

**Transparency or Opacity? Global Evidence on Financial Statement
Comparability and Stock Price Crash Risk**

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Abstract

Using 183,177 firm-year observations from 21,179 firms across 45 countries between 1998 and 2024, we find that higher financial statement comparability (FSC) is associated with significantly lower future stock price crash risk. This relation is robust to alternative fixed-effects specifications, an alternative crash-risk measure, entropy balancing, and instrumental-variable estimation. It also extends to longer-term crash risk and persists after excluding U.S. firms. Further analyses show that higher FSC is associated with lower future financial reporting opacity, consistent with comparability facilitating external monitoring and making it more difficult for managers to conceal or delay the disclosure of adverse information. Higher FSC is also associated with lower unexpected investment, although this evidence is less robust outside the U.S. Cross-sectional analyses show that the negative FSC–crash-risk relation is concentrated among firms with lower insider ownership and lower analyst following, consistent with comparability being particularly valuable when investors rely more heavily on public financial information and alternative information-production mechanisms are limited. In contrast, we find little evidence that government effectiveness or public enforcement systematically moderates the relation. Overall, our findings provide international evidence that FSC enhances the corporate information environment, facilitates external monitoring, and is associated with lower future stock price crash risk across global capital markets.

Keywords: Financial statement comparability; Stock price crash risk; Financial reporting opacity; Bad-news hoarding; International capital markets

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1. Introduction

Stock price crash risk has attracted considerable attention because sudden and extreme declines in share prices can destroy shareholder wealth, undermine investor confidence, and impair financial market stability. A central explanation for stock price crashes is managerial bad-news hoarding, whereby managers conceal adverse firm-specific information until the accumulation of such information eventually triggers a sharp downward price correction.¹ Consistent with this explanation, prior research shows that the quality and transparency of firms' information environments are important determinants of future crash risk (Hutton et al., 2009; Kim et al., 2011a, 2011b; Hong et al., 2017). Yet an important dimension of the information environment, financial statement comparability (FSC), has received considerably less attention in the crash-risk literature. FSC enables investors and other market participants to evaluate a firm's financial outcomes relative to those of economically similar firms, potentially making anomalous reporting choices and deteriorating performance easier to detect. Despite these potential informational and monitoring benefits, it remains unclear whether greater FSC constrains managerial bad-news hoarding and thereby reduces the risk of future stock price crashes. Moreover, because the effectiveness of comparability as a monitoring mechanism may depend on the institutional environment in which firms operate, whether this relation holds across countries remains an important empirical question.

¹ Jin and Myers (2006) develop a theoretical framework in which managers conceal firm-specific adverse information, allowing bad news to accumulate within the firm. Because such information cannot be withheld indefinitely, once the accumulated bad news reaches a tipping point, it is released to the market, triggering a sharp downward price adjustment.

We address this question by examining the relation between FSC and future stock price crash risk in a global setting. Comparability is a fundamental qualitative characteristic of financial reporting that enables users to identify similarities and differences in firms' economic performance (FASB, 2010). Consistent with worldwide regulatory efforts to enhance this characteristic, Conaway (2022) documents that global financial reporting comparability increased over 2002–2018, with the increase concentrated among firms applying local accounting standards, and that improvements in comparability are associated with sustained improvements in market liquidity. Financial statements are more comparable when similar economic events are translated into similar accounting outcomes. By enabling investors and other market participants to benchmark a firm's financial performance against that of economically similar firms, FSC can reduce information-processing costs, facilitate the interpretation of accounting information, and improve the corporate information environment (De Franco et al., 2011; Horton et al., 2013). Prior research shows that greater comparability improves analyst forecast accuracy (De Franco et al., 2011), enhances the information environment (Horton et al., 2013; Jain & Madadian, 2026), facilitates more efficient acquisition decisions and capital allocation (Chen et al., 2018), constrains earnings management and fraud (Blanco et al., 2022), and strengthens external monitoring (Nam & Thompson, 2023). Taken together, these informational and monitoring benefits provide a strong basis for expecting FSC to constrain managers' ability to accumulate and conceal adverse firm-specific information.

We argue that FSC reduces the risk of future stock price crashes by constraining managerial bad-news hoarding. FSC enables investors to benchmark a firm's reported outcomes against those of its industry peers, making anomalous reporting choices and deteriorating performance easier to detect. The resulting scrutiny reduces managers' ability and incentive to conceal adverse information. FSC also lowers the costs of acquiring and processing financial information (De

Franco et al., 2011), thereby strengthening monitoring by investors, analysts, auditors, and other information intermediaries. Moreover, peer-firm disclosures can reveal deteriorating fundamentals or unusually optimistic reporting even before managers fully disclose the underlying problems. Anticipating that withheld adverse information is more likely to be detected, managers have less scope and incentive to delay its disclosure. Consequently, negative information is more likely to be released and incorporated into prices earlier and incrementally, rather than accumulating within the firm and eventually triggering a sudden price correction.

However, the effect of FSC on crash risk is not theoretically unambiguous. Greater comparability can impose proprietary and reputational costs by making firm-specific information more readily interpretable relative to competitors. Managers facing high proprietary disclosure costs may respond by withholding voluntary information, including information communicated through conference calls (Park et al., 2025). Such strategic withholding could increase rather than reduce managerial opacity. Comparability may also create incentives for managers to mimic the reporting or operating choices of peer firms. Although greater FSC can constrain accrual-based earnings management, Sohn (2016) shows that it may encourage managers to substitute toward real earnings management. Because real earnings management can distort operating and investment decisions and destroy firm value, it may contribute to the accumulation of adverse information and increase the risk of subsequent crashes (Khurana et al., 2018). Thus, while the informational and monitoring benefits of FSC predict lower crash risk, managers' strategic responses to greater comparability could offset these benefits. The net effect of FSC on the future risk of stock price crashes is therefore ultimately an empirical question.

An international setting is particularly useful for examining this relation. The effectiveness of FSC is unlikely to be uniform across countries because firms operate within markedly different institutional environments. Differences in government effectiveness, legal enforcement, investor protection, disclosure regimes, and capital market development can affect both managers' opportunities to conceal adverse information and outsiders' ability to use comparable financial information for monitoring. On the one hand, FSC may substitute for weak external institutions by providing investors with an alternative means of benchmarking firms and detecting unusual financial outcomes. On the other hand, strong institutions may increase the credibility and usefulness of accounting information and enable market participants to use comparable financial statements more effectively. The latter possibility implies complementarity between FSC and institutional quality. Accordingly, examining FSC across countries allows us not only to assess whether its implications for crash risk generalize internationally but also to investigate how the broader institutional environment shapes those implications.

Using 183,177 firm-year observations from 21,179 firms across 45 countries over the 1998–2024 period, we find a significant negative association between FSC and the risk of future stock price crashes. Firms with more comparable financial statements experience lower crash risk in the subsequent year after controlling for a comprehensive set of firm and country-level characteristics and country, industry, and year fixed effects. The finding is robust to alternative fixed-effects specifications and an alternative measure of crash risk. We further address potential endogeneity using entropy balancing and an instrumental-variable approach based on country-year median FSC, with the results continue to support a negative relation between comparability and future crash risk. Importantly, the effect persists for up to three years and remains robust after excluding U.S. firms,

indicating that the findings are neither short-lived nor driven by the disproportionately large representation of U.S. firms in the global sample.

We next investigate the mechanisms through which FSC may reduce crash risk. Guided by the bad-news-hoarding framework, we focus on financial reporting opacity (Hutton et al., 2009) and overinvestment, measured using unexpected investment (Khurana et al., 2018). We find strong evidence that FSC is associated with lower financial reporting opacity. This effect persists for up to three years and remains robust after excluding U.S. firms, consistent with the notion that comparability constrains managers' ability to obscure adverse information. We also find that FSC is associated with lower unexpected investment over all three forecast horizons in the full sample, suggesting that comparability facilitates the monitoring of managerial investment decisions and constrains overinvestment. However, this association becomes statistically insignificant after excluding U.S. firms. Thus, while the evidence provides some support for overinvestment as an additional channel, reduced financial reporting opacity emerges as the more robust mechanism through which FSC is associated with lower future crash risk.

We also examine whether the relationship between FSC and future crash risk varies with firms' insider ownership and information environments, as well as with country-level institutional characteristics. The negative association is concentrated among firms with lower insider ownership and lower analyst following. The insider-ownership result is particularly pronounced after excluding U.S. firms, while the analyst-following evidence in the full international sample is consistent with FSC and analyst monitoring operating as substitute information mechanisms. In contrast, formal coefficient-difference tests provide little evidence that the FSC–crash-risk relation varies systematically with government effectiveness or public enforcement. Thus, the cross-

sectional evidence points primarily to the importance of firm-level ownership and information environments in shaping the crash-risk implications of comparability.

Our study makes several contributions. First, we contribute to the literature on the economic consequences of FSC by providing global evidence on its implications for extreme downside risk. De Franco et al. (2011) show that comparability lowers information-acquisition costs, increases analyst following and forecast accuracy, and reduces forecast dispersion, while subsequent research documents its benefits for a range of corporate and capital-market outcomes. In a U.S. setting, Kim et al. (2016) show that FSC reduces investors' perceptions of crash risk by constraining managers' incentives to withhold bad news. Recent international studies further demonstrate that the benefits of comparability extend to cross-border supply-chain relationships (Peng et al., 2024) and employee monitoring and relational contracting (Khurana & Zhong, 2026). Despite these advances, it remains unclear whether the crash-risk benefits of FSC generalize beyond the unique institutional and regulatory environment of the U.S. This question is particularly important because countries differ substantially in investor protection, disclosure regulation, enforcement quality, and information intermediation, all of which may affect the extent to which comparability facilitates external monitoring and makes it more difficult for managers to conceal or delay the disclosure of adverse information. Using 183,177 firm-year observations from 21,179 firms across 45 countries, we document a robust negative association between FSC and future stock price crash risk that persists over longer horizons and remains significant after excluding U.S. firms. Our findings, therefore, show that the crash-risk implications of comparability extend beyond the U.S. market to countries with diverse information, regulatory, and institutional environments.

Second, we contribute to the growing international literature on the determinants of stock price crash risk. Prior studies identify a range of firm- and country-level factors associated with crash risk worldwide, including mandatory IFRS adoption (DeFond et al., 2015), deviations between cash-flow rights and voting rights (Hong et al., 2017), national culture (An et al., 2018), the staggered implementation of M&A laws (Balachandran et al., 2020), corporate board reforms (Hu et al., 2020), and media coverage of bad news (Liu et al., 2023). We extend this literature by identifying financial statement comparability as an important firm-level informational determinant of future stock price crash risk in a worldwide setting. In doing so, our study broadens the understanding of the determinants of extreme downside risk by showing that the comparability of firms' financial information has implications for crash risk across diverse international capital markets.

Third, we provide direct evidence on mechanisms underlying the FSC–crash-risk relation. The bad-news-hoarding explanation of stock price crashes predicts that opacity enables managers to conceal adverse information until the accumulation of such information reaches a threshold, after which it is released abruptly (Jin & Myers, 2006; Hutton et al., 2009). Consistent with this mechanism, we find that FSC is associated with significantly lower subsequent financial reporting opacity over multiple horizons, both in the full sample and after excluding U.S. firms. This evidence extends Kim et al. (2016), who infer a bad-news-hoarding mechanism from cross-sectional variation in managerial incentives and asymmetric market reactions to good and bad news, by providing more direct evidence that FSC reduces the reporting opacity through which adverse information can be concealed. We also find that FSC is associated with lower unexpected investment in the full sample, consistent with the view that greater comparability may improve investment efficiency, although

this relation is less robust after excluding U.S. firms. Overall, the mechanism tests identify reduced financial reporting opacity as the more robust channel linking FSC to lower future crash risk.

Finally, our cross-sectional analyses provide new evidence on when comparability matters most for mitigating crash risk. Specifically, we examine whether the benefits of comparability vary with the availability of alternative information and monitoring mechanisms. We find that the negative association between FSC and future crash risk is concentrated among firms with lower insider ownership, particularly after excluding U.S. firms, consistent with comparability being more valuable when outside investors rely more heavily on publicly available financial information. We also find a stronger FSC effect among firms with lower analyst following. This result complements De Franco et al. (2011), who show that comparability improves analysts' information environment, by demonstrating that FSC is particularly important for mitigating crash risk when analyst-based information production is limited. The evidence is consistent with comparability and analyst monitoring serving as substitute information mechanisms in constraining managerial bad-news hoarding. Overall, our findings show that FSC enhances the information environment in which outsiders monitor firms, reduces financial reporting opacity, and mitigates extreme downside risk across global capital markets.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the sample selection, variable construction, descriptive statistics, and correlation analysis. Section 4 presents the baseline results, addresses endogeneity using instrumental-variable estimation and selection bias using entropy balancing, and reports additional robustness checks. Section 5 examines financial reporting opacity and

overinvestment as potential channels through which FSC affects crash risk. Section 6 presents cross-sectional analyses based on firm- and country-level governance mechanisms. Section 7 concludes.

2. Literature review and hypothesis development

Financial statement comparability (FSC) can affect stock price crash risk by shaping the information environment in which managers and outside investors interact. Prior research links crash risk to managerial incentives and opportunities to withhold unfavorable information from outside investors. Because managers possess superior firm-specific knowledge, they may delay the disclosure of bad news to protect their reputation, compensation, career prospects, or personal wealth (Kothari et al., 2009). Such concealment can temporarily sustain overvalued stock prices, but adverse information cannot be suppressed indefinitely. Once accumulated bad news is released, stock prices may fall sharply, triggering a crash (Jin & Myers, 2006; Kim & Zhang, 2014; Chang et al., 2017). Managers' ability to hoard bad news depends importantly on the prevailing information environment. When outside investors face greater difficulty assessing a firm's underlying performance, managers have greater scope to conceal adverse developments or manipulate reported outcomes, increasing the likelihood of overvaluation and subsequent crashes (Bleck & Liu, 2007; Hutton et al., 2009; Kim et al., 2011; Roychowdhury et al., 2019). Consistent with this argument, firms operating in less transparent information environments exhibit greater crash risk (Hutton et al., 2009; Lang & Maffett, 2011).

FSC can improve the information environment by enabling investors to evaluate firms' economic performance relative to comparable peers. Specifically, FSC reflects the extent to which similar economic events lead to similar accounting outcomes, while different economic events result in different accounting outcomes (De Franco et al., 2011; Nam, 2020). Greater comparability

facilitates cross-firm benchmarking, reduces information acquisition and processing costs, and improves users' ability to interpret firm-specific financial information (De Franco et al., 2011; Horton et al., 2013; Shakespeare, 2020). Without comparable financial information, investors may find it more difficult to determine whether performance differences across firms reflect underlying economic fundamentals or simply differences in accounting choices (Choi et al., 2019).

The informational benefits of comparability also extend beyond conventional investor decision-making. International evidence shows that FSC reduces information barriers to establishing cross-border supply-chain relationships (Peng et al., 2024), while Khurana and Zhong (2026) show that comparability facilitates employees' benchmarking of firms' behavior against peers, thereby strengthening employee monitoring and relational contracting. Collectively, this evidence reinforces the broader role of FSC in facilitating peer-based information acquisition and monitoring across different users and institutional settings.

These benchmarking benefits have direct implications for managerial bad-news hoarding. Greater FSC makes it easier for investors and other outside stakeholders to identify unusual performance and reporting choices by comparing a firm with economically similar peers, thereby constraining managers' ability to conceal adverse information or engage in opportunistic financial reporting. Consistent with this monitoring mechanism, Hong et al. (2023) show that comparability facilitates external parties' detection of atypical corporate tax strategies, thereby constraining firms' ability to pursue tax positions that deviate substantially from those of their industry peers. Consistent with this argument, Kim et al. (2016) show in a U.S. setting that FSC is negatively associated with expected crash risk and that this relation is stronger when managers have greater incentives to withhold bad news. Furthermore, peer-firm disclosures may also provide information

about common economic conditions and deteriorating fundamentals, making unusually optimistic firm-specific reporting easier to detect. Anticipating greater scrutiny through cross-firm comparisons, managers may have weaker incentives and less ability to delay the disclosure of adverse information. As a result, negative information is more likely to be incorporated into stock prices in a timely manner, reducing the accumulation of undisclosed bad news that can ultimately trigger a stock price crash.

However, the benefits of FSC may not be universal. Greater comparability may encourage managers to substitute toward less detectable forms of real earnings management (Sohn, 2016), while its informational and monitoring benefits may vary across institutional environments. For example, DeFond et al. (2015) show that although mandatory IFRS adoption generally reduces crash risk, its effect can be adverse in weakly regulated banking environments. Recent evidence also suggests that firms facing high proprietary costs may respond to disclosure requirements by reducing the informativeness of voluntary disclosures (Park et al., 2025). These findings suggest that whether the transparency and monitoring benefits of FSC dominate its potential costs remains an empirical question, particularly in a global setting characterized by substantial variation in information and institutional environments.

On balance, we expect the transparency and monitoring benefits of FSC to outweigh these potential costs. By facilitating peer benchmarking, reducing information asymmetry, and strengthening external monitoring, FSC should make it more difficult for managers to conceal or delay the disclosure of adverse information, thereby promoting its timelier incorporation into stock prices and reducing the accumulation of undisclosed bad news. We therefore propose the following hypothesis:

H1: Financial statement comparability is negatively associated with future stock price crash risk.

3.0 Research design

3.1 Data and sample

We obtain firm-level accounting data from Worldscope, while stock return data are sourced from Datastream. Analyst coverage data are extracted from I/B/E/S, while country-level macroeconomic variables are collected from the World Bank database. To ensure meaningful comparability across domestic industry peers, we exclude financial firms (SIC codes 6000-6999), utility firms (SIC codes 4900-4999), and firms with total assets below US\$10 million. In measuring stock price crash risk, we follow prior literature (e.g., Balachandran et al., 2020; Kim et al., 2011a, 2011b) by excluding weekly returns exceeding 300% that are reversed in the subsequent week. We also require each firm-year observation to maintain at least 26 weeks of return data and exclude countries with fewer than 25 unique firms. We further exclude observations with missing values for any variables included in the baseline regressions and countries with fewer than 50 firm-year observations. We winsorize all continuous variables at the 1st and 99th percentiles of their respective sample distributions to mitigate the influence of outliers. Our final sample consists of 183,177 firm-year observations representing 21,179 unique firms across 45 countries over the period 1998-2024. A detailed reconciliation of this sample filtering procedure is provided in Table IA1 in the Internet Appendix.

3.2 Measure of Key Variables

3.2.1 Measure of FSC

We follow Khurana and Zhong (2026) in measuring firm-level FSC. It captures the extent to which a firm's accounting system resembles those of its domestic peers within the same three-digit SIC industry in mapping economic events into financial statement disclosures. Specifically, for each

firm, we estimate rolling cross-sectional regressions of net income on concurrent stock returns over a four-year window spanning years $t-3$ to t .

$$Net\ Income_{it} = \beta_{0i} + \beta_{1i}Return_{it} + \epsilon_{it},$$

where *Net Income* is the firm's net income for fiscal year t , scaled by beginning-of-year market capitalization, and *Return* is the firm's annual stock return over the same fiscal year. The estimated intercept and slope coefficient characterize firm i 's accounting function. We then estimate the expected earnings for firm i using both its own accounting function and those of each of its industry peers, as follows.

$$E(Net\ Income)_{iit} = \hat{\beta}_{0i} + \hat{\beta}_{1i}Return_{it};$$

$$E(Net\ Income)_{ijt} = \hat{\beta}_{0j} + \hat{\beta}_{1j}Return_{it}$$

Where j denotes an industry peer of firm i . Pairwise comparability between firms i and j in year t is measured as the negative absolute difference in their expected net incomes, averaged over the four-year period from $t-3$ to t . We then calculate FSC for firm i as the average of its pairwise comparability across all industry peers. A higher FSC value indicates greater comparability between firm i 's financial reporting and that of its industry peers.

3.2.2 Measures of Crash Risk

Consistent with prior research on stock price crash risk (e.g., Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011 a&b), we employ two widely used proxies for crash risk: the negative conditional skewness of firm-specific weekly returns (*NCSKEW*) and the relative volatility of firm-specific returns during down versus up weeks (*DUVOL*). Detailed procedures for constructing *NCSKEW* and *DUVOL* are provided in Section A of the Internet Appendix.

3.2.3 Control Variables

Following the existing literature, we incorporate a comprehensive set of firm-level control variables, measured at year t , to account for factors that may systematically affect stock price crash risks. First, we include detrended average monthly turnover (*DTURN*) to capture abnormal trading activity, which has been associated with subsequent crash risk. We also account for the persistence of firms' return distributions by controlling for the skewness (*LNCSKEW*), standard deviation (*STDEV*), and mean (*RET*) of firm-specific weekly returns over the current fiscal year. In addition, we control for several fundamental firm characteristics that may shape crash risk. These include firm size (*LSIZE*), measured as the natural logarithm of market capitalization; growth opportunities (*MTB*), captured by the market-to-book ratio; financial leverage (*LEV*); operating performance (*ROA*), measured by return on assets; and financial reporting opacity (*OPAQUE*), defined as the three-year moving sum of the absolute value of discretionary accruals estimated using the Modified Jones model. Prior research generally indicates that larger firms, firms with greater growth opportunities, and firms with greater information opacity are more susceptible to stock price crashes, whereas the empirical evidence regarding the effects of financial leverage and operating performance on crash risk is mixed. We also account for firm age (*LAGE*), measured as the natural logarithm of the number of years since incorporation, as a proxy for information asymmetry, and analyst coverage (*LANALYST*), measured as the natural logarithm of the number of analysts following the firm, which captures the role of external monitoring in constraining managers' incentives to conceal unfavorable information.

We also include additional controls to account for potential confounding effects arising from differences in institutional and macroeconomic environments across countries. IFRS is an indicator variable that equals one if a firm prepares its financial statements in accordance with IFRS or IAS in a given year, and zero otherwise. Government effectiveness (*GOVEFF*), obtained from

Kaufmann et al. (2011), reflects the perceived quality of public services and the civil service, the independence of public institutions from political pressures, the quality of policy formulation and implementation, and the credibility of government commitments. We further control for country-level economic conditions using GDP growth ($GDPG$) and capture the development of domestic equity markets using stock market capitalization relative to GDP ($STMCAP$).

3.3 *Baseline regression model*

We use the following regression model as our baseline specification.

$$NCSKEW_{cit+1} = \beta_0 + \beta_1 FSC_{cit} + \gamma' Controls + \gamma_c + \psi_k + \phi_t + \varepsilon_{cit} \quad (1)$$

where c , i , t , and k denote country, firm, year, and industry, respectively. The dependent variable, stock price crash risk ($NCSKEW$), is measured in year $t+1$, while all explanatory variables, including our main variable of interest, FSC , are measured in year t . The coefficient β_1 is expected to be negative, indicating that greater financial statement comparability is associated with a lower stock price crash. The dependent variable, stock price crash risk ($NCSKEW$), is measured in year $t+1$, while all explanatory variables, including our main variable of interest, FSC , are measured in year t . The coefficient β_1 is expected to be negative, reflecting a negative effect of FSC on the risk of stock price crashes. The model includes country fixed effects (γ_c) to control for time-invariant country-level differences, as well as year fixed effects (ϕ_t) to capture common time-varying factors. We include three-digit SIC industry fixed effects (ψ_k). This specification ensures that we control for industry-specific factors at the same level of industry classification used to construct our FSC measure. Standard errors are clustered at the firm level to account for within-firm correlation in the error terms.

3.4 Descriptive statistics

Table 1 reports the summary statistics for the variables used in the analysis. The final sample comprises 183,177 firm-year observations over the period 1998–2024. The mean (median) value of the dependent variable, *NCSKEW*, is -0.070 (-0.082), indicating substantial variation in stock price crash risk across firms. The average value of *FSC* is -0.172 , with a standard deviation of 0.245 , indicating considerable cross-sectional variation in financial statement comparability and sufficient variation to identify its association with crash risk.

The control variables exhibit values comparable to those reported in the prior literature. The average firm has a market-to-book ratio of 2.33 , leverage of 12.1% , and return on assets of 5.3% . Approximately 24% of firm-year observations prepare financial statements under IFRS. The sample also displays substantial heterogeneity in analyst following, government effectiveness, and stock market development, highlighting the broad institutional diversity represented in the international sample.

Insert Table 1

3.5 Country Distribution and Country-Level Summary Statistics

Table 2 presents the distribution of observations across 43 countries, along with country-level averages of stock price crash risk and *FSC*. The sample is geographically diverse, comprising 183,177 firm-year observations from 19,364 unique firms. The largest contributors are Japan (48,056 observations), the United States (35,900), China (17,379), South Korea (14,572), India (10,018), the United Kingdom (5,976), Canada (5,792), and Malaysia (5,414), ensuring that the empirical analysis is not driven by a small number of countries.

Substantial cross-country variation exists in both crash risk and *FSC*. Mean *NCSKEW* ranges from -0.38 in Jordan and -0.36 in Russia to 0.13 in the United States, while average *FSC* ranges

from approximately -0.49 in Argentina to around -0.05 in China and Saudi Arabia. These differences likely reflect variations in accounting standards, institutional quality, enforcement mechanisms, investor protection, and capital market development across countries. The considerable cross-country heterogeneity further supports the use of country fixed effects in the multivariate analyses to control for time-invariant, country-specific unobservable factors.

Insert Table 2

3.6 *Correlation matrix*

Table 3 reports Pearson correlation coefficients based on country-level averages. The simple correlation between FSC and stock price crash risk (NCSKEW) is negative (-0.044), providing preliminary evidence that countries with higher average comparability tend to exhibit lower crash risk. Although the correlation is economically modest and statistically insignificant, it remains directionally consistent with our hypothesized negative association. The correlation matrix also reveals several intuitive relationships. FSC is positively associated with stock returns (RET) and negatively associated with stock return volatility (STDEV) and financial reporting opacity (OPAQUE), suggesting that greater comparability is generally accompanied by a more transparent information environment. Meanwhile, NCSKEW is correlated positively with analyst following, government effectiveness, firm size, and leverage, but negatively with stock returns and GDP growth. This simple univariate analysis should be interpreted with caution because they do not control for confounding firm- and country-level characteristics. Importantly, none of the pairwise correlations among the explanatory variables appears sufficiently large to raise serious multicollinearity concerns. The strongest correlations occur among variables that capture related stock return characteristics, such as RET and STDEV, which is expected given their underlying construction.

Insert Table 3

3.7 Visual analysis

We begin our empirical analysis by plotting the country-level FSC measure against the average country-level stock price crash risk across the entire sample period. This visual representation, presented in Figure 1, clearly illustrates a negative association between FSC and stock price crash risk, which is directionally consistent with our core hypothesis. Naturally, we cannot draw definitive conclusions from a simple bivariate graph, given that it relies on aggregate country-level averages over the entire sample timeframe. Consequently, this illustration omits important controls for confounding firm- and country-level characteristics and, more significantly, obscures any time-series variation in both FSC and crash risk. Nevertheless, this visual mapping provides useful preliminary evidence supporting the hypothesized negative association.

Insert Figure 1

4. Results

4.1 Baseline Regression Results

Table 4 presents the baseline regression results examining the association between FSC and subsequent stock price crash risks. Across all specifications, the coefficient on *FSC* is negative and statistically significant at the 1% level. In Column (1), which includes the standard firm-level determinants of crash risk, the coefficient on *FSC* is -0.021 ($t = -3.09$). The coefficient remains highly stable after introducing additional firm-level controls in Column (2) (-0.020 , $t = -2.92$) and country-level controls in Column (3) (-0.020 , $t = -2.86$). These results indicate that greater FSC is associated with lower future stock price crash risks. The economic magnitude of the association is modest but meaningful. Based on the fully specified model in Column (3), a one-standard-deviation increase in *FSC* (0.245) is associated with a reduction in *NCSKEW* of approximately 0.0049 ($= 0.020 \times 0.245$), equivalent to approximately 0.73% of one standard deviation of *NCSKEW* (0.675).

While this magnitude is relatively modest, it is economically relevant because *FSC* represents only one component of firms' broader information environments and stock price crashes are extreme outcomes influenced by multiple firm- and market-level factors.

Because U.S. firms constitute a substantial proportion of the international sample and may differ from firms in other countries in terms of their information environments, reporting practices, and capital-market institutions, Column (4) re-estimates the model after excluding U.S. observations. The coefficient on *FSC* remains negative and statistically significant at the 1% level, increasing in magnitude to -0.025 ($t = -3.43$). Thus, the negative association between *FSC* and future crash risk is not driven by U.S. firms and extends to the broader international sample. Taken together, the stability of the *FSC* coefficient across Columns (1) to (3), together with the stronger result after excluding U.S. firms, provides consistent evidence of a negative relation between *FSC* and subsequent crash risk.

The estimated effects of the control variables are generally consistent with prior studies. Past crash risk (*LNCSKEW*) is strongly and positively associated with future crash risk, indicating persistence in crash risks over time. Firms with larger market capitalization (*LSIZE*), higher growth opportunities (*MTB*), greater profitability (*ROA*), and stronger analyst following (*LANALYST*) exhibit higher subsequent crash risk, whereas firms with higher stock returns (*RET*), lower reporting opacity (*OPAQUE*), IFRS adoption, and older listing age (*LAGE*) generally experience lower crash risk. At the country level, greater government effectiveness and stronger economic growth are associated with lower crash risk, while more developed stock markets are associated with slightly higher crash risk.

Overall, the baseline evidence supports *H1*. Higher financial statement comparability is consistently associated with lower subsequent stock price crash risk across alternative specifications and after excluding U.S. firms. These findings are consistent with the argument that greater comparability improves firms' information environments and facilitates external monitoring, thereby limiting managers' ability to withhold and accumulate adverse firm-specific information that could ultimately result in a stock price crash.

Insert Table 4 here

4.2 Long-Term Effects

In this section, we examine whether the relation between *FSC* and future stock price crash risk persists over longer horizons and present the results in Table 5 over cumulative two-, three-, and four-year horizons. Panel A presents results for the full sample, while Panel B reports results after excluding U.S. firms. Panel A shows that the coefficient on *FSC* for the full sample is -0.025 ($t = -2.78$) for $NCSKEW_{t+1-t+2}$, -0.028 ($t = -2.98$) for $NCSKEW_{t+1-t+3}$, and -0.025 ($t = -2.56$) for $NCSKEW_{t+1-t+4}$, with all three coefficients statistically significant at the 1% level. These results indicate that the negative association between *FSC* and future stock price crash risk is not confined to the subsequent year but remains evident when crash risk is measured over horizons extending through $t+4$.

The economic magnitudes reinforce this conclusion. Given the standard deviation of *FSC* of 0.245, a one-standard-deviation increase in *FSC* is associated with reductions in cumulative *NCSKEW* of approximately 0.0061, 0.0069, and 0.0061 over the $t+1$ to $t+2$, $t+1$ to $t+3$, and $t+1$ to $t+4$ horizons, respectively. Relative to the corresponding standard deviations of the cumulative *NCSKEW* measures (0.665, 0.629, and 0.598), these effects represent approximately 0.92%, 1.09%,

and 1.02% of one standard deviation of crash risk, respectively. Thus, the economic significance of FSC remains broadly stable across the longer horizons, with the largest estimated effect observed over the three-year horizon.

Panel B examines whether the long-term results are driven by U.S. firms, which account for a substantial proportion of the global sample. Consistent with the baseline analysis, the results remain qualitatively unchanged after excluding U.S. observations. The coefficient on FSC is -0.031 ($t = -3.34$) for $NCSKEW_{t+1_t+2}$, -0.031 ($t = -3.16$) for $NCSKEW_{t+1_t+3}$, and -0.027 ($t = -2.64$) for $NCSKEW_{t+1_t+4}$, with all coefficients significant at the 1% level. Notably, the estimated coefficients in Panel B are larger in magnitude than those reported for the full sample, suggesting that the negative association between FSC and future crash risk is, if anything, stronger outside the United States. These findings indicate that the long-term effects of FSC are not driven by the institutional characteristics of the U.S. market and are evident across a broad range of international settings.

Collectively, the results in Panels A and B are consistent with the view that the informational and monitoring benefits associated with FSC extend beyond the immediate reporting period. Greater comparability facilitates benchmarking across peer firms, reduces information-processing costs, and enhances external monitoring. As a result, managers face greater constraints in withholding adverse information, allowing bad news to be incorporated into stock prices more gradually rather than accumulating and ultimately triggering a sharp stock price decline. The persistence of the FSC coefficient across all horizons, therefore, suggests that the effects of comparability on firms' information environments and crash risk are enduring rather than transitory.

Overall, Table 5 complements the baseline findings by demonstrating that the negative association between FSC and future stock price crash risk persists over extended horizons. While

the baseline analysis shows that greater FSC is associated with lower crash risk in the subsequent year, the long-term results indicate that this association remains statistically and economically significant when crash risk is measured cumulatively over periods extending through $t+4$. Furthermore, the stronger coefficients observed after excluding U.S. firms suggest that the relation is not driven by the U.S. market. Taken together, these findings provide additional support for *H1* and indicate that greater FSC has persistent implications for reducing future stock price crash risks.

4.3 *Endogeneity Tests*

Although our baseline specifications include an extensive set of firm-level controls and fixed effects, the documented negative association between FSC and future stock price crash risk may still be affected by endogeneity. In particular, firms with high and low FSC may differ systematically in observable characteristics that are also associated with crash risk, and reverse causality may arise if firms' exposure to crash risk influences their financial reporting choices and, consequently, their FSC. We employ two complementary approaches to mitigate these concerns. First, we use an instrumental-variable (IV) approach to address potential reverse causality and other sources of endogeneity in section 4.3.1, and Second, employ entropy balancing to reduce systematic differences in observable characteristics between firms with high and low FSC in section 4.3.2. Because these approaches address different dimensions of the endogeneity concern, we view the resulting evidence as complementary to our baseline findings.

4.3.1 *Instrumental-Variable Estimation*

To address potential reverse causality, we employ a two-stage least squares (2SLS) approach using the annual country median FSC as an instrument for firm-level FSC. Identifying a suitable instrument for FSC in an international setting is challenging because factors that systematically

affect firms' comparability may also be related to the broader information and institutional environment that influences crash risk. Following Roberts and Whited (2013), a valid instrument should satisfy two conditions: relevance and the exclusion restriction. We therefore evaluate both conditions below, while recognizing that the exclusion restriction cannot be directly tested and that the IV results should be interpreted with caution as complementary evidence.

The relevance condition requires the instrument to be sufficiently correlated with firm-level FSC. The country-year median FSC captures the broader reporting and comparability environment in which firms operate. Firms operating in country-years characterized by greater overall comparability are therefore expected to exhibit higher firm-level FSC. The exclusion restriction requires that the country-year median FSC affect firm-specific crash risk primarily through its effect on the firm's own FSC. Because the instrument reflects the comparability of the broader population of firms within a country-year rather than firm-specific reporting choices or crash-risk determinants, it is less likely to be directly related to an individual firm's crash risk. Moreover, our specifications control for a comprehensive set of firm- and country-level characteristics and include country, industry, and year fixed effects, thereby mitigating concerns that the instrument captures systematic cross-country or temporal differences associated with crash risk. Nevertheless, because the exclusion restriction cannot be directly tested, we interpret the IV results with appropriate caution as complementary evidence.

Table 6 presents the IV results. Panel A reports the results for the full sample, while Panel B excludes U.S. firms. In the first stage, we regress firm-level FSC on the country-year median FSC and the full set of controls from Column (3) of Table 4. In the second stage, instrumented FSC is used to estimate its association with subsequent crash risk measured over one-year and cumulative

two-, three-, and four-year horizons. The first-stage results demonstrate a strong positive relation between the country-year median FSC and firm-level FSC. In Panel A, the coefficient on the instrument is 0.8242 ($t = 22.45$), while in Panel B it is 0.8187 ($t = 22.33$), with both coefficients statistically significant at the 1% level. The identification diagnostics further support the instrument's relevance. The under-identification tests are statistically significant at the 1% level across all specifications, rejecting the null of under-identification. The Cragg–Donald Wald F-statistics range from 9,643.263 to 13,059.58 for the full sample and from 8,521.737 to 11,767.51 after excluding U.S. firms, substantially exceeding conventional weak-instrument thresholds. Collectively, these results indicate that the country-year median FSC is a strong predictor of firm-level FSC and that weak identification is unlikely to explain the IV results.

The second-stage results in Panel A show that instrumented FSC is negatively and significantly associated with future crash risk across all horizons. The coefficient on FSC is -0.0797 ($t = -3.43$) for $NCSKEW_{t+1}$, -0.1378 ($t = -4.77$) for $NCSKEW_{t+1_t+2}$, -0.1774 ($t = -6.00$) for $NCSKEW_{t+1_t+3}$, and -0.1851 ($t = -6.38$) for $NCSKEW_{t+1_t+4}$. All coefficients are statistically significant at the 1% level. Thus, the negative association between FSC and crash risk remains evident after accounting for the potential endogeneity of FSC and persists when crash risk is measured over progressively longer cumulative horizons. Panel B provides similar evidence after excluding U.S. firms. The coefficients on instrumented FSC are -0.0979 ($t = -4.12$), -0.1449 ($t = -4.89$), -0.1716 ($t = -5.65$), and -0.1744 ($t = -5.87$) for the one-, two-, three-, and four-year horizons, respectively, with all coefficients significant at the 1% level. The similarity of the results across Panels A and B indicates that the IV findings are not driven by U.S. observations and provides further evidence that the negative relation between FSC and future crash risk extends across the broader international sample.

The economic magnitudes of the IV estimates are also meaningful. Using the standard deviation of FSC reported in Table 1 (0.245), the full-sample estimates in Panel A imply that a one-standard-deviation increase in instrumented FSC is associated with reductions in *NCSKEW* of approximately 0.0195, 0.0338, 0.0435, and 0.0453 over the one-, two-, three-, and four-year horizons, respectively. For the one-year horizon, the estimated reduction represents approximately 2.89% of one standard deviation of *NCSKEW* (0.675). For the cumulative horizons, using the corresponding standard deviations of 0.665, 0.629, and 0.598, the effects represent approximately 5.08%, 6.91%, and 7.58%, respectively, of a one standard deviation change in cumulative crash risk. The IV estimates are therefore larger than their corresponding OLS estimates and suggest that the baseline regressions may understate the magnitude of the negative association between FSC and future crash risk.

The endogeneity tests provide additional support for treating FSC as endogenous in the IV analysis. For the full sample, the endogeneity-test χ^2 statistics increase from 6.822 for the one-year horizon to 30.934 for the four-year horizon, while the corresponding statistics for the sample excluding U.S. firms range from 9.659 to 25.260. All are statistically significant at the 1% level, rejecting the null that FSC can be treated as exogenous. These findings indicate that accounting for the potential endogeneity of FSC is empirically relevant and provide additional justification for the IV specification.

Overall, the IV analysis corroborates the baseline and long-term findings. After instrumenting firm-level FSC with country-year median FSC, greater comparability remains negatively and significantly associated with future stock price crash risk across one- to four-year horizons, both in the full international sample and after excluding U.S. firms. The increasing economic magnitude

over the cumulative horizons is also consistent with the long-term evidence in Table 5, suggesting that the association between comparability and crash risk is persistent rather than short-lived. Taken together, these findings provide further support for *H1* and are consistent with the view that greater FSC improves the information environment, strengthens external monitoring, and limits managerial bad-news hoarding, thereby reducing future stock price crashes.

4.3.2 Entropy Balancing

To address potential endogeneity arising from systematic observable differences between firms with high and low FSC, we employ the entropy balancing approach developed by Hainmueller (2012). Specifically, within each country-year, firms with FSC above the country-year median are classified as the treatment group (HFSC), while firms with FSC at or below the median are classified as the control group (LFSC). Entropy balancing assigns continuous weights to observations in the control group so that the distributions of observable covariates closely match those of the treatment group. We balance the first three moments of the covariate distributions—the mean, variance, and skewness. By substantially reducing observable differences between high- and low-FSC firms, this approach mitigates concerns that differences in observable firm characteristics, rather than FSC, explain the documented association with future stock price crash risk.

Table 7 presents the entropy balancing results. Panel A reports the post-weighting covariate distributions for the full sample and the sample excluding U.S. firms, while Panel B presents the corresponding entropy-weighted regression estimates. Panel A1 shows that, for the full sample, the treatment and entropy-weighted control groups have virtually identical means across the covariates used in the balancing procedure. For example, the mean values of *LNCSKEW*, *LSIZE*, *MTB*, *LEV*, *ROA*, *IFRS*, *LAGE*, *LANALYST*, *GOVEFF*, and *GDPG* are essentially identical between the two

groups. The variances and skewness measures are also substantially aligned. Panel A2 shows a similarly high degree of covariate balance when U.S. firms are excluded. Overall, the balance statistics indicate that the entropy weighting procedure substantially improves the comparability of high- and low-FSC firms across observable firm- and country-level characteristics.

Panel B1 reports the entropy-weighted regression results for the full sample. The coefficient on *FSC* is negative across all four horizons. Specifically, the coefficient is -0.015 ($t = -1.71$) for $NCSKEW_{t+1}$, -0.025 ($t = -2.18$) for $NCSKEW_{t+1_t+2}$, -0.033 ($t = -2.66$) for $NCSKEW_{t+1_t+3}$, and -0.028 ($t = -2.17$) for $NCSKEW_{t+1_t+4}$. The coefficient is statistically significant at the 10% level for the one-year horizon, at the 5% level for the two- and four-year horizons, and at the 1% level for the three-year horizon. Thus, after reweighting high- and low-FSC firms to make them more comparable in terms of observable characteristics, greater FSC remains negatively associated with future crash risk. The relatively larger coefficients over the cumulative horizons are also consistent with the long-term results reported in Table 5.

Panel B2 shows that the results remain robust after excluding U.S. firms. The coefficient on *FSC* is -0.018 ($t = -1.99$) for $NCSKEW_{t+1}$, -0.029 ($t = -2.44$) for $NCSKEW_{t+1_t+2}$, -0.033 ($t = -2.63$) for $NCSKEW_{t+1_t+3}$, and -0.026 ($t = -2.07$) for $NCSKEW_{t+1_t+4}$. The one-, two-, and four-year coefficients are statistically significant at the 5% level, while the three-year coefficient is significant at the 1% level. The similarity of the results across the full and non-U.S. samples indicates that the entropy balancing findings are not driven by the disproportionately large representation of U.S. firms in the international sample.

The economic magnitudes are also informative. Using the standard deviation of FSC reported in Table 1 (0.245), the full-sample coefficients imply that a one-standard-deviation increase in FSC

is associated with reductions in crash risk of approximately 0.0037, 0.0061, 0.0081, and 0.0069 over the one-, two-, three-, and four-year horizons, respectively. Relative to the corresponding standard deviations of *NCSKEW*, 0.675 for the one-year measure and 0.665, 0.629, and 0.598 for the cumulative two-, three-, and four-year measures, these effects represent approximately 0.54%, 0.92%, 1.29%, and 1.15% of one standard deviation of crash risk, respectively. The economic association is therefore more pronounced over the longer cumulative horizons, particularly over the three-year period.

Overall, the entropy balancing analysis reinforces the baseline and long-term findings. After reweighting the sample to substantially reduce observable differences between high- and low-FSC firms, FSC remains negatively associated with future stock price crash risk across one- to four-year horizons. The persistence of the results after excluding U.S. firms further indicates that the findings are not attributable to the composition of the international sample. Taken together, the entropy balancing evidence provides additional support for *H1* and is consistent with the view that greater FSC improves firms' information environments and constrains managers' ability to accumulate adverse information, thereby lowering subsequent stock price crash risk.

4.4 *Alternative Fixed Effects and Longer-Horizon Crash Risk*

This section examines whether the negative association between FSC and future stock price crash risk is robust to controlling for firm and year fixed effects. Firm fixed effects absorb time-invariant firm characteristics that may jointly influence comparability and crash risk, thereby providing a more stringent test based on within-firm variation in FSC over time. Table 8 reports the results for crash risk measured over one-year and cumulative two-, three-, and four-year horizons.

Panel A presents the results for the full sample, while Panel B reports the corresponding results after excluding U.S. firms.

Panel A shows that the negative association between FSC and future crash risk generally persists after controlling for firm and year fixed effects. For the one-year horizon, the coefficient on *FSC* is -0.016 ($t = -1.72$), statistically significant at the 10% level. The association becomes stronger over longer cumulative horizons. The coefficient is -0.024 ($t = -2.20$) for $NCSKEW_{t+1-t+2}$ and -0.028 ($t = -2.46$) for $NCSKEW_{t+1-t+3}$, both statistically significant at the 5% level. For the four-year horizon, the coefficient remains negative at -0.022 ($t = -1.92$) and is significant at the 10% level. Thus, even after controlling for time-invariant firm-specific heterogeneity, within-firm increases in FSC are associated with lower future crash risk across all four horizons.

Panel B provides broadly similar evidence when U.S. firms are excluded. The coefficient on *FSC* is -0.019 ($t = -1.98$) for $NCSKEW_{t+1}$, -0.028 ($t = -2.39$) for $NCSKEW_{t+1-t+2}$, and -0.026 ($t = -2.19$) for $NCSKEW_{t+1-t+3}$, with all three coefficients statistically significant at the 5% level. For the four-year horizon, the coefficient remains negative (-0.018 , $t = -1.45$), although it is no longer statistically significant at conventional levels. These results indicate that the negative relation between FSC and future crash risk is not driven by the large representation of U.S. firms in the international sample and remains evident outside the United States over horizons extending through three years.

Overall, Table 8 provides additional evidence that the negative association between FSC and future stock price crash risk is robust to controlling for firm and year fixed effects. The results are particularly informative because identification in these specifications comes from changes in FSC within the same firm over time, thereby reducing concerns that the baseline findings reflect

unobserved, time-invariant differences across firms. The negative coefficients across all horizons in both samples, together with statistically significant effects through the three-year horizon after excluding U.S. firms, reinforce the baseline and long-term findings and provide further support for Hypothesis 1. The evidence is consistent with the view that improvements in FSC are associated with a more transparent information environment and a lower likelihood of future stock price crashes.

4.5 *Alternative Measure of Stock Price Crash Risk*

We examine whether our findings are robust to using *DUVOL*, the down-to-up volatility measure, as an alternative proxy for stock price crash risk. Table 9 reports the results for *DUVOL* measured over one-year and cumulative two-, three-, and four-year horizons. For each horizon, we estimate specifications with country, industry, and year fixed effects and, more stringently, firm and year fixed effects. We report results for both the full sample and the sample excluding U.S. firms.

Panel A reports the results for $DUVOL_{t+1}$. The coefficient on *FSC* is negative and statistically significant across all four specifications. Using country, industry, and year fixed effects, the coefficient is -0.012 ($t = -3.28$) for the full sample and -0.015 ($t = -3.93$) after excluding U.S. firms, with both estimates significant at the 1% level. When firm and year fixed effects are employed, the coefficients remain negative and significant at -0.010 ($t = -2.01$) and -0.012 ($t = -2.38$) for the full and non-U.S. samples, respectively. Thus, the negative association between *FSC* and subsequent crash risk is robust to using the *DUVOL* as a crash risk measure and persists after controlling for time-invariant firm-specific heterogeneity.

The results remain consistent when crash risk is measured over longer cumulative horizons. For $DUVOL_{t+1:t+2}$, the coefficients on *FSC* range from -0.011 to -0.015 and are statistically

significant at the 1% level across all four specifications. Similarly, for $DUVOL_{t+1_t+3}$, the coefficients range from -0.011 to -0.013 and remain statistically significant at either the 1% or 5% level. These findings indicate that the negative association between FSC and crash risk is not confined to the subsequent year but remains evident when crash risk is measured cumulatively over periods extending through $t+3$. The results for the four-year horizon provide further evidence of persistence. For $DUVOL_{t+1_t+4}$, the coefficient on FSC is -0.010 ($t = -2.45$) for the full sample and -0.012 ($t = -2.77$) for the non-U.S. sample when country, industry, and year fixed effects are included. Under the more stringent firm and year fixed-effects specification, the corresponding coefficients are -0.011 ($t = -2.24$) and -0.009 ($t = -1.86$). Thus, FSC remains negatively associated with cumulative crash risk through the four-year horizon across all specifications, although the non-U.S. firm fixed-effects estimate is statistically significant only at the 10% level.

Importantly, excluding U.S. firms does not materially alter the results. The coefficient on FSC remains negative and statistically significant across all horizons and specifications in the non-U.S. sample, with significance ranging from the 1% to the 10% level. The results, therefore, indicate that the negative association between FSC and future crash risk is not driven by the disproportionately large representation of U.S. firms in the international sample.

Overall, Table 9 provides consistent evidence that the main findings are robust to using *DUVOL* as an alternative measure of stock price crash risk, controlling for firm-specific time-invariant heterogeneity, excluding U.S. firms, and measuring crash risk over cumulative horizons extending through four years. Together with the results based on *NCSKEW*, these findings provide further support for *H1* and reinforce the conclusion that FSC is associated with persistently lower future stock price crash risk.

5. Channel Analysis: Financial Reporting Opacity and Overinvestment

To provide further evidence on the mechanisms through which FSC may be associated with lower future stock price crash risk, we examine two potential channels: financial reporting opacity and overinvestment. Hutton et al. (2009) show that greater financial reporting opacity, reflecting firms' use of discretionary accruals and earnings management, is associated with higher future crash risk. Khurana et al. (2018) further document that overinvestment in unprofitable projects increases future crash risk. Building on this literature, we examine whether financial reporting opacity and overinvestment represent potential channels underlying the negative relation between FSC and future crash risk.

Greater FSC facilitates the interpretation and benchmarking of firms' financial information against that of peer firms, potentially strengthening outsiders' ability to evaluate managerial reporting and investment decisions. Enhanced monitoring may constrain managers' ability to obscure adverse information and undertake value-destroying investments. Accordingly, we expect higher FSC to be associated with lower financial reporting opacity and less overinvestment, thereby reducing the likelihood that adverse information accumulates and ultimately results in a stock price crash. Sections 5.1 and 5.2 examine financial reporting opacity and overinvestment, respectively.

5.1 Financial Reporting Opacity as a Channel

Our baseline results provide initial evidence consistent with financial reporting opacity as a potential channel. As shown in Table 4, *OPAQUE* is positively and significantly associated with the risk of subsequent stock price crashes. The coefficients on *OPAQUE* are 0.041 ($t = 3.71$) and 0.042 ($t = 3.77$) in Columns (2) and (3), respectively, with both estimates significant at the 1% level. Given the standard deviation of *OPAQUE* of 0.154, these estimates imply that a one-standard-

deviation increase in opacity is associated with increases in *NCSKEW* of approximately 0.0063 and 0.0065, equivalent to approximately 0.94% and 0.96% of one standard deviation of *NCSKEW*, respectively. These findings are consistent with the bad-news-hoarding explanation and establish the first component of the proposed channel: firms with greater financial reporting opacity exhibit higher subsequent crash risk.

Panel A of Table 10 next examines whether *FSC* is associated with lower subsequent financial reporting opacity. Because *OPAQUE* is constructed as a three-year moving measure of the absolute value of discretionary accruals, we examine opacity over two overlapping three-year windows, $OPAQUE_{t,t+2}$ and $OPAQUE_{t+1,t+3}$. For the full sample, the coefficient on *FSC* is -0.038 ($t = -12.07$) for $OPAQUE_{t,t+2}$ and -0.026 ($t = -8.52$) for $OPAQUE_{t+1,t+3}$, with both coefficients statistically significant at the 1% level. These results indicate that firms with greater financial statement comparability exhibit significantly lower financial reporting opacity over subsequent multi-year periods. The results remain highly significant when U.S. firms are excluded. The coefficient on *FSC* is -0.035 ($t = -10.57$) for $OPAQUE_{t,t+2}$ and -0.024 ($t = -7.44$) for $OPAQUE_{t+1,t+3}$, again significant at the 1% level. The similarity of the estimates between the full and non-U.S. samples indicates that the negative association between *FSC* and reporting opacity is not driven by the large representation of U.S. firms in the international sample.

The economic magnitude of this relation is also meaningful. Given a standard deviation of *FSC* of 0.245 and a standard deviation of *OPAQUE* of 0.154, the full-sample coefficient of -0.038 implies that a one-standard-deviation increase in *FSC* is associated with a reduction in $OPAQUE_{t,t+2}$ of approximately 0.0093 ($= 0.038 \times 0.245$), equivalent to approximately 6.0% of one standard deviation of opacity. For $OPAQUE_{t+1,t+3}$, the coefficient of -0.026 implies a reduction of

approximately 0.0064, equivalent to approximately 4.1% of one standard deviation of opacity. Thus, the association remains economically meaningful even when opacity is measured over an extended horizon.

Collectively, the results provide consistent evidence for financial reporting opacity as a potential channel linking FSC to future crash risk. The baseline analysis shows that greater opacity is associated with higher subsequent crash risk, while the channel analysis demonstrates that greater FSC is associated with significantly lower opacity over subsequent multi-year periods. These findings are consistent with the argument that greater comparability improves the transparency of firms' information environments and constrains managers' ability to obscure adverse firm-specific information, thereby limiting the accumulation of hidden bad news that can ultimately precipitate a stock price crash.

5.2 *Overinvestment as a Channel*

Panel B of Table 10 examines overinvestment as a second potential channel. Overinvestment is measured using unexpected investment. Unexpected investment is estimated as the residual from a regression of investment in year $t+1$ on growth opportunities, profitability, cash holdings, firm age, leverage, firm size, and investment in year t , together with industry and year fixed effects. Positive unexpected investment is classified as overinvestment, while observations without positive unexpected investment are assigned a value of zero. We examine overinvestment over one-year and cumulative two- and three-year horizons.

For the full sample, the coefficient on *FSC* is negative and statistically significant across all three horizons. The coefficient is -0.003 ($t = -2.11$) for $OVERINVEST_{t+1}$, -0.007 ($t = -2.22$) for $OVERINVEST_{t+1_t+2}$, and -0.010 ($t = -2.19$) for $OVERINVEST_{t+1_t+3}$, with all three coefficients

significant at the 5% level. Thus, firms with greater financial statement comparability exhibit lower subsequent overinvestment, both in the immediately following year and when inefficient investment is measured cumulatively over longer periods.

The magnitude of the association becomes larger as the measurement horizon extends. The coefficient increases in absolute magnitude from -0.003 for the one-year measure to -0.007 for the cumulative two-year measure and -0.010 for the cumulative three-year measure. This pattern is consistent with the possibility that the investment-disciplining benefits associated with comparability accumulate over time. Greater comparability may facilitate external benchmarking and monitoring of managerial investment decisions, making it more difficult for managers to persist with or accumulate inefficient investments. The evidence, however, is considerably weaker outside the United States. After excluding U.S. firms, the coefficients on *FSC* remain negative but are small and statistically insignificant: -0.000 ($t = -0.22$) for $OVERINVEST_{t+1}$, -0.001 ($t = -0.30$) for $OVERINVEST_{t+1:t+2}$, and -0.002 ($t = -0.36$) for $OVERINVEST_{t+1:t+3}$. Thus, unlike the opacity results, the association between *FSC* and lower overinvestment does not generalize to the non-U.S. sample.

Overall, the channel analyses provide stronger, more internationally robust evidence of financial reporting opacity than of overinvestment. Greater *FSC* is consistently associated with lower financial reporting opacity in both the full and non-U.S. samples, whereas greater opacity, in turn, is associated with higher subsequent crash risk. In contrast, *FSC* is associated with lower overinvestment only in the full sample, and this relation becomes statistically insignificant once U.S. firms are excluded. Accordingly, the evidence is consistent with financial reporting opacity

serving as a more robust channel through which FSC is associated with lower future stock price crash risk, whereas overinvestment represents a possible but less generalizable mechanism.

6. Cross-sectional Analysis on FSC and stock price crash risk

To better understand the conditions under which FSC is associated with lower future stock price crash risk, we examine cross-sectional variation in two firm-level characteristics: insider ownership and analyst following, and two country-level institutional characteristics: government effectiveness and public enforcement. Detailed coefficient estimates and tests of differences across the one-year and cumulative two-, three-, and four-year crash-risk horizons are reported in Table IA2 of the Internet Appendix, with further discussion provided in Section C of the Internet Appendix.

Insider ownership affects the extent to which outside investors rely on publicly available financial information, while analyst following captures external information production and monitoring. We expect FSC to be particularly valuable when external investors depend more heavily on public financial information and when analyst monitoring is limited. At the country level, government effectiveness and public enforcement capture broader institutional mechanisms that may either complement FSC or reduce its incremental monitoring role.

The results provide four main insights. First, the negative association between FSC and future crash risk is concentrated among firms with lower insider ownership. FSC is significantly associated with lower crash risk across all horizons for these firms, but is generally insignificant among firms with higher insider ownership. The coefficient differences are particularly pronounced after excluding U.S. firms. This pattern is consistent with FSC being more valuable when outside

investors rely more heavily on publicly available financial information to monitor firm performance.

Second, FSC is more strongly associated with lower crash risk among firms with lower analyst following. In the full sample, FSC is negative and significant across all horizons for firms with low analyst following, but insignificant for firms with high analyst following; the coefficient differences are statistically significant across all horizons. This evidence is consistent with FSC and analyst monitoring operating as substitute information mechanisms: when analyst coverage is limited, comparability plays a greater role in facilitating cross-firm benchmarking, reducing information asymmetry, and strengthening external monitoring. The subsample pattern persists after excluding U.S. firms, although the coefficient-difference evidence becomes weaker.

Third, we find little evidence that government effectiveness systematically moderates the relation between FSC and crash risk. Although FSC is negatively associated with crash risk in some subsamples, the formal differences between high- and low-government-effectiveness countries are statistically insignificant across all horizons, both in the full sample and after excluding U.S. firms. Finally, FSC is consistently negatively associated with future crash risk in countries with lower public enforcement, but not in countries with higher public enforcement. However, the differences in FSC coefficients between the two groups are statistically insignificant across all horizons. Thus, while the subsample pattern is consistent with FSC being more valuable in weaker public-enforcement environments, the evidence does not establish that public enforcement systematically moderates the FSC–crash-risk relation.

Overall, FSC is more strongly associated with lower future crash risk among firms with lower insider ownership and lower analyst following, consistent with comparability being particularly

valuable when outside investors rely more heavily on publicly available accounting information and when alternative information-production mechanisms are limited. In contrast, the formal coefficient-difference tests provide little evidence that the effect of FSC varies systematically with government effectiveness or public enforcement. These findings are generally robust to the exclusion of U.S. firms.

7. Conclusion

This study examines whether financial statement comparability (FSC) mitigates the risk of future stock price crashes in an international setting. Using 183,177 firm-year observations from 21,179 firms across 45 countries over 1998–2024, we find that greater FSC is associated with significantly lower future crash risk. The results are robust to firm- and country-level controls, alternative fixed-effects specifications, an alternative crash-risk measure, entropy balancing, and instrumental-variable estimation. The negative association extends beyond the subsequent year, remains evident using cumulative long-term crash-risk measures, and persists after excluding U.S. firms.

Our mechanism analyses indicate that higher FSC is associated with lower future financial reporting opacity, consistent with comparability facilitating benchmarking and external monitoring, thereby constraining managerial bad-news hoarding. This result persists after excluding U.S. firms, although its magnitude attenuates over time. FSC is also associated with lower unexpected investment in the full sample, consistent with improved monitoring of managerial investment decisions, but this evidence becomes insignificant after excluding U.S. firms. Thus, financial reporting opacity provides the more robust mechanism linking FSC to lower future crash risk.

The cross-sectional evidence is strongest for firms' ownership and information environments. The negative FSC–crash-risk relation is concentrated among firms with lower insider ownership, with the differences becoming particularly pronounced after excluding U.S. firms. FSC is also more strongly associated with lower crash risk among firms with lower analyst following, consistent with FSC and analyst monitoring operating as substitute information mechanisms. In contrast, formal coefficient-difference tests provide little evidence that the relation varies systematically with government effectiveness or public enforcement. These findings suggest that FSC is particularly valuable when outside investors rely more heavily on publicly available accounting information and when alternative information-production and monitoring mechanisms are limited.

Our findings have implications for investors, regulators, and accounting standard setters. For investors, FSC facilitates not only firm valuation and peer benchmarking but also the monitoring of information environments associated with extreme downside risk. For regulators and standard setters, the findings reinforce the importance of comparability as a qualitative characteristic of financial reporting. Reporting practices that facilitate meaningful cross-firm comparisons may strengthen external monitoring and constrain managers' ability to conceal adverse information.

Our study is subject to several limitations. First, although entropy balancing and instrumental-variable estimation mitigate endogeneity concerns, establishing causality remains challenging in an observational setting. In particular, entropy balancing addresses selection on observable characteristics but cannot account for unobserved differences across firms, while the validity of our instrumental-variable estimates depends on the exclusion restriction. Accordingly, we cannot fully rule out alternative explanations for the documented relation between FSC and future crash risk. Second, although our international setting enhances the generalizability of the findings, measures

of FSC and related constructs may not fully capture differences in institutional and financial reporting environments across countries. Future research could exploit exogenous regulatory or institutional changes that generate variation in FSC and examine additional mechanisms and institutional conditions that shape its relation with extreme downside risk.

Overall, we provide comprehensive international evidence that higher FSC is associated with a lower risk of future stock price crashes. The relation is robust, persists over longer horizons, and is most consistently linked to reduced financial reporting opacity. Taken together, the evidence suggests that financial statement comparability strengthens the corporate information environment, constrains managerial bad-news hoarding, and helps mitigate extreme downside risk in global capital markets.

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Table 1 Summary statistics

	N	Mean	SD	p25	Median	p75
Main Dependent Variables						
<i>NCSKEW_{t+1}</i>	183177	-0.070	0.675	-0.464	-0.082	0.299
<i>NCSKEW_{t+1 t+2}</i>	138096	-0.039	0.665	-0.428	-0.060	0.314
<i>NCSKEW_{t+1 t+3}</i>	132893	-0.025	0.629	-0.401	-0.044	0.312
<i>NCSKEW_{t+1 t+4}</i>	121029	-0.012	0.598	-0.374	-0.027	0.314
Main independent variable and other controls in year <i>t</i>						
<i>FSC</i>	183177	-0.172	0.245	-0.182	-0.098	-0.056
<i>DTURN</i>	183177	-0.001	0.135	-0.019	-0.001	0.017
<i>LNCSKEW</i>	183177	-0.055	0.653	-0.447	-0.073	0.301
<i>STDEV</i>	183177	0.041	0.018	0.028	0.038	0.051
<i>RET</i>	183177	-0.100	0.091	-0.130	-0.071	-0.038
<i>LSIZE</i>	183177	6.005	1.936	4.562	5.875	7.28
<i>MTB</i>	183177	2.330	2.824	0.798	1.433	2.676
<i>LEV</i>	183177	0.121	0.135	0.005	0.076	0.195
<i>ROA</i>	183177	0.053	0.088	0.018	0.052	0.095
<i>OPAQUE</i>	183177	0.176	0.154	0.077	0.129	0.219
<i>IFRS</i>	183177	0.239	0.427	0.000	0.000	0.000
<i>LAGE</i>	183177	2.736	0.415	2.398	2.773	3.045
<i>LANALYST</i>	183177	1.097	1.175	0.000	0.693	2.079
<i>GOVEFF</i>	183177	1.268	0.613	0.859	1.458	1.705
<i>GDPG</i>	183177	0.027	0.030	0.014	0.025	0.041
<i>STMCAP</i>	183177	1.383	1.893	0.724	1.024	1.336

This table presents the summary statistics of the variables used in the primary analysis. The main dependent variables are calculated for the period 1999-2025. The main independent variable and other controls are calculated for the period 1998-2024. *NCSKEW* is the negative skewness of firm-specific weekly returns. *FSC* is the measure of financial statement comparability, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. *DTURN* is the change in average monthly share turnover over the preceding year, where monthly share turnover is the monthly trading volume divided by the total number of shares outstanding. *LNCSKEW* is the negative skewness of firm-specific weekly returns over the fiscal-year period. *STDEV* is the standard deviation of firm-specific weekly returns over the fiscal-year period. *RET* is the mean of firm-specific weekly returns over the fiscal-year period, multiplied by 100. *LSIZE* is the natural logarithm of the market value of equity. *MTB* is the market value of equity divided by the book value of equity. *LEV* is total long-term debts divided by total assets. *ROA* is operating income divided by total assets. *OPAQUE* is the 3-year moving sum of the absolute value of annual discretionary accruals, where discretionary accruals are the difference between its total accruals and the fitted normal accruals derived from the modified Jones model. *IFRS* is a dummy variable that equals one if the firm uses IAS or IFRS to prepare its financial statements. *LAGE* is the natural logarithm of one plus the number of years since the firm's first public listing. *LANALYST* is the natural logarithm of one plus the number of analysts following the firm in a fiscal year. *GOVEFF* is the government effectiveness index from Kaufmann et al. (2011). *GDPG* is the annual growth rate of gross domestic product. *STMCAP* is the market capitalization of listed domestic companies divided by GDP.

Table 2 - Sample distribution by country and country-level summary statistics

Country	N	# Firms	NCSKEW			FSC		
			Mean	Median	SD	Mean	Median	SD
Argentina	65	13	-0.13	-0.09	0.59	-0.49	-0.21	0.56
Australia	3841	604	0.05	0.03	0.62	-0.25	-0.16	0.29
Austria	92	8	-0.05	-0.03	0.59	-0.12	-0.06	0.12
Belgium	337	37	-0.08	-0.08	0.71	-0.14	-0.10	0.13
Brazil	315	57	0.03	0.06	0.49	-0.42	-0.18	0.51
Canada	5792	887	0.03	0.02	0.58	-0.27	-0.18	0.31
Chile	294	31	-0.11	-0.11	0.57	-0.16	-0.04	0.29
China	17379	2531	-0.23	-0.23	0.58	-0.05	-0.04	0.04
Denmark	79	27	-0.20	-0.22	0.64	-0.08	-0.05	0.07
Egypt	271	56	-0.26	-0.29	0.64	-0.13	-0.09	0.12
France	3465	411	-0.09	-0.09	0.68	-0.14	-0.09	0.16
Germany	2988	343	0.01	0.01	0.65	-0.17	-0.11	0.23
Greece	709	133	-0.01	0.01	0.53	-0.31	-0.14	0.43
Hong Kong	6622	798	-0.10	-0.11	0.62	-0.34	-0.25	0.30
India	10018	1426	-0.24	-0.24	0.58	-0.37	-0.19	0.44
Indonesia	1861	255	-0.14	-0.15	0.64	-0.30	-0.15	0.39
Israel	934	131	-0.01	-0.01	0.57	-0.17	-0.09	0.27
Italy	636	127	-0.20	-0.17	0.60	-0.23	-0.10	0.36
Japan	48056	3729	-0.07	-0.08	0.69	-0.12	-0.08	0.12
Jordan	50	12	-0.38	-0.43	0.72	-0.12	-0.11	0.07
Kuwait	52	17	-0.29	-0.18	0.72	-0.15	-0.10	0.23
Malaysia	5414	663	-0.17	-0.15	0.64	-0.20	-0.14	0.22
Mexico	454	56	-0.05	-0.06	0.61	-0.11	-0.04	0.23
Netherlands	563	71	-0.03	-0.06	0.67	-0.10	-0.06	0.14
New Zealand	190	30	-0.01	0.01	0.60	-0.11	-0.06	0.16
Nigeria	81	22	-0.20	-0.19	0.62	-0.18	-0.13	0.21
Norway	590	94	-0.05	-0.05	0.58	-0.41	-0.22	0.47
Pakistan	500	82	-0.22	-0.23	0.52	-0.18	-0.12	0.19
Philippines	778	88	-0.13	-0.10	0.58	-0.21	-0.10	0.32
Poland	1183	212	-0.07	-0.10	0.62	-0.25	-0.13	0.35
Portugal	203	20	-0.09	-0.04	0.55	-0.24	-0.09	0.36
Russia	148	46	-0.36	-0.37	0.68	-0.39	-0.22	0.39
Saudi Arabia	502	75	-0.27	-0.24	0.64	-0.06	-0.04	0.05
Singapore	2225	313	-0.10	-0.09	0.66	-0.18	-0.14	0.19
South Africa	1385	149	0.01	0.02	0.54	-0.16	-0.07	0.27
South Korea	14572	1715	-0.23	-0.22	0.58	-0.27	-0.16	0.35
Spain	530	59	-0.07	-0.07	0.61	-0.18	-0.08	0.26
Sweden	98	41	-0.04	-0.10	0.53	-0.09	-0.07	0.07
Switzerland	1483	137	-0.03	-0.07	0.67	-0.12	-0.06	0.18
Thailand	3215	380	-0.14	-0.13	0.72	-0.15	-0.09	0.20
Tunisia	60	16	-0.26	-0.27	0.79	-0.13	-0.07	0.13
Turkey	1577	178	-0.25	-0.24	0.62	-0.18	-0.13	0.18
United Kingdom	5976	1118	-0.03	-0.04	0.70	-0.16	-0.10	0.19
United States	35900	3637	0.13	0.09	0.75	-0.14	-0.09	0.18
Vietnam	1694	344	-0.15	-0.15	0.56	-0.19	-0.12	0.22

This table reports country-level summary statistics including the number of firm-year observations and the number of unique firms in a country. Mean, median, and standard deviation are computed using all firm-year observations within each country. *NCSKEW* is negative skewness of firm-specific weekly returns. *FSC* is the measure of financial statement comparability, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms.

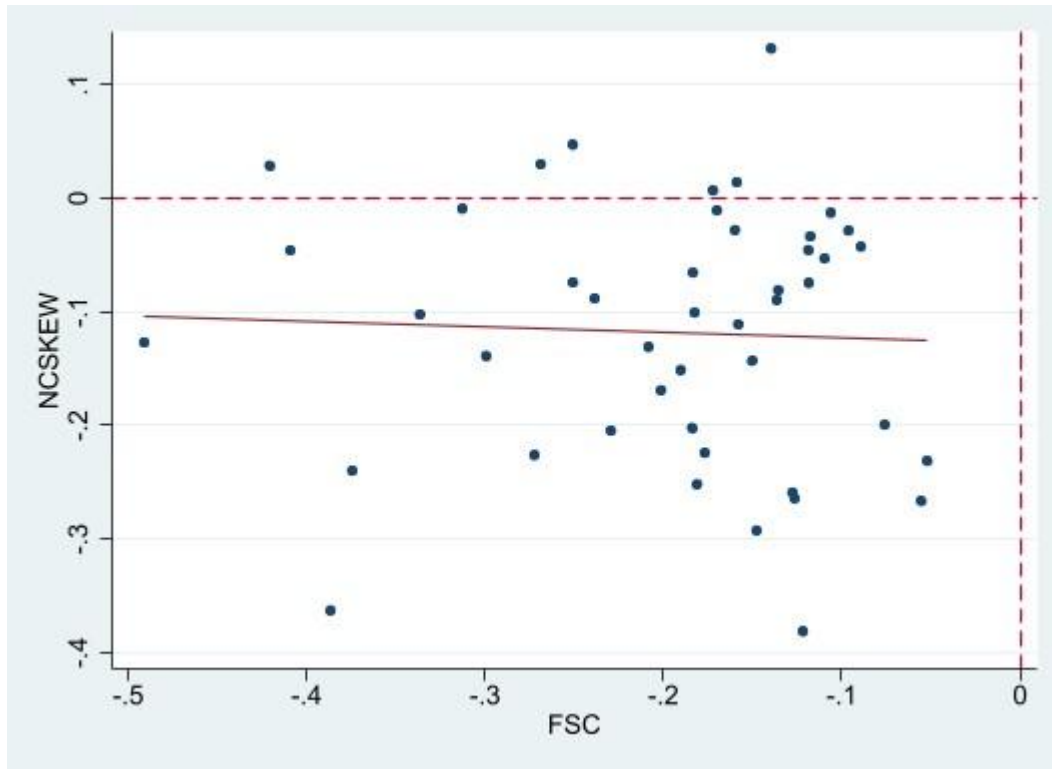
Table 3 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) <i>NCSKEW</i>	1.000								
(2) <i>FSC</i>	-0.044	1.000							
(3) <i>DTURN</i>	-0.032	0.121	1.000						
(4) <i>LNCSKEW</i>	0.950***	0.029	0.039	1.000					
(5) <i>STDEV</i>	0.309**	-0.520***	-0.073	0.309**	1.000				
(6) <i>RET</i>	-0.345**	0.504***	0.092	-0.342**	-0.990***	1.000			
(7) <i>LSIZE</i>	0.269*	0.105	0.069	0.357**	-0.301**	0.285*	1.000		
(8) <i>MTB</i>	0.102	0.110	0.079	0.067	-0.140	0.133	0.447***	1.000	
(9) <i>LEV</i>	0.432***	-0.286*	-0.058	0.418***	-0.202	0.187	0.582***	0.236	1.000
(10) <i>ROA</i>	-0.151	-0.136	-0.032	-0.112	-0.140	0.185	0.270*	0.340**	0.089
(11) <i>OPAQUE</i>	-0.002	-0.581***	-0.222	-0.068	0.579***	-0.544***	-0.309**	-0.048	-0.159
(12) <i>IFRS</i>	0.131	-0.160	-0.040	0.170	-0.108	0.109	0.242*	-0.178	0.312**
(13) <i>LAGE</i>	-0.016	-0.121	-0.266*	0.001	-0.072	0.076	0.233	-0.181	0.040
(14) <i>LANALYST</i>	0.612***	0.162	0.022	0.689***	0.007	-0.028	0.626***	0.304**	0.478***
(15) <i>GOVEFF</i>	0.559***	0.205	0.014	0.577***	0.035	-0.089	0.192	0.040	0.177
(16) <i>GDPG</i>	-0.235	0.049	-0.021	-0.277*	0.153	-0.122	-0.198	0.098	-0.368**
(17) <i>STMCAP</i>	0.108	-0.114	-0.028	0.084	0.195	-0.245*	0.046	-0.116	-0.160
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	
(10) <i>ROA</i>	1.000								
(11) <i>OPAQUE</i>	0.218	1.000							
(12) <i>IFRS</i>	-0.067	-0.103	1.000						
(13) <i>LAGE</i>	0.338**	0.101	0.272*	1.000					
(14) <i>LANALYST</i>	-0.018	-0.291*	0.218	-0.023	1.000				
(15) <i>GOVEFF</i>	-0.395***	-0.199	0.060	-0.193	0.513***	1.000			
(16) <i>GDPG</i>	0.166	0.287*	-0.545***	-0.036	-0.328**	-0.155	1.000		
(17) <i>STMCAP</i>	-0.252*	0.105	-0.205	0.056	-0.002	0.278*	0.022	1.000	

This table presents the correlation coefficients among the country-level averages of key variables, calculated as the mean of each variable across all firm-year observations within a country. *NCSKEW* is the negative skewness of firm-specific weekly returns. *FSC* is the measure of financial statement comparability, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. *DTURN* is the change in average monthly share turnover over the preceding year, where monthly share turnover is the monthly trading volume divided by the total number of shares outstanding. *LNCSKEW* is the negative skewness of firm-specific weekly returns over the fiscal-year period. *STDEV* is the standard deviation of firm-specific weekly returns over the fiscal-year period. *RET* is the mean of firm-specific weekly returns over the fiscal-year period, multiplied by 100. *LSIZE* is the natural logarithm of the market value of equity. *MTB* is the market value of equity divided by the book value of equity. *LEV* is total long-term debts divided by total assets. *ROA* is operating income divided by total assets. *OPAQUE* is the 3-year moving sum of the absolute value of annual

discretionary accruals, where discretionary accruals are the difference between its total accruals and the fitted normal accruals derived from the modified Jones model. *IFRS* is a dummy variable that equals one if the firm uses IAS or IFRS to prepare its financial statements. *LAGE* is the natural logarithm of one plus the number of years since the firm's first listed price is available. *LANALYST* is the natural logarithm of one plus the number of analysts following the firm in a fiscal year. *GOVEFF* is the government effectiveness index from Kaufmann et al. (2011). *GDPG* is the annual growth rate of gross domestic product. *STMCAP* is the market capitalization of listed domestic companies divided by GDP. Variable definitions are provided in Appendix A. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 1 Relation between country-level financial statement comparability and stock price crash risk



This figure plots the average country-level financial statement comparability measure (x-axis) against the average country-level stock price crash risk measure (y-axis). *NCSKEW* is negative skewness of firm-specific weekly returns. *FSC* is the measure of financial statement comparability, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms.

Table 4 Baseline results: Effect of FSC on Stock Price Crash Risk

	(1) <i>NCSKEW_{t+1}</i>	(2) <i>NCSKEW_{t+1}</i>	(3) <i>NCSKEW_{t+1}</i>	(4) <i>NCSKEW_{t+1}</i>
<i>FSC</i>	-0.021*** (-3.09)	-0.020*** (-2.92)	-0.020*** (-2.86)	-0.025*** (-3.43)
<i>DTURN</i>	-0.008 (-0.73)	0.003 (0.25)	0.004 (0.35)	0.003 (0.29)
<i>LNCSKEW</i>	0.040*** (13.98)	0.038*** (13.10)	0.038*** (13.09)	0.042*** (13.07)
<i>STDEV</i>	-0.181 (-0.43)	-0.808* (-1.93)	-0.867** (-2.07)	-2.116*** (-4.51)
<i>RET</i>	-0.174** (-2.26)	-0.250*** (-3.27)	-0.258*** (-3.37)	-0.476*** (-5.34)
<i>LSIZE</i>	0.028*** (23.40)	0.018*** (11.33)	0.018*** (11.21)	0.017*** (9.61)
<i>MTB</i>	0.006*** (8.31)	0.005*** (7.69)	0.005*** (7.70)	0.007*** (9.02)
<i>LEV</i>	-0.034** (-2.46)	-0.044*** (-3.15)	-0.046*** (-3.26)	-0.011 (-0.68)
<i>ROA</i>	0.175*** (8.74)	0.173*** (8.65)	0.176*** (8.77)	0.131*** (5.47)
<i>OPAQUE</i>		0.041*** (3.71)	0.042*** (3.77)	0.019 (1.53)
<i>IFRS</i>		-0.017** (-2.54)	-0.017*** (-2.60)	-0.028*** (-4.02)
<i>LAGE</i>		-0.041*** (-7.79)	-0.042*** (-7.81)	-0.051*** (-8.76)
<i>LANALYST</i>		0.026*** (11.48)	0.026*** (11.48)	0.031*** (12.55)
<i>GOVEFF</i>			-0.029*** (-3.00)	-0.050*** (-4.65)
<i>GDPG</i>			-0.251** (-2.53)	-0.247** (-2.40)
<i>STMCAP</i>			0.007** (2.33)	0.004 (1.42)
Country, industry, year FE	Yes	Yes	Yes	Yes
Exc. the U.S.				Yes
Adjusted R ²	0.055	0.057	0.057	0.044
Observations	183177	183177	183177	147277

This table presents regression results examining the impact of financial statement comparability on stock price crash risk. The sample period spans 1998-2024. The dependent variable is *NCSKEW*, defined as the negative skewness of firm-specific weekly returns in year $t+1$. The main independent variable, *FSC*, is the measure of financial statement comparability in year t , calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. *DTURN* is the change in average monthly share turnover over the preceding year, where monthly share turnover is the monthly trading volume divided by the total number of shares outstanding. *LNCSKEW* is the negative skewness of firm-specific weekly returns over the fiscal-year period. *STDEV* is the standard deviation of firm-specific weekly returns over the fiscal-year period. *RET* is the mean of firm-specific weekly returns over the fiscal-year period, multiplied by 100. *LSIZE* is the natural logarithm of the market value of equity. *MTB* is the market value of equity divided by the book value of equity. *LEV* is total long-term debts divided by total assets. *ROA* is operating income divided by total assets. *OPAQUE* is the 3-year moving sum of the absolute value of annual discretionary accruals, where discretionary accruals are the difference between its total accruals and the fitted normal accruals derived from the modified Jones model. *IFRS* is a dummy variable that equals one if the firm uses IAS or IFRS to prepare its financial statements. *LAGE* is the natural logarithm of one plus the number of years since the firm's stock price was first listed in the database. *LANALYST* is the natural logarithm of one plus the number of analysts following the firm in a fiscal year. *GOVEFF* is the government effectiveness index from Kaufmann et al. (2011). *GDPG* is the annual growth rate of gross domestic product. *STMCAP* is the market capitalization of listed domestic companies divided by GDP. All specifications include country, industry, and year fixed effects. Standard errors are clustered at the firm level. Variable definitions are provided in the Appendix ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 - Long-Term Effects of FSC on Stock Price Crash Risk

Panel A – Full Sample			
	(1)	(2)	(3)
	$NCSKEW_{t+1_t+2}$	$NCSKEW_{t+1_t+3}$	$NCSKEW_{t+1_t+4}$
<i>FSC</i>	-0.025*** (-2.78)	-0.028*** (-2.98)	-0.025*** (-2.56)
All controls	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes
Adjusted R ²	0.113	0.142	0.169
Observations	138096	132893	121029
Panel B – Excluding US firms			
	(1)	(2)	(3)
	$NCSKEW_{t+1_t+2}$	$NCSKEW_{t+1_t+3}$	$NCSKEW_{t+1_t+4}$
<i>FSC</i>	-0.031*** (-3.34)	-0.031*** (-3.16)	-0.027*** (-2.64)
All controls	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes
Adjusted R ²	0.090	0.113	0.134
Observations	106529	10408	94677

This table presents regression results examining the long-term impacts of financial statement comparability on stock price crash risk. Panel A presents results for the full sample, while Panel B reports results after excluding U.S. firms. The sample period spans 1998-2024. The dependent variables are $NCSKEW_{t+1_t+2}$, $NCSKEW_{t+1_t+3}$, and $NCSKEW_{t+1_t+4}$ for the 2-, 3-, and 4-year periods, respectively. Panel A (B) presents results for the full sample (excluding US firms). The main independent variable, *FSC*, is the measure of financial statement comparability in year *t*, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. *NCSKEW* is the negative skewness of firm-specific weekly returns. All specifications include country, industry, and year fixed effects. Standard errors are clustered at the firm level. Variable definitions are provided in the Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6 – Effect of FSC on Stock Price Crash Risk -Instrumental Variable Analysis

<i>Panel A - Full Sample</i>					
	<i>Stage 1</i>	<i>Stage 2</i>			
	<i>FSC</i>	<i>NCSKEW_{t+1}</i>	<i>NCSKEW_{t+1-t+2}</i>	<i>NCSKEW_{t+1-t+3}</i>	<i>NCSKEW_{t+1-t+4}</i>
	(1)	(2)	(3)	(4)	(5)
<i>FSC</i>		-0.0797*** (-3.43)	-0.1378*** (-4.77)	-0.1774*** (-6.00)	-0.1851*** (-6.38)
<i>Yearly Country Median FSC</i>	0.8242*** (22.45)				
Endogeneity test (χ^2)		6.822***	15.789***	25.828***	30.934***
Underidentification test (χ^2)		270.898***	232.214***	219.695***	219.212***
Weak identification test: (Cragg–Donald Wald F-statistic)		13059.58***	9750.086***	9643.263***	9841.663***
Country, industry, year FE	YES	YES	YES	YES	YES
Observations	183177	183177	138096	132893	121029
R ²	0.3114	0.0099	0.0222	0.0282	0.0330
<i>Panel B - Excluding US firms</i>					
	<i>Stage 1</i>	<i>Stage 2</i>			
	<i>FSC</i>	<i>NCSKEW_{t+1}</i>	<i>NCSKEW_{t+1-t+2}</i>	<i>NCSKEW_{t+1-t+3}</i>	<i>NCSKEW_{t+1-t+4}</i>
	(1)	(2)	(3)	(4)	(5)
<i>FSC</i>		-0.0979*** (-4.12)	-0.1449*** (-4.89)	-0.1716*** (-5.65)	-0.1744*** (-5.87)
<i>Yearly Country Median FSC</i>	0.8187*** (22.33)				
Endogeneity test (χ^2)		9.659***	15.322***	21.930***	25.260***
Underidentification test (χ^2)		269.899***	230.014***	217.961***	218.479***
Weak identification test: (Cragg–Donald Wald F-statistic)		11767.51***	8521.737***	8532.566***	8707.257***
Country, industry, year FE	YES	YES	YES	YES	YES
Observations	147277	147277	106529	104080	94677
R ²	0.3288	0.0113	0.0271	0.0346	0.0408

This table presents instrumental-variable (IV) regression results examining the long-term effect of financial statement comparability (*FSC*) on stock price crash risk. The instrumental variable is the yearly median *FSC* for each country. Panel A (B) presents results for the full sample (excluding US firms). We use the country-year median of *FSC* as an instrument for firm-level *FSC*. The control variables are those included in Column (3) of Table

4. The sample period spans 1998–2024. In the first-stage regression, the dependent variable is firm-level FSC , and the instrument is the country-year median FSC . We use the control variables in column 3 of Table 4. The sample period spans 1998–2024. The dependent variable in stage 1 is FSC . The dependent variables in stage 2 are $NCSKEW_{t+1}$, $NCSKEW_{t+1-t+2}$, $NCSKEW_{t+1-t+3}$, and $NCSKEW_{t+1-t+4}$ for 1-, 2-, 3-, and 4-year periods, respectively. All specifications include country, industry, and year fixed effects. Standard errors are clustered at the firm level. Variable definitions are provided in the Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7 - Effect of FSC on Stock Price Crash Risk -Entropy Analysis based on yearly Country median FSC

	Panel A1 – All Countries						Panel A2 – Excluding US firms					
	Treat HFSC N = 91384			Control LFSC N = 91793			Treat – Non-US firms HFSC N = 73441			Control – Non-US firms LFSC N = 73836		
	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness
<i>DTURN</i>	-0.001	0.013	0.113	-0.001	0.014	0.461	-0.002	0.015	0.122	-0.002	0.016	0.426
<i>LNCSKEW</i>	-0.040	0.440	0.316	-0.040	0.423	0.343	-0.092	0.398	0.245	-0.092	0.388	0.268
<i>STDEV</i>	0.037	0.000	0.995	0.037	0.000	1.051	0.036	0.000	1.013	0.036	0.000	1.076
<i>RET</i>	-0.077	0.005	-2.220	-0.077	0.005	-2.312	-0.074	0.004	-2.281	-0.074	0.005	-2.374
<i>LSIZE</i>	6.344	3.626	0.255	6.344	4.196	0.334	6.056	3.244	0.316	6.054	3.686	0.376
<i>MTB</i>	2.360	7.185	3.429	2.360	8.195	3.357	2.081	5.683	3.704	2.083	6.887	3.717
<i>LEV</i>	0.118	0.017	1.217	0.118	0.017	1.274	0.103	0.015	1.407	0.103	0.013	1.372
<i>ROA</i>	0.068	0.005	0.083	0.068	0.006	-0.052	0.061	0.005	0.014	0.061	0.006	0.053
<i>OPAQUE</i>	0.144	0.014	2.461	0.144	0.013	2.333	0.144	0.014	2.519	0.145	0.013	2.388
<i>IFRS</i>	0.240	0.183	1.216	0.240	0.183	1.216	0.299	0.210	0.879	0.299	0.210	0.878
<i>LAGE</i>	2.759	0.172	-0.209	2.759	0.174	-0.207	2.749	0.171	-0.201	2.748	0.172	-0.187
<i>LANALYST</i>	1.238	1.451	0.347	1.238	1.496	0.379	1.048	1.349	0.606	1.047	1.374	0.628
<i>GOVEFF</i>	1.269	0.375	-0.934	1.269	0.382	-0.902	1.198	0.437	-0.635	1.198	0.443	-0.613
<i>GDPG</i>	0.027	0.001	-0.153	0.027	0.001	-0.077	0.028	0.001	-0.175	0.028	0.001	-0.091
<i>STMCAP</i>	1.383	3.583	4.863	1.383	3.560	4.905	1.380	4.436	4.398	1.381	4.379	4.446

Panel B – Entropy Balancing Regression								
	Panel B1 – All Countries				Panel B2 – Excluding US firms			
	(1) NCSKEW _{t+1}	(2) NCSKEW _{t+1,t+2}	(3) NCSKEW _{t+1,t+3}	NCSKEW _{t+1,t+4}	(1) NCSKEW _{t+1}	(2) NCSKEW _{t+1,t+2}	(3) NCSKEW _{t+1,t+3}	NCSKEW _{t+1,t+4}
<i>FSC</i>	-0.015*	-0.025**	-0.033***	-0.028**	-0.018**	-0.029**	-0.033***	-0.026**
	(-1.71)	(-2.18)	(-2.66)	(-2.17)	(-1.99)	(-2.44)	(-2.63)	(-2.07)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.058	0.112	0.140	0.166	0.047	0.091	0.113	0.134
Observations	183177	138096	132893	121029	147277	106529	104080	94677

This table presents the results of entropy balancing analyses designed to mitigate systematic differences between firms with relatively high and low financial statement comparability (*FSC*). In each country-year, firms with *FSC* above the country-year median are classified as the treatment group, while firms with *FSC* at or below the country-year median are classified as the control group. We implement the entropy balancing procedure using Hainmueller's Stata code and reweight the control group to achieve balance with the treatment group on the first three moments—mean, variance, and skewness—of the covariate distributions. Panel A reports the mean, variance, and skewness of the covariates for the treatment and entropy-balanced control groups and shows that balance is achieved on all three specified moments. Panel B reports weighted multivariate regressions using the entropy-balancing weights. The control variables are those included in Column (3) of Table 4. The sample period spans 1998–2024. The dependent variables are $NCSKEW_{t+1}$, $NCSKEW_{t+1,t+2}$, $NCSKEW_{t+1,t+3}$, and $NCSKEW_{t+1,t+4}$ representing stock

price crash risk over 1-, 2-, 3-, and 4-year periods. The main independent variable, *FSC*, measures financial statement comparability in year t and is calculated as the negative average difference between a firm's expected earnings based on its own accounting function and expected earnings based on the accounting functions of its domestic peer firms. *NCSKEW* is the negative skewness of firm-specific weekly returns. All specifications include country, industry, and year fixed effects. Standard errors are clustered at the firm level. Variable definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effect of FSC on Stock Price Crash Risk - Alternative fixed effects

Panel A – Full sample				
	(1)	(2)	(3)	(4)
	$NCSKEW_{t+1}$	$NCSKEW_{t+1_t+2}$	$NCSKEW_{t+1_t+3}$	$NCSKEW_{t+1_t+4}$
<i>FSC</i>	-0.016*	-0.024**	-0.028**	-0.022*
	(-1.72)	(-2.20)	(-2.46)	(-1.92)
All controls	Yes	Yes	Yes	Yes
Firm, year FE	Yes	Yes	Yes	Yes
Adjusted R ²	0.179	0.305	0.383	0.452
Observations	180509	135454	130746	119275
Panel B – Exc. the U.S firms				
	(1)	(2)	(3)	(4)
	$NCSKEW_{t+1}$	$NCSKEW_{t+1_t+2}$	$NCSKEW_{t+1_t+3}$	$NCSKEW_{t+1_t+4}$
<i>FSC</i>	-0.019**	-0.028**	-0.026**	-0.018
	(-1.98)	(-2.39)	(-2.19)	(-1.45)
All controls	Yes	Yes	Yes	Yes
Firm, year FE	Yes	Yes	Yes	Yes
Adjusted R ²	0.174	0.293	0.366	0.434
Observations	145073	104263	102247	93181

This table presents the impact of financial statement comparability on stock price crash risk with alternative fixed effects. The sample period spans 1998-2024. The dependent variables are $NCSKEW_{t+1}$, $NCSKEW_{t+1_t+2}$, $NCSKEW_{t+1_t+3}$, and $NCSKEW_{t+1_t+4}$ for 1-, 2-, 3-, and 4-year periods, respectively. $NCSKEW$ is defined as the negative skewness of firm-specific weekly returns. The main independent variable, *FSC*, is the measure of financial statement comparability in year *t*, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. Column 1-2 includes country $\times$ year fixed effects, while Columns 3-4 include firm and year fixed effects. Columns 1 and 3 include all countries, while Columns 2 and 4 exclude U.S. firms. Standard errors are clustered at the firm level. Variable definitions are provided in the Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9 - Effect of Financial Statement Comparability on Stock Price Crash Risk - Robustness checks using Alternative Measure of Crash Risk

<i>Panel A - DUVOL_{t+1}</i>				
	(1)	(2)	(3)	(4)
FSC	-0.012*** (-3.28)	-0.015*** (-3.93)	-0.010** (-2.01)	-0.012** (-2.38)
All controls	Yes	Yes	Yes	Yes
Country, industry and year FE	Yes	Yes	Yes	Yes
Firm, year FE				Yes
Exc. the U.S.		Yes		
Adjusted R ²	0.062	0.050	0.185	0.179
Observations	183177	147277	180509	145073
<i>Panel B - DUVOL_{t+1,t+2}</i>				
	(1)	(2)	(3)	(4)
FSC	-0.011*** (-2.68)	-0.014*** (-3.31)	-0.013*** (-2.58)	-0.015*** (-2.78)
All controls	Yes	Yes	Yes	Yes
Country, industry and year FE	Yes	Yes		
Firm, year FE			Yes	Yes
Exc. the U.S.		Yes		Yes
Adjusted R ²	0.138	0.112	0.329	0.317
Observations	138096	106529	135454	104263
<i>Panel B - DUVOL_{t+1,t+3}</i>				
	(1)	(2)	(3)	(4)
FSC	-0.011*** (-2.89)	-0.013*** (-3.21)	-0.013*** (-2.73)	-0.013** (-2.46)
All controls	Yes	Yes	Yes	Yes
Country, industry and year FE	Yes	Yes		
Firm, year FE			Yes	Yes
Exc. the U.S.		Yes		Yes
Adjusted R ²	0.178	0.144	0.419	0.402
Observations	132893	104080	130746	102247
<i>Panel B - DUVOL_{t+1,t+4}</i>				
	(1)	(2)	(3)	(4)
FSC	-0.010** (-2.45)	-0.012*** (-2.77)	-0.011** (-2.24)	-0.009* (-1.86)
All controls	Yes	Yes	Yes	Yes
Country, industry and year FE	Yes	Yes		
Firm, year FE			Yes	Yes
Exc. the U.S.		Yes		Yes
Adjusted R ²	0.214	0.174	0.497	0.480
Observations	121029	94677	119275	93181

This table reports robustness tests of the association between financial statement comparability (FSC) and future stock price crash risk using down-to-up volatility (*DUVOL*) as an alternative measure of crash risk. Panel A reports results for *DUVOL* measured in year $t+1$. Panels B–D report results using cumulative *DUVOL* measured over years $t+1$ to $t+2$, $t+1$ to $t+3$, and $t+1$ to $t+4$, respectively. Columns (1) and (2) include country, industry, and year fixed effects, while Columns (3) and (4) include firm and year fixed effects. Columns (1) and (3) use the full sample, whereas Columns (2) and (4) exclude U.S. firms. All regressions include the full set of control variables. Variable definitions are provided in the Appendix. t -statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Effect of Financial Statement Comparability on Stock Price Crash Risk - Channel Analysis

Panel A -The impact of FSC on Opacity						
	$OPAQUE_{t,t+2}$		$OPAQUE_{t+1,t+3}$			
	(3)	(4)	(5)	(6)		
FSC_t	-0.038*** (-12.07)	-0.035*** (-10.57)	-0.026*** (-8.52)	-0.024*** (-7.44)		
All controls in year t, excluding $OPAQUE_t$	Yes	Yes	Yes	Yes		
Country, industry, year FE	Yes	Yes	Yes	Yes		
Excluding US firms		Yes		Yes		
Adjusted R ²	0.247	0.237	0.240	0.232		
Observations	158676	127180	141780	113278		
Panel B - The Impact of FSC on Overinvestment						
	$OVERINVEST_{t+1}$		$OVERINVEST_{t+1,t+2}$		$OVERINVEST_{t+1,t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
FSC_t	-0.003** (-2.11)	-0.000 (-0.22)	-0.007** (-2.22)	-0.001 (-0.30)	-0.010** (-2.19)	-0.002 (-0.36)
All controls in year t	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes
Excluding US firms		Yes		Yes		Yes
Adjusted R ²	0.078	0.071	0.112	0.097	0.137	0.117
Observations	60351	42426	53731	38085	44551	31279

Panel A of this table presents regression results examining the impact of FSC_t on opacity, measured over three-year periods from year t to year t+2 ($OPAQUE_{t,t+2}$) and from year t+1 to year t+3 ($OPAQUE_{t+1,t+3}$). Panel B of this table presents regression results examining the impact of FSC_t on overinvestment ($OVERINVEST$), measured over 1-, 2-, and 3-year periods. The sample period spans 1998-2024. The dependent variables are all measured in year t+1. $OPAQUE$ is the 3-year moving sum of the absolute value of annual discretionary accruals, where discretionary accruals are the difference between its total accruals and the fitted normal accruals derived from the modified Jones model. The main independent variable, FSC , is the measure of financial statement comparability in year t, calculated as the negative average difference between a firm's expected earnings based on its own accounting function and those based on the accounting functions of domestic peer firms. All specifications include country, industry, and year fixed effects. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix A. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix - Variable definitions		
Variable	Description	Data source
$NCSKEW_{t+1}$	Negative skewness of firm-specific weekly returns in year $t+1$, measured over a one-year period from three months after the balance sheet date of year t .	Datastream
$NCSKEW_{t+1_t+2}$	The negative skewness of firm-specific weekly returns is measured over a longer two-year forecasting window starting three months after the balance sheet date of year t . Following Kim et al. (2011b), we require at least 100 firm-specific weekly return observations over the two-year period.	Datastream
$NCSKEW_{t+1_t+3}$	The negative skewness of firm-specific weekly returns is measured over a longer three-year forecasting window starting three months after the balance sheet date of year t . We require at least 150 firm-specific weekly return observations over the three-year period.	Datastream
$NCSKEW_{t+1_t+4}$	The negative skewness of firm-specific weekly returns is measured over a longer four-year forecasting window starting three months after the balance sheet date of year t . We require at least 200 firm-specific weekly return observations over the four-year measurement period.	Datastream
$DUVOL_{t+1}$	The natural logarithm of the ratio of the standard deviations of down-week to up-week firm-specific weekly returns in year $t+1$, measured over a one-year period from three months after the balance sheet date of year t .	Datastream
$DUVOL_{t+1_t+2}$	The natural logarithm of the ratio of the standard deviations of down-week to up-week firm-specific weekly returns is measured over a longer two-year forecasting window starting three months after the balance sheet date of year t . Following Kim et al. (2011b), we require at least 100 firm-specific weekly return observations over the two-year period.	Datastream
$DUVOL_{t+1_t+3}$	The natural logarithm of the ratio of the standard deviations of down-week to up-week firm-specific weekly returns is measured over a longer three-year forecasting window starting three months after the balance sheet date of year t . We require at least 150 firm-specific weekly return observations over the three-year period.	Datastream
$DUVOL_{t+1_t+4}$	The natural logarithm of the ratio of the standard deviations of down-week to up-week firm-specific weekly returns is measured over a longer four-year forecasting window starting three months after the balance sheet date of year t . We require at least 200 firm-specific weekly return observations over the four-year measurement period.	Datastream
FSC	The average pairwise comparability between a firm and all industry peers within the same 3-digit SIC industry and country. Pairwise comparability is measured as the negative absolute difference between the firm's expected earnings based on its own accounting function and those based on a domestic peer's accounting function, averaged over the four-year period from $t-3$ to t . The accounting function is estimated by regressing earnings on stock returns.	Worldscope
$DTURN$	The change in average monthly share turnover over the preceding year, where monthly share turnover is the monthly trading volume	Datastream

	divided by the total number of shares outstanding.	
<i>LNCSKEW</i>	Negative skewness of firm-specific weekly returns over the fiscal-year period.	Datastream
<i>STDEV</i>	Standard deviation of firm-specific weekly returns over the fiscal-year period.	Datastream
<i>RET</i>	Mean of firm-specific weekly returns over the fiscal-year period, multiplied by 100.	Datastream
<i>LSIZE</i>	Natural logarithm of the market value of equity.	Worldscope
<i>MTB</i>	Market value of equity divided by book value of equity.	Worldscope
<i>LEV</i>	Total long-term debts divided by total assets.	Worldscope
<i>ROA</i>	Operating income divided by total assets.	Worldscope
<i>OPAQUE</i>	The 3-year moving sum of the absolute value of annual discretionary accruals, where discretionary accruals are the difference between its total accruals and the fitted normal accruals derived from modified Jones model.	Worldscope
<i>IFRS</i>	An indicator variable that equals one if the firm uses IAS or IFRS to prepare for its financial statements.	Worldscope
<i>LAGE</i>	Natural logarithm of one plus the number of years since the first has its listed price.	Worldscope
<i>LANALYST</i>	Natural logarithm of one plus the number of analysts following the firm in a fiscal year.	I/B/E/S
<i>GOVEFF</i>	The government effectiveness index.	Kaufmann et al. (2011)
<i>GDPG</i>	Annual growth rate of gross domestic product.	World Bank
<i>STMCAP</i>	Market capitalization of listed domestic companies divided by GDP.	World Bank
<i>OVERINVEST</i>	We follow Khuruna et al. (2018) and Balachandran et al. (2020) and measure overinvestment as the amount of unexpected investment for firm-years with positive unexpected investment, and zero otherwise. Unexpected investment is measured as the residual from a regression of <i>INVEST</i> in year t+1 on <i>MTB</i> , <i>ROA</i> , <i>CASH</i> , <i>AGE</i> , <i>LEV</i> , <i>LASSET</i> , and <i>INVEST</i> in year t, including industry and year fixed effects. <i>INVEST</i> is defined as capital expenditures, R&D expense, net assets from acquisitions, and depreciation less disposal of fixed assets, scaled by lagged total assets. <i>CASH</i> is cash and equivalents scaled by lagged total assets, and <i>LASSET</i> is natural logarithm of total assets. Other variables are defined above.	Worldscope
<i>INSIDER</i>	The number of shares held by insiders divided by the total number of shares outstanding.	Worldscope
<i>PUBENF</i>	Index of public enforcement, including fines and prison terms for related parties in self-dealing if all disclosure and approval requirements have been met.	Djankov et al. (2008)

Internet Appendix

Transparency or Opacity? Global Evidence on Financial Statement Comparability and Stock Price Crash Risk

We structure the Internet Appendix as follows. We present this cleaning procedure in Section A and Table IA1 in the internet appendix. Section B presents the procedure we have adopted to estimate our crash risk measures. Section C examines cross-sectional variation in two firm-level characteristics, insider ownership (*INSIDER*) and analyst following (*LNANALYST*); two country-level institutional characteristics, government effectiveness (*GOVEFF*) and public enforcement (*PUBENF*).

Section A -Data cleaning procedure

Table IA1 summarizes the sample construction procedure. We begin with 1,025,119 firm-year observations representing 75,513 firms across 92 countries from the merged Worldscope–Datastream sample over the period 1998–2024. After excluding financial and utility firms, the sample decreases to 834,600 observations from 60,734 firms across 91 countries. We then exclude firms with total assets below US\$10 million, reducing the sample to 632,469 observations from 54,577 firms. Merging the stock price crash risk measures results in 546,194 observations from 50,687 firms across 68 countries, while merging the financial statement comparability measure further reduces the sample to 280,226 observations from 27,194 firms across 65 countries. After excluding observations with missing data on the baseline variables, the sample comprises 183,512 observations from 21,265 firms across 60 countries. Finally, we exclude countries with fewer than 50 firm-year observations, yielding a final sample of 183,177 firm-year observations representing 21,179 firms across 45 countries.

Section B – Crash Risk Measures

To calculate crash risk, we assign weekly returns over the 12-month period ending three months after each firm's fiscal year-end. Following the approach of Jin and Myers (2006), we estimate firm-specific weekly returns for each firm-year using the following extended market model:

$$\begin{aligned}
 r_{ijt} = & \alpha + \beta_1 r_{mjt} + \beta_2 (r_{US,t} + EX_{jt}) + \beta_3 r_{mjt-1} + \beta_4 (r_{US,t-1} + EX_{jt-1}) + \beta_5 r_{mjt-2} \\
 & + \beta_6 (r_{US,t-2} + EX_{jt-2}) + \beta_7 r_{mjt+1} + \beta_8 (r_{US,t+1} + EX_{jt+1}) + \beta_9 r_{mjt+2} \\
 & + \beta_{10} (r_{US,t+2} + EX_{jt+2}) + \varepsilon_{ijt}
 \end{aligned} \tag{1}$$

where r_{ijt} is the stock return for firm i in week t in country j ; r_{mjt} is the return on the local market index, calculated as the equally weighted average of all weekly individual stock returns (excluding stock i); $r_{US,t}$ is the U.S. market index return, used as a proxy for the global market; EX_{jt} is the change in country j 's U.S. dollar exchange rate; and ε_{ijt} represents unspecified factors. The expression $r_{US,t} + EX_{jt}$ translates U.S. market returns into local currency units. We allow for nonsynchronous trading by including two lead and lag terms for market index returns. Finally, the firm-specific weekly return for firm i in week t in country j , denoted as W_{ijt} , is defined as the logarithm of one plus the residual return estimated from Equation (1), that is,

$$W_{ijt} = \ln(1 + \varepsilon_{ijt}) \tag{2}$$

The primary measure of stock price crash risk in our study is the negative conditional skewness of firm-specific weekly returns (*NCSKEW*). We calculate this by taking the negative of the third central moment of firm-specific weekly returns and dividing it by the third power of the standard deviation of firm-specific weekly returns. Thus, for a stock i over a fiscal year t (12-month period ending three months after each firm's fiscal year-end t , in country j , we have

$$NCSKEW_{ijt} = - \frac{n(n-1)^{\frac{3}{2}} \sum (W_{ijt} - \bar{W}_{ijt})^3}{(n-1)(n-2) \left[\sum (W_{ijt} - \bar{W}_{ijt})^2 \right]^{\frac{3}{2}}} \quad (3)$$

where W_{ijt} is the firm-specific weekly return, $\bar{W}_{ijt}$ is the average firm-specific weekly return over the 12-month period ending three months after each firm's fiscal year-end year t , and n is the number of observations in the 12-month period. The minus sign in front of the right-hand side ensures that an increase in the value of $NCSKEW$ corresponds to a stock having a more left-skewed distribution, that is, more “crash-prone.”

We also calculate an alternative measure of crash risk, down-to-up volatility ($DUVOL$). To calculate this measure for each firm i over the 12-month period ending three months after each firm's fiscal year-end in year t , we first separate firm-specific weekly returns into two groups: down (up) weeks are those with returns below (above) the annual mean. We then calculate the standard deviation of firm-specific weekly returns separately for these groups. For each firm in year t , $DUVOL$ is calculated as the natural logarithm of the ratio of the standard deviation of firm-specific down weekly returns to that of up weekly returns during the 12-month period ending three months after the firm's fiscal year-end in year t . Specifically, $DUVOL$ is computed as follows:

$$DUVOL_{ijt+1} = \ln \left[\frac{(n_u-1) \sum_{DOWN} (W_{ijt+1} - \bar{W}_{ijt+1})^2}{(n_d-1) \sum_{UP} (W_{ijt+1} - \bar{W}_{ijt+1})^2} \right] \quad (4)$$

where $n_d(n_u)$ is the number of down (up) weeks. A higher $DUVOL$ value corresponds to a greater crash risk.

Section C – Cross-Sectional Analysis

To better understand the conditions under which FSC is associated with lower future stock price crash risk, we examine cross-sectional variation in two firm-level characteristics, insider ownership (*INSIDER*) and analyst following (*LANALYST*), and two country-level institutional characteristics, government effectiveness (*GOVEFF*) and public enforcement (*PUBENF*). Table IA2 presents the results. For *INSIDER* and *LANALYST*, we partition firms using the yearly industry median; for *GOVEFF*, we use the yearly median; and for *PUBENF*, we use the sample median. We estimate the association between FSC in year (t) and crash risk in year (t+1), as well as cumulative crash risk over years (t+1) to (t+2), (t+1) to (t+3), and (t+1) to (t+4). We also report formal tests of differences in the FSC coefficients across the respective subsamples. To assess whether the results are disproportionately influenced by U.S. firms, we repeat each analysis after excluding U.S. observations.

C1. Insider Ownership

Panel A examines whether the association between FSC and future crash risk varies with insider ownership. In the full sample (Panel A1), the negative association between FSC and crash risk is concentrated among firms with insider ownership at or below the yearly industry median. For these firms, the coefficients on *FSC* are -0.027 ($t=-2.37$), -0.043 ($t=-3.13$), -0.047 ($t=-3.26$), and -0.046 ($t=-3.10$) for *NCSKEW* measured in year (t+1) and cumulatively over years (t+1) to (t+2), (t+1) to (t+3), and (t+1) to (t+4), respectively. In contrast, the corresponding coefficients for firms with above-median insider ownership range from -0.008 to -0.016 and are statistically insignificant across all four horizons. The difference in FSC coefficients between the

two groups is statistically significant for cumulative crash risk over years (t+1) to (t+3), although the differences are not statistically significant for the other horizons.

The distinction becomes considerably stronger when U.S. firms are excluded (Panel A2). FSC remains negatively and significantly associated with crash risk in the low-insider-ownership group across all four horizons, with coefficients of -0.042 , -0.068 , -0.066 , and -0.062 , respectively. In contrast, the coefficients for the high-insider-ownership group range from -0.009 to -0.015 and remain statistically insignificant. More importantly, the differences between the high- and low-insider-ownership groups are statistically significant across all four horizons.

Taken together, these results indicate that the crash-risk-reducing effect of FSC is concentrated among firms with relatively low insider ownership. One interpretation is that when insider ownership is lower, outside investors depend more heavily on publicly available financial information, increasing the value of comparable financial statements for benchmarking firm performance and constraining managerial bad-news hoarding. When insider ownership is relatively high, insiders' greater access to firm-specific information and stronger influence over the firm's information environment may reduce the incremental monitoring benefits provided by FSC. The stronger coefficient-difference tests after excluding U.S. firms reinforce this interpretation.

C2. Analyst Following

Panel B examines whether analyst following moderates the association between FSC and the risk of future stock price crashes. Financial analysts serve as important information intermediaries by collecting, processing, and disseminating firm-specific information, thereby reducing information asymmetry and increasing external scrutiny of managerial actions. If FSC

and analyst monitoring operate as substitute information mechanisms, FSC should play a greater role when analyst following is relatively low.

Panel B1 reports the results for the full sample. Among firms with analyst following above the yearly industry median, the coefficients on *FSC* are 0.016 ($t=1.32$), 0.011 ($t=0.76$), 0.009 ($t=0.59$), and 0.014 ($t=0.87$) across the four crash-risk horizons, and none is statistically significant. In contrast, among firms with analyst following at or below the yearly industry median, the coefficients on *FSC* are -0.031 ($t=-3.67$), -0.032 ($t=-3.07$), -0.034 ($t=-3.05$), and -0.029 ($t=-2.49$), respectively, and are statistically significant throughout. The differences in FSC coefficients between the high- and low-analyst-following groups are 0.047, 0.043, 0.043, and 0.043 across the four horizons. The corresponding F-tests are statistically significant at conventional levels in every case. Thus, in the full sample, the negative association between FSC and future crash risk is significantly stronger among firms with relatively low analyst following, and this difference persists across both the one-year and cumulative long-term crash-risk measures.

Panel B2 repeats the analysis after excluding U.S. firms. The results remain qualitatively similar. Among firms with high analyst following, the coefficients on *FSC* are small and statistically insignificant across all four horizons. In contrast, among firms with low analyst following, *FSC* remains negatively and significantly associated with future crash risk, with coefficients of -0.029 , -0.031 , -0.029 , and -0.024 , respectively. The coefficient differences between the high- and low-analyst-following groups are not statistically significant for the first three horizons, although the difference becomes significant at the 10% level for cumulative crash risk over years $(t+1)$ to $(t+4)$.

Overall, the results are consistent with FSC and analyst monitoring operating as substitute information mechanisms. When analyst following is low, greater comparability appears to play a more important informational role by facilitating cross-firm benchmarking, reducing information asymmetry, and helping outside investors detect unusual firm performance. When analyst coverage is high, analysts already perform substantial information-production and monitoring functions, reducing the incremental informational benefit of FSC. The formal coefficient-difference tests provide particularly strong support for this interpretation in the full international sample, although the evidence becomes weaker after excluding U.S. firms.

C3. Government Effectiveness

Panel C examines whether the association between FSC and future crash risk varies with government effectiveness. In the full sample (Panel C1), the coefficients on *FSC* for countries with above-median government effectiveness are -0.021 , -0.030 , -0.031 , and -0.022 across the four horizons. The coefficients are marginally significant for the cumulative $(t+1)$ to $(t+2)$ and $(t+1)$ to $(t+3)$ measures but statistically insignificant for the one-year and longest cumulative measures. For countries with government effectiveness at or below the yearly median, the corresponding coefficients range from -0.006 to -0.015 and are not statistically significant.

Importantly, however, the formal tests of differences in FSC coefficients between the high- and low-government-effectiveness groups are statistically insignificant across all four horizons. Thus, the differences in the statistical significance of individual subsample coefficients should not be interpreted as evidence that government effectiveness significantly moderates the relation between FSC and crash risk.

Panel C2 repeats the analysis after excluding U.S. firms. The FSC coefficients remain generally negative in both government-effectiveness groups, with some marginal significance in the low-government-effectiveness group for the cumulative (t+1) to (t+2) and (t+1) to (t+3) measures. However, none of the differences in coefficients between the two groups is statistically significant. The non-U.S. results therefore reinforce the conclusion that there is little evidence of systematic cross-country variation in the FSC–crash-risk relation according to government effectiveness. Taken together, these findings do not support either a strong substitution or complementarity relation between FSC and government effectiveness. Although FSC is negatively associated with crash risk in some government-effectiveness subsamples, the formal cross-group tests indicate that the magnitude of this relation does not differ significantly between stronger and weaker government institutional environments.

C4. Public Enforcement

Panel D examines whether the association between FSC and future crash risk varies with the strength of public enforcement. In the full sample (Panel D1), the coefficients on *FSC* in countries with public enforcement at or below the sample median are -0.031 ($t = -2.62$), -0.032 ($t = -2.14$), -0.035 ($t = -2.32$), and -0.033 ($t = -2.19$) across the four crash-risk horizons, respectively. Thus, FSC is consistently negatively and significantly associated with future crash risk in countries with relatively weak public enforcement. In contrast, the corresponding coefficients in countries with above-median public enforcement range from -0.002 to -0.007 and are statistically insignificant throughout.

Despite this difference in the significance of the subsample coefficients, none of the formal tests of coefficient differences between the high- and low-public-enforcement groups is

statistically significant. Accordingly, the subsample pattern is consistent with FSC playing a greater role where public enforcement is weaker, but the formal tests do not establish statistically significant moderation by public enforcement. The same pattern is observed after excluding U.S. firms (Panel D2). FSC remains negative and statistically significant in the low-public-enforcement group across all four horizons, with coefficients ranging from -0.031 to -0.035 , whereas the coefficients in the high-public-enforcement group remain small and statistically insignificant. Nevertheless, the coefficient differences between the two groups remain statistically insignificant across all horizons. Taken together, the public-enforcement results suggest that the negative association between FSC and crash risk is concentrated in weaker public-enforcement environments. However, because the formal tests of cross-group differences are statistically insignificant, this pattern should be interpreted as suggestive rather than as evidence that public enforcement systematically moderates the FSC–crash-risk relation.

Overall, the cross-sectional evidence is strongest for the firm-level information environment. FSC is more strongly associated with lower future crash risk among firms with lower insider ownership and lower analyst following. The insider-ownership results are particularly pronounced after excluding U.S. firms, whereas the analyst-following results provide strong evidence of coefficient differences in the full international sample. By contrast, although the subsample estimates for public enforcement suggest a stronger FSC effect in weaker-enforcement environments, the formal coefficient-difference tests do not establish systematic institutional moderation. Similarly, there is little evidence that government effectiveness significantly alters the relation between FSC and future crash risk. Collectively, the results suggest that FSC is particularly valuable when outside investors rely more heavily on publicly available accounting information and when alternative firm-level information-production mechanisms are relatively limited.

Table IA1: Sample construction – Cleaning procedure

	N	# of firms	# of countries
all observations in Worldscoop-Datastream merged sample during 1998-2024	1,025,119	75,513	92
<i>% drop relative to the original sample</i>	18.59%	19.57%	1.09%
exclude financial and utilities firms	834,600	60,734	91
<i>% drop relative to the original sample</i>	19.72%	8.15%	0.00%
exclude firms with total assets below US\$10 million	632,469	54,577	91
<i>% drop relative to the original sample</i>	8.42%	5.15%	25.00%
merge the crash risk measure	546,194	50,687	68
<i>% drop relative to the original sample</i>	25.95%	31.11%	3.26%
merge the financial statement comparability measure	280,226	27,194	65
<i>% drop relative to the original sample</i>	9.43%	7.85%	5.43%
exclude missing observations for all baseline variables	183,512	21,265	60
<i>% drop relative to the original sample</i>	0.03%	0.11%	16.30%
exclude countries with fewer than 50 firm-year observations	183,177	21,179	45

Table IA2 Effect of Financial Statement Comparability on Stock Price Crash Risk - Additional Cross-sectional analysis

Panel A - INSIDER									
Panel A1 - All Countries - The impact of FSC on future crash risk in high and low INSIDER subgroups									
FSC_t	<i>Diff. F-statistic</i>	$NCSKEW_{t+1}$		$NCSKEW_{t+1,t+2}$		$NCSKEW_{t+1,t+3}$		$NCSKEW_{t+1,t+4}$	
		<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		-0.008	-0.027**	-0.013	-0.043***	-0.016	-0.047***	-0.016	-0.046***
		(-0.82)	(-2.37)	(-1.07)	(-3.13)	(-1.31)	(-3.26)	(-1.25)	(-3.10)
		0.019 (1.46)		0.030 (2.18)		0.031 (4.49)**		0.030 (1.78)	
All controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²		0.048	0.060	0.104	0.112	0.130	0.144	0.155	0.173
Observations		82774	85727	60305	65851	58332	62944	52750	57034
Panel A2 - Excluding US firms - The impact of FSC on future crash risk in high and low INSIDER subgroups									
FSC_t	<i>Diff. F-statistic</i>	$NCSKEW_{t+1}$		$NCSKEW_{t+1,t+2}$		$NCSKEW_{t+1,t+3}$		$NCSKEW_{t+1,t+4}$	
		<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>	<i>Insider > Yearly industry median</i>	<i>Insider ≤ Yearly industry median</i>
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		-0.009	-0.042***	-0.014	-0.068***	-0.015	-0.066***	-0.015	-0.062***
		(-0.90)	(-3.39)	(-1.13)	(-4.43)	(-1.23)	(-4.27)	(-1.15)	(-3.88)
		0.033 (3.42)*		0.054 (7.30)***		0.051 (6.60)**		0.047 (5.75)**	
All controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²		0.042	0.050	0.088	0.096	0.110	0.121	0.130	0.148
Observations		75533	57986	53906	41423	52414	40732	47265	36811

Panel B – Analysts Following (LANALYST)									
Panel B1 - All Countries - The impact of FSC on future crash risk in high and low LANALYST subgroups									
		NCSKEW _{t+1}		NCSKEW _{t+1_t+2}		NCSKEW _{t+1_t+3}		NCSKEW _{t+1_t+4}	
		LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST
		> Yearly	≤ Yearly	> Yearly	≤ Yearly	> Yearly	≤ Yearly	> Yearly	≤ Yearly
		industry	industry	industry	industry	industry	industry	industry	industry
		median	median	median	median	median	median	median	median
<i>FSC_t</i>		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		0.016	-0.031***	0.011	-0.032***	0.009	-0.034***	0.014	-0.029**
		(1.32)	(-3.67)	(0.76)	(-3.07)	(0.59)	(-3.05)	(0.87)	(-2.49)
	<i>Diff.</i>		0.047		0.043		0.043		0.043
	<i>F-statistic</i>		(3.07)*		(4.68)**		(4.87)**		(6.17)**
All controls, excluding		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LNANLYSTS									
Country, industry, year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²		0.053	0.049	0.097	0.102	0.124	0.127	0.150	0.149
Observations		79595	103577	63106	74980	59768	73116	54576	66448
Panel B2 - Excluding US firms - The impact of FSC on future crash risk in high and low LANALYST subgroups									
		NCSKEW _{t+1}		NCSKEW _{t+1_t+2}		NCSKEW _{t+1_t+3}		NCSKEW _{t+1_t+4}	
		LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST	LANALYST
		> Yearly	≤ Yearly	> Yearly	≤ Yearly	> Yearly	≤ Yearly	> Yearly	≤ Yearly
		industry	industry	industry	industry	industry	industry	industry	industry
		median	median	median	median	median	median	median	median
<i>FSC_t</i>		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		0.004	-0.029***	-0.004	-0.031***	-0.002	-0.029**	0.004	-0.024**
		(0.28)	(-3.35)	(-0.26)	(-2.74)	(-0.10)	(-2.48)	(0.22)	(-2.00)
	<i>Diff.</i>		0.033		0.027		0.027		0.028
	<i>F-statistic</i>		(0.46)		(1.58)		(1.58)		(3.37)*
All controls, excluding		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LNANLYSTS									
Country, industry, year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²		0.047	0.040	0.086	0.080	0.109	0.099	0.135	0.115
Observations		55387	91882	41744	64772	40342	63728	36893	57775

Panel C - GOVEFF								
Panel C1 - All Countries - The impact of FSC on future crash risk in high and low GOVEFF subgroups								
	NCSKEW _{t+1}		NCSKEW _{t+1,t+2}		NCSKEW _{t+1,t+3}		NCSKEW _{t+1,t+4}	
	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤
	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>FSC_t</i>	-0.021 (-1.56)	-0.006 (-0.75)	-0.030* (-1.81)	-0.011 (-1.04)	-0.031* (-1.79)	-0.015 (-1.35)	-0.022 (-1.31)	-0.011 (-0.94)
<i>Diff.</i> <i>F-statistic</i>		0.015 (0.28)		0.019 (0.93)		0.016 (0.20)		0.011 (0.00)
All controls, excluding GOVEFF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.049	0.067	0.098	0.140	0.119	0.176	0.141	0.200
Observations	74227	108942	62448	75640	60172	72713	54198	66824
Panel C2 - Excluding US firms - The impact of FSC on future crash risk in high and low GOVEFF subgroups								
	NCSKEW _{t+1}		NCSKEW _{t+1,t+2}		NCSKEW _{t+1,t+3}		NCSKEW _{t+1,t+4}	
	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤	GOVEFF >	GOVEFF ≤
	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median	Yearly median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>FSC_t</i>	-0.024 (-1.61)	-0.012 (-1.41)	-0.030 (-1.63)	-0.021* (-1.91)	-0.031 (-1.63)	-0.020* (-1.76)	-0.018 (-0.94)	-0.016 (-1.35)
<i>Diff.</i> <i>F-statistic</i>		0.012 (0.00)		0.009 (0.01)		0.009 (0.00)		0.002 (0.25)
All controls, excluding GOVEFF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.047	0.043	0.089	0.093	0.109	0.114	0.128	0.132
Observations	59672	87597	49035	57487	47415	56658	42047	52623

Panel D - <i>PUBENF</i>								
Panel D1 - All Countries - The impact of FSC on future crash risk in high and low <i>PUBENF</i> subgroups								
	<i>NCSKEW</i> _{<i>t</i>+1}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+2}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+3}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+4}	
	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤
	Sample	sample	Sample	sample	Sample	sample	Sample	sample
	median	median	median	median	median	median	median	median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>FSC</i> _{<i>t</i>}	-0.002	-0.031***	-0.005	-0.032**	-0.007	-0.035**	-0.002	-0.033**
	(-0.18)	(-2.62)	(-0.43)	(-2.14)	(-0.57)	(-2.32)	(-0.17)	(-2.19)
Diff.		0.029		0.027		0.028		0.031
<i>F</i> -statistic		(0.51)		(0.21)		(0.39)		(0.14)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.061	0.050	0.126	0.096	0.164	0.119	0.194	0.139
Observations	84176	77978	74101	62050	67667	63005	61726	58017
Panel D2 - Excluding US firms - The impact of FSC on future crash risk in high and low <i>PUBENF</i> subgroups								
	<i>NCSKEW</i> _{<i>t</i>+1}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+2}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+3}		<i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+4}	
	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤	<i>PUBENF</i> >	<i>PUBENF</i> ≤
	Sample	sample	Sample	sample	Sample	sample	Sample	sample
	median	median	median	median	median	median	median	median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>FSC</i> _{<i>t</i>}	-0.008	-0.031***	-0.009	-0.032**	-0.006	-0.035**	-0.001	-0.033**
	(-0.74)	(-2.62)	(-0.68)	(-2.14)	(-0.44)	(-2.32)	(-0.04)	(-2.19)
Diff.		0.023		0.023		0.029		0.032
<i>F</i> -statistic		(0.18)		(0.00)		(0.02)		(0.00)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country, industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.050	0.050	0.104	0.096	0.136	0.119	0.164	0.139
Observations	48271	77978	42534	62050	38854	63005	35374	58017
This table presents cross-sectional analyses examining whether the relation between financial statement comparability and future stock price crash risk varies with firm-level insider ownership (<i>INSIDER</i>), analyst following (<i>LANALYST</i>), government effectiveness (<i>GOVEFF</i>), and public enforcement (<i>PUBENF</i>). The dependent variables are <i>NCSKEW</i> _{<i>t</i>+1} , <i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+2} , <i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+3} , and <i>NCSKEW</i> _{<i>t</i>+1:<i>t</i>+4} representing stock price crash risk over 1-, 2-, 3-, and 4-year periods. The main independent variable, <i>FSC</i> , is financial statement comparability in year (<i>t</i>). <i>INSIDER</i> is the proportion of shares held by insiders relative to total shares outstanding. <i>LANALYST</i> is the natural logarithm of one plus the number of analysts following the firm during the fiscal year. <i>GOVEFF</i> is the government effectiveness index. <i>PUBENF</i> is the public-enforcement index of Djankov et al. (2008). The <i>INSIDER</i> and <i>LANALYST</i> subsamples are partitioned by their respective yearly industry medians; <i>GOVEFF</i> is partitioned by the yearly median; and <i>PUBENF</i> is partitioned by the sample median. <i>Diff.</i> reports the difference in the estimated <i>FSC</i> coefficients between the high and low subsamples, and the <i>F</i> -statistic tests the statistical significance of this difference. All specifications include the indicated control variables and country, industry, and year fixed effects. Standard errors are clustered at the firm level. Detailed variable definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.								