otherwise.

Appendix B. Measuring conditional conservatism

Following Khan and Watts (2009), we use the firm-year conditional conservatism measure *CSCORE* to measure the degree of accounting conservatism. Firms with a higher *CSCORE* are considered to be more conservative. The *CSCORE*s are estimated by using the following regression model:

$$CSCORE_{i,t} = \lambda_1 + \lambda_2 SIZE_{i,t} + \lambda_3 MB_{i,t} + \lambda_4 LEV_{i,t} \tag{B.1}$$

where *SIZE* is the natural log of the book value of total assets; *MB* is the market-to-book ratio; and *LEV* is the liability-to-assets ratio;

and λ_1, λ_2, λ_3, and λ_4 are the coefficients estimated by the following regression:

$$\begin{aligned} X_{i,t} = \beta_1 + \beta_2 D_{i,t} + R_{i,t}(\mu_1 + \mu_2 SIZE_{i,t} + \mu_3 MB_{i,t} + \mu_4 LEV_{i,t}) \\ + D_{i,t} \times R_{i,t}(\lambda_1 + \lambda_2 SIZE_{i,t} + \lambda_3 MB_{i,t} \\ + \lambda_4 LEV_{i,t}) + (\delta_1 SIZE_{i,t} + \delta_2 MB_{i,t} + \delta_3 LEV_{i,t} \\ + \delta_4 D_{i,t} SIZE_{i,t} + \delta_5 D_{i,t} MB_{i,t} + \delta_6 D_{i,t} LEV_{i,t}) + \varepsilon_{i,t} \end{aligned} \tag{B.2}$$

where $X_{i,\,t}$ is measured as $EPS_{i,\,t}/P_{i,\,t\text{-}1}$, with $EPS_{i,\,t}$ as the earnings per share of firm i at year t measured by operating profit deflated by the number of shares outstanding, and $P_{i,\,t\text{-}1}$ is the share price at the end of year t-1; $R_{i,\,t}$ is the buy-and-hold return of firm i for year t from the fifth month after the fiscal year-end of year t to the fourth month into year $t+1$, adjusted by the corresponding market return; $D_{i,\,t}$ is a dummy variable that equals one if $R_{i,\,t} < 0$ and zero otherwise.

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