Local FinTech Development and Stock Price Crash Risk

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Abstract

This study investigates the effect of financial technology (FinTech) development on stock price crash risk. We show that the development of FinTech can inhibit management from deliberately hiding bad news and alleviate information asymmetry, thereby reducing stock price crash risk. This effect is more pronounced among non-state-owned enterprises, firms with poor information environments and low-quality internal controls, and those in competitive industries and regions with high marketization. Overall, these findings suggest that the development of FinTech can mitigate the deliberate concealment of bad news by management and improve the timeliness of disclosure, leading to lower risks faced by investors.

Keywords: Local FinTech development; stock price crash risk; China

JEL: G10, G30

1. Introduction

Financial technology (FinTech) is technology-driven financial innovation, a new financial ecology outside the traditional financial system. FinTech development can substantially impact financial markets, financial institutions, and the delivery of financial services (Financial Stability Board, 2016). In recent years, the global market share of FinTech lenders has increased from approximately 3% in 2007 to 12% in 2015 (Buchak et al., 2018). The growth of FinTech investment by value is also significant, from $930 million in 2008 to $4.1 billion in 2013 (Athwal, 2016).[1] In China, FinTech has gradually expanded from microfinance in its infancy to integrated financial services, including payments, credit, and other services, which are gradually changing consumer lifestyles and business behaviors (Ding et al., 2022).[2]

Prior studies have mainly focused on the effects of FinTech on the macro-level. For example, the existing literature finds that FinTech can facilitate the systematic and transparent conduct of monetary policy (Bordo and Levin, 2017), boost employment (Acemoglu and Restrepo, 2018), increase population income (Hua et al., 2021), and promote the long-term growth of GDP per capita (Heiskanen, 2017; Kanga et al., 2022), thus increasing consumer spending (Li et al., 2020) and alleviating income disparity (Maskara et al., 2021; Demir et al., 2022). Furthermore, prior literature has also explored the impact of FinTech on banks and finds that information technology is an important factor driving the development of the banking industry (Berger, 2003). With its unique advantages in the network economy, the FinTech industry continuously weakens the role of commercial banks as financial intermediaries and reshapes the market competition landscape of the entire banking industry (Thakor 2020).[3]

Besides the macro-level research, there is an emerging stream of research investigating the effects of FinTech at the micro-level. This stream of research mainly focuses on the debt market and argues that FinTech can optimize credit resource allocation (Fuster et al., 2019; Cornelli et al., 2022). Additionally, this stream of research finds that FinTech can mitigate corporate financing constraints (Cheng et al., 2014) and improve corporate innovation capacity (Ding et al., 2022). However, the impact of FinTech on the capital market at the micro-level remains largely unexplored.

In this paper, we investigate whether the degree of local FinTech development affects a firm's stock price crash risk. Theoretically, there is an upper limit for firms to accommodate negative news. Once the accumulated negative information exceeds the upper limit, the management has to release such information in a concentrated manner, resulting in a substantial impact on the firm's stock price and triggering a share price crash (Jin and Myers, 2006). We argue that the rationale for how FinTech

[1] In 2014 alone, the growth of FinTech investment by value tripled in size to $12.2 billion and then almost doubled in 2015 to $22.3 billion. In 2017, FinTech firms raised $100.2 billion globally, four times the amount invested by venture capitalists (IOSCO, 2017). Ernst and Young (2017) also expects the global adoption rate of FinTech to reach 52% in 20 major global markets.

[2] The "Financial Technology Development Plan (2019–2021)," released by the People's Bank of China in August 2019, clarifies the positioning of FinTech for the first time, defining FinTech as an application of emerging technologies that requires the establishment of sound "four beams and eight pillars" for the development of FinTech in China by 2021.

[3] First, FinTech improves the information processing capabilities of commercial banks and widens the information gap between competitors (Hauswald and Marquez, 2003). Adopting FinTech can help banks gain greater market power and reduce competition in the banking industry (Hauswald and Marquez, 2003). Second, FinTech, however, allows data information to be widely disseminated and shared within the industry. Other competitors can access information at a low cost (Hauswald and Marquez, 2003). As a result, FinTech may reduce the market power of major banks and promote competition in the banking industry. In addition, the development of FinTech can bring significant positive technological spillovers to the banking industry, such as interest payment cost reductions and an improvement in banks' performances (Jagtiani and Lemieux, 2019; Tantri, 2021).

reduces stock price crash risk is twofold. First, FinTech is gradually penetrating all aspects of corporate production and operations, which can strengthen the ability of decision-makers to utilize soft information and mitigate information asymmetry (Fuster et al., 2019). For example, FinTech plays an information technology monitoring and governance role, which can help analysts make more accurate earnings forecasts (Cheng et al., 2016). Second, investors can use FinTech to detect the concealment of bad news by management at an early stage, which constrains managerial opportunistic behaviors (Zhu, 2019). Thus, we expect that the degree of local Fintech development is negatively associated with firms' stock price crash risk.

Using the number of FinTech firms in the firm's prefecture-level city as a proxy for the degree of local FinTech development, we find that local FinTech development can inhibit management's deliberate hiding of bad news, mitigate information asymmetry, and thus stabilize stock prices. Furthermore, we find that the stabilizing effect of FinTech on stock prices is more pronounced among non-state-owned enterprises (non-SOEs), firms with poor external information environments and low quality of internal controls, and those in competitive industries and regions with a high degree of marketization.

Our study makes two contributions. First, we complement the micro-level literature on the role of FinTech in the stabilization and development of capital markets and economies. The existing literature mainly explores the role of FinTech in overcoming information asymmetries, thereby reducing the intermediation costs of credit markets (Ntwiga, 2020), alleviating corporate financing constraints (Ding et al., 2022), and increasing firm value (Chen et al., 2019). Following the information asymmetry perspective, our study extends the literature to the stock market and reveals the role and mechanism of FinTech in stabilizing share prices.

Second, this study adds to the literature on managers' disclosure decisions regarding negative information. Prior literature documents that managers have opportunistic motives in suppressing negative information and pursuing their personal interests.[4] In particular, managers tend to hide bad news for extended periods of time, which eventually increases the risk of a collapse in the firm's stock price in the future. The existing literature documents several internal and external factors that restrict managers' ability to hide negative information.[5] Our study adds to this literature stream and reveals the important role of technology development in constraining managers' ability to conceal bad news deliberately. Our study provides supportive evidence on the role of FinTech development in disseminating and sharing information and improving the timeliness and transparency of corporate disclosures, thereby reducing the risk of share price callapse.

2. Hypothesis development

The existing literature on stock price crash risk is mainly built on Jin and Myers' (2006) bad news concealment hypothesis. Jin and Myer (2006) argue that a stock price crash is a sharp decline caused by a sudden outbreak of bad news that management has hidden for critical reasons, such as a waterfall of negative information. Based on this argument, a stream of literature explores whether and how the ability and motivation of managers to hide bad news influence the risk of stock price

[4] Managers may choose to hide negative information to avoid investors rejecting bad projects (Malmendier et al., 2011), pursue personal benefits such as excess allowances (Xu et al., 2014), and avoid reputational damage, termination risks, and even legal sanctions.

[5] These factors include, for example, improved accounting robustness (Kim and Zhang, 2016), improved internal controls (Kim et al., 2011; De Fond et al., 2015; Callen and Fang, 2017), high-quality external audits (Robin and Zhang, 2015; Li et al., 2022), and legal solid institutional safeguards (Ma Y, 2020).

collapse. For example, Malmendier et al. (2011) find that the decision-making power of firms tends to be concentrated in the hands of chief executive officers (CEOs). The concentration of decision-making power can therefore support their hoarding of bad news (Malmendier et al. 2011).

Following this line of reasoning, the literature documents that early disaster experience of CEOs (Chen et al., 2021) and local gambling preferences (Ji et al., 2021) are positively associated with managers' tolerance for the risk of hiding bad news. The stock price crash risk is also positively related to the political corruption environment (Chen et al., 2018) and the opacity of operating cash flows (Cheng et al., 2020). Conversely, increased accounting robustness limits the ability of managers to exaggerate performance and conceal bad news, leading to a lower risk of a stock price crash (Kim and Zhang, 2014).[6] In addition, some external factors may encourage managers to disclose bad news promptly, thus reducing the risk of share price collapse. Chowdhury et al. (2020) find that external labor market incentives encourage CEOs to value their long-term reputation and provide timely disclosure of news, including bad news. (Chowdhury et al., 2020). In addition, the mandatory adoption of Extended Audit Reports (EARs) and International Financial Reporting Standards (IFRS) can encourage managers to disclose bad news before the auditor reports are released (DeFond et al., 2015; Li et al., 2022).

In addition to the above external factors, FinTech enables firms to collect information in more dimensions via the Internet and big data technology. The information is analyzed by artificial intelligence, cloud computing, and blockchain, which enables firms to centralize a large amount of data to solve their most critical information asymmetry problems (Lapavitsas and Dos Santos, 2008). The literature shows that FinTech can use these comparative advantages in information technology to empower traditional financial institutions (Lin et al., 2013; Huang et al., 2018), help external investors access soft information more easily (Mocetti et al., 2017), and improve the ability of banks to screen borrowers (Berg, 2020). Furthermore, FinTech can capture unstructured corporate data such as news images, video, and audio from multiple levels and channels and perform structured transformations, intelligent classifications, and real-time intelligent monitoring of structured data of the supply chain. Investors can also use FinTech and investment signals to improve the accuracy and quality of existing information in the stock market (Grennan and Michaely, 2021) and enrich the understanding of existing information to improve the efficiency of financial market investment (Fuster et al., 2019).

Along with the development of FinTech, governments and other regulatory authorities can also reduce regulatory costs and improve regulatory transparency and efficiency. In an enhanced regulatory environment, regulatory authorities are more efficient in detecting the behaviors of managers who are hiding bad news (Zhu, 2019). Altogether, we expect that the development of FinTech will increase costs and weaken opportunistic motives for managers to suppress bad news, leading to a lower risk of stock price collapse. Accordingly, our hypothesis is stated as follows:

***H*₁**: *The degree of local FinTech development is negatively associated with a firm's stock price crash risk.*

[6] From the perspective of agency, performance pressure is a strong motivation for managers to hide bad news (Chen et al., 2019), especially for young CEOs (Andreou et al., 2017). In addition, managers may adjust their corporate and disclosure decisions to meet the needs of other stakeholders and the regulatory environment. For example, managers may increase stock liquidity to attract more temporary institutional investors. However, temporary institutional investors focus short-term on performance, encouraging managers to hoard bad news (Chang et al., 2017).

3. Sample and research design

3.1 Sample construction

Our sample begins with all A-share listed firms available from the China Stock Market and Accounting Research (CSMAR) database from 2005 to 2019, with a supplement from the Wind database for missing information. Macro-level data is from the China Economic Information Network (CEINET) statistics database and the China Statistical Yearbook. The samples are processed as follows: (1) firms from finance and insurance industries are excluded; (2) ST and PT listed companies are excluded; (3) firms with operating revenue of less than 50 million are excluded; (5) the observations that have missing values for the main variables are excluded. The final sample consists of 23,593 firm-year observations, with 2,891 A-share listed firms. To eliminate the undue influence of outliers, we winsorize the top and bottom one percentile of all continuous variables.

3.2 Research design and variable measurement

We first use the following regression model to test the relationship between the level of FinTech development and the stock price crash risk of listed firms:

$$NCSKEW_{it}/DUVOL_{it} = \alpha_0 + \alpha_1\, Fintech_{it} + \alpha_2 Controls + i.Industry + i.Year + \varepsilon_{it} \quad (1)$$

where the subscript *i* denotes the firm, *t* denotes the year, $NCSKEW_{it}$ and $DUVOL_{it}$ are measures of stock price crash risk; *Fintech* is the degree of financial technology development; *Controls* is the ensemble of control variables;[7] *Industry* represents industry fixed effects; *Year* denotes year fixed effects; ε_{it} is the error term. The variable of interest is *Fintech,* and the coefficient α_1 represents the marginal impact of FinTech on the stock price crash risk. We define *Fintech* as the natural logarithm of the number of FinTech firms at the local and municipal levels. We use the natural logarithmic treatment to reduce the effect of the left-skewed or right-skewed characteristics of the number of FinTech firms. Following the prior literature (Hutton et al., 2009; Kim et al., 2011), we employ the negative return skewness coefficient (*NCSKEW*) and earnings up and down ratio (*DUVOL*) to measure stock price crash risk.[8]

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[7] Control variables include firm size (*Size*), firm age (*ListAge*), gearing (*Lev*), profitability (*ROA*), growth (*Growth*), operating cashflow (*Cashflow*), firm social wealth creativity (*TobinQ*), equity checks and balances (*Balance*), the level of economic development of the municipality where the firm is located (*G_ Gdp*), and the size of the local municipality (*Pop*).

[8] First, we use model (2) to compute the market-adjusted return of stock for firm *i* by using weekly return data of stock *i*:

$$\mathrm{R}_{i,t} = \alpha_0 + \beta_{1,i}\,\mathrm{R}_{m,t-2} + \beta_{2,i}\,\mathrm{R}_{m,t-1} + \beta_{3,i}\,\mathrm{R}_{m,t} + \beta_{4,i}\,\mathrm{R}_{m,t+1} + \beta_{5,i}\,\mathrm{R}_{m,t+2} + \varepsilon_{i,t}$$

$$R_{i,t} = \alpha_0 + \beta_1 R_{m,t-2} + \beta_2 R_{m,t-1} + \beta_{3,i} R_{m,t} + \beta_{4,i} R_{m,t+1} + \beta_{5,i} R_{m,t+2} + \varepsilon_{i,t} \quad (2),$$

where $R_{i,t}$ is the return of listed firm *i* in week t considering cash dividend reinvestment, and $R_{m,t}$ is the average return of all stocks of A-share listed firms weighted by market capitalization outstanding in week *t*. In addition, lagged and ahead terms of market returns are added to the model to adjust for the effect of non-synchronous stock trading (Dimson, 1979). The final return specific to stock *i* in week *t* is calculated from the residual ε_{it} of model (2) as:

$$\mathrm{W}_{i,t} = \ln\left((1 + \varepsilon_{i,t}\right) \quad (3)$$

We then construct the main dependent variables $NCSKEW_{it}$ and $DUVOL_{it}$ based on $W_{i,t}$. $NCSKEW_{it}$ is estimated using model (4) as follows:

$$NCSKEW_{it} = -\left[n(n-1)^{\frac{3}{2}} \sum \mathrm{W}_{i,t}{}^{3}\right] \Big/ \left[(n-1)(n-2)\left(\sum \mathrm{W}_{i,t}{}^{2}\right)^{\frac{3}{2}}\right] \quad (4),$$

where *n* is the number of trading weeks of firm *i* per year, and, finally, the negative skewness of the market-adjusted weekly return of stock *i*. The larger the value of *NCSKEW*, the greater the risk of stock price collapse.

Next, we estimate DUVOL using model (5) as follows:

$$DUVOL_{it} = \ln\left\{\left[(n_u - 1)\sum\nolimits_{down} W_{i,t}{}^{2}\right] \Big/ \left[(n_d - 1)\sum\nolimits_{up} W_{i,t}{}^{2}\right]\right\} \quad (5),$$

where n_u is the number of weeks in which the weekly unique return $W_{i,t}$ is greater than the annual average return W_i, and n_d is the number of weeks in which the weekly unique return $W_{i,t}$ of stock *i* is less than the annual average return W_i. The larger the value of *DUVOL,* the greater the risk of stock price collapse.

4. Main empirical results

4.1 Descriptive statistics

We report descriptive statistics for the variables used in the analysis in Table 1. The mean values of the stock price crash risk indicators (*NCSKEW* and *DUVOL*) are -0.322 and -0.220, respectively, while the standard deviations are 0.701 and 0.471. These figures suggest that stock price crash risks vary significantly among our sample firms. The mean (median) for the level of FinTech development is 3.593 (3.135). Consistent with prior literature, the median of the FinTech development level indicators measured by the number of FinTech companies is closer to the mean after the logarithmic treatment. Other control variables have similar characteristics to results from previous studies.

[Table 1 about here]

4.2 Baseline regression

Table 2 presents the results for the effect of the level of FinTech development on share price stability using model (1). The results in Table 2 show that *Fintech* is negatively associated with *NCSKEW* (α_1 = -0.0072, *t*-stat = -2.8487) and *DUVOL* (α_1 = -0.0044, *t*-stat = -2.5982). These results support our hypothesis and indicate that the development of FinTech significantly reduces the risk of share price collapse and improves firms' share price stability.

[Table 2 about here]

4.3 Robustness tests

4.3.1 Excluding the effect of omitted variables

During the sample period, the level of FinTech development may be correlated with a series of event shocks, which are difficult to eliminate completely.[9] In order to reduce the endogeneity of these events, we adopt the permutation tests (Fisher, 1935; Ludbrook and Dudley, 1998) to test whether the level of FinTech development directly affects the stability of firms' stock prices.

We first rearrange data from different years within our sample. Subsequently, we simulate model (1) 1000 times, controlling fixed effects for the broad industry categories (*Ind FE (1)*) and three-digit industry code (*Ind FE (3)*). Table 3 Panel A shows that for *NCSKEW*, only four and 11 times in the 1000 repetitions of the simulation have coefficients smaller than the previously obtained benchmark coefficients. Similarly, for *DUVOL*, only seven times and 15 times have coefficients smaller than the results obtained from the benchmark regression. The above findings suggest that the reduction in stock price crash risk for our sample is more directly related to the increase in FinTech development than the effects of co-existing events.

Prior literature suggests that omitted variables are an important source of endogeneity. There are many other factors that may impact the risk of the stock price collapse. Following Oster (2019), we re-estimate model (1) using a linear probability model to discover the confidence interval of the true β.[10] We expect that the new R^2 of model (1) will change to 1.3 times the original R^2 after introducing omitted variables. Additionally, the effects of omitted variables on dependent variables

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[9] During the sample period, a series of event shocks occurred, such as the Global Financial Crisis, the dramatic development of artificial intelligence, and the popularity of big data. There are concerns that our results may be simultaneous with other events that are not observed in this study.

[10] Oster (2019) argues that when a model has unobservable omitted variables, a consistent estimate of the true coefficients can be obtained using the estimator $\beta^* = \beta^* (R_{max}, \delta)$, where R*max* refers to the maximum goodness of fit of the regression equation if the unobservable omitted variables can be observed; δ is the selection ratio, which measures the strength of the correlation between the observable variable and the variable of interest compared with the correlation between the unobservable omitted variable and the variable of interest.

are at least as significant as the effect of the model's observed variables. Based on the true β values reported in Table 3 Panel B, we find that the true β values are within the original 99.5% confidence interval, indicating that no omitted variable is as important as the explanatory variables in our regression model. Furthermore, we find that when β is zero, δ is 2.58 or more. These results suggest that if omitted variables lead to biased estimations, the omitted variables should be about 2.58 times more important than the currently observed control variables. Altogether, these results indicate that the problem of omitted variables is unlikely to significantly impact our main results, reported in Table 2.

[Table 3 about here]

4.3.2 Instrumental variables method

We select two instrumental variables for FinTech development to further address the endogeneity concern. We first follow Bartik (2006) to construct the share shift method instrumental variable (*IVFin*).[11] Our second instrumental variable is the number of Internet users at the local and municipal levels (*Internet*). Results in Table 4 remain robust after using the instrumental variable approach to mitigate the endogeneity problem.

[Table 4 about here]

4.3.3 Replacement of explanatory and explained variables

Prior literature also measures stock price crash risk in different ways. Following Callen and Fang (2015) and Hutton et al. (2009), we define a dummy variable for crash risk (*Crash*) equal to one if the unique weekly returns ($W_{i,t}$) of a firm's stock is below the mean of its distribution by 3.09 standard deviations and zero otherwise. We then regress *Crash* on the variable of interest and control variables using fixed-effects, Logit, and Probit models. The results reported in Table 5 Panel A show that *Fintech* is negatively associated with *Crash*, consistent with the main results.

Next, we replace the variable of interest in *Fintech* with two alternative measures of the level of FinTech development, namely the Peking University Digital Inclusive Finance index (*Index*) and the breadth of coverage (*Coverage*).[12] The results reported in Table 5 Panel B show that both *Index* and *Coverage* are negatively associated with crash risk at least at the 10% level, consistent with the results from the baseline regression.

[Table 5 about here]

5. Tests of possible mechanisms and heterogeneity

5.1 Tests of managerial bad-news hoarding

Prior research argues that information manipulation and information asymmetry are the main contributors to a stock price collapse. When negative news accumulates to a certain threshold, the bad news will be released centrally, leading to a severe negative impact on the firm's stock price (Jin and Myers, 2006). In addition, Andreou et al. (2017) suggest that an unexpected interruption in continuous earnings growth implies a sudden disclosure of bad news. Therefore, we further examine whether the development of FinTech may encourage managers to disclose bad news promptly and prevent them from manipulating earnings and hoarding bad news.

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[11] We use the growth rate of the number of national FinTech firms multiplied by the number of regional FinTech firms lagged by one period and then take the natural logarithm to simulate the estimated level of regional FinTech development in all years.

[12] *Index* is the Peking University Digital Inclusive Finance Index, which is based on structured data of representative FinTech firms' transactions (Guo et al., 2020). *Coverage* consists of following elements: (1) the number of Alipay accounts per 10,000 people; (2) the proportion of Alipay card-tied users; and (3) the average number of bank cards tied to each Alipay account. *Coverage* is correlated with the local economy but is not directly affected by firm-level factors.

First, we test the effect of FinTech development on management disclosure behaviors in relation to bad news using three dummy variables, namely *CRASH_BREAK_STRING1*, *CRASH_BREAK_STRING2*, and *SURP_UE.*[13] The results reported in Columns (1) through (3) in Table 6 suggest that FinTech development can significantly reduce the risk of a tendency by management to hide bad news and then suddenly release it in the future.

Second, we test whether the development of FinTech will improve earnings quality and information transparency.[14] Prior studies find that firms tend to engage in earnings manipulation to hide bad news (Zhu, 2016). With bad news accumulating, managers eventually need to restate earnings to their intrinsic value because releasing bad news may increase the probability of future stock price collapse (Kim and Zhang, 2014). Furthermore, Ertugrul et al. (2017) find that firms with high information asymmetry are usually more vulnerable to stock price crashes due to low financial reporting quality. Consistent with the prior literature, the results presented in Columns (4) to (6) show that the development of FinTech can significantly improve accrual quality, reduce the likelihood of restatement, and improve information transparency. These results further support that FinTech development can motivate management to disclose bad news as early as possible, thus improving stock price stability.

[Table 6 about here]

5.2 Cross-sectional heterogeneity

5.2.1 Company ownership and internal control

In China, state-owned enterprises (SOEs) are fundamentally different from non-SOEs. Thus, it is warranted to examine whether the role of FinTech development in reducing crash risks varies across SOEs and non-SOEs. The results in Columns (1) to (4) in Table 7 Panel A show that FinTech development mainly reduces the risk of stock price collapse for non-SOEs. Our results are consistent with the notion that SOEs are strictly regulated compared to non-SOEs. Therefore, an SOE's management has fewer incentives to hide bad news (Jiang and Kim, 2015). As a result, FinTech plays a less significant role in mitigating agency problems and information asymmetry for SOEs, leading to a lower impact on stock price crash risk.

Internal control quality is another important mechanism that can restrain management's opportunistic behaviors. The severity of agency problems and information asymmetry varies among firms with different levels of internal control quality. Accordingly, we expect that the relationship between FinTech development and crash risk varies across firms with different degrees of internal control quality. We divide our sample into two sub-samples based on the annual median of the internal control index (*IC index*).[15] The results reported in Columns (5) through (8) in Table 7 Panel A suggest

[13] *CRASH_BREAK_STRING1* is assigned to 1 if the firm experiences a stock price crash in the current year and its earnings decrease in the current year but increased in the previous year. *CRASH_BREAK_STRING2* is assigned a value of 1 if the firm's earnings decreased in the year of the crash but increased in the previous two years. *SURP_UE* is assigned a value of 1 if a firm's windfall in year t is in the bottom decile and non-negative in year t-1. Following Kothari et al. (2006), we calculate a firm's windfall as the change in income before extraordinary items in years t and t-1 divided by the market value of equity in year t-1.

[14] We use discretionary accruals from Jones' (1991) model (*DA*) and the likelihood of financial restatements as proxies for earnings quality (*Restate*). We measure the information transparency indicator (*ASY*) as extracting the first principal components of the liquidity ratio (*LR*), the illiquidity ratio (*ILL*), and the yield reversal indicator (*GAM*). The larger the value of *ASY*, the lower the information transparency.

[15] We use the Diebold China Listed Companies Risk Control Evaluation Index to measure the quality of corporate internal control. The index is derived from the construction and evaluation of the index system by setting 65 secondary indicators from the five core elements of internal control: internal environment, risk assessment, control activities, information and communication, and internal oversight.

that the stabilizing effect of FinTech development on stock price is significant for firms with low-quality internal controls but insignificant for firms with relatively high-quality internal controls.

5.2.2 Information environment

Good information environments reduce information asymmetry between investors and firms (Hutton et al., 2009). As information transmitters in the capital market, financial analysts use their expertise to collect and interpret firms' information and share it with market participants. Existing research suggests that high analyst coverage is positively associated with a better information environment. Therefore, we expect that the impact of FinTech development on stabilizing stock prices is more pronounced among firms with less analyst coverage. In Panel B of Table 7, we find that FinTech development plays a more significant role in stabilizing stock prices for firms with less analyst coverage compared with those with high analyst attention and better information environments. Overall, the results provide further evidence of the path of information asymmetry through which local FinTech development impacts stock price stability.

5.2.3 Agency issues

We use management expense ratios and management ownership as proxies for firms' agency problems.[16] A higher management expense ratio and lower management ownership imply the possibility of a higher degree of deviation from the interests of shareholders and greater agency problems. We divide our sample based on the median values of the annual distribution of these two variables and re-estimate the regression model. The results in Panel C in Table 7 show that the effect of FinTech development on reducing stock price crash risk is significant for firms with high management expenses and low management ownership, while the FinTech effect is insignificant for those with low management expenses and high management ownership. These results show that FinTech development can reduce agency costs by alleviating the agency problem between shareholders and managers, thus suppressing the risk of stock price collapse.

5.2.4 Industry and regional effects

The degree of competition in a firm's industry is an important external governance mechanism. Firms in competitive industries are likely to hide negative information in order to avoid being at a disadvantage. However, managerial decisions to hide negative information from their peers are likely to cause severe information asymmetry (Verrecchia, 1983). Furthermore, these decisions bring greater external pressure on management when making corporate decisions and induce managers to behave more aggressively. To investigate whether the effects of FinTech development on crash risk vary across competitors within an industry, we use the Lerner index as a proxy for industry competition and divide our sample based on the annual median value of the index. The results presented in Columns (1) through (4) of Panel D in Table 7 suggest that FinTech development is more capable of stabilizing stock prices for firms in more competitive industries.

In addition, the degree of marketization indicates the level of regional economic development and competition within an industry.We divide our sample based on the annual median values of the marketization index of a firm's region. The results presented in Columns (5) through (8) of Panel D in Table 7 show that coefficients on *Fintech* are significantly larger for firms located in high marketization regions than for those in low marketization regions. In particular, the coefficients on *Fintech* are insignificant for firms located in regions with low marketization, with a magnitude close

[16] We measure the management expense ratio as management expenses divided by main business income.

to zero. Overall, these results reveal the effects of FinTech development in stabilizing stock prices are more pronounced in highly competitive environments.

[Table 7 about here]

6. Conclusion

The development of FinTech has given rise to a series of new financial business models and has dramatically changed human social life. This study uses the stock market as a setting to explore the impact of FinTech on an important dimension of market stability, namely, stock price crash risk. We find that FinTech can suppress the risk of stock price crashes by alleviating the information asymmetry between firms and investors and constraining managerial bad-news hoarding, thereby improving information environments. These findings are robust after a variety of additional tests.

The cross-sectional heterogeneity tests find that the degree of FinTech development has a more significant dampening effect on the risk of stock price collapse when firms are non-SOEs. Furthermore, we find that the effects of FinTech development on stock price stabilization are more pronounced in firms with relatively low internal control quality and poor external information environments and in firms in highly competitive industries and in regions with a high degree of marketization. Overall, the findings support the positive role of FinTech development in stabilizing the capital market and provide novel evidence on how to develop FinTech in an orderly manner, which can accelerate the empowerment of traditional financial institutions and promote the development of the economy.

Appendix: Definitions of variables

Variables	Description
Dependent variables	
Negative return skewness coefficient (*NCSKEW*)	See equation (4) for the specific calculation
Earnings up/down ratio (*DUVOL*)	See equation (5) for the specific calculation
Independent variables	
Financial technology development level (Fintech)	The natural logarithm of the number of local FinTech firms plus one
Firm size (*Size*)	The natural logarithm of market capitalization
Firm age (*Age*)	The natural logarithm of the number of years since the establishment of the business
Leverage (*Lev*)	The ratio of total debt over total assets
Return on assets (*ROA*)	Net profits divided by total assets
Operating income growth rate (*Growth*)	Difference between current year's operating income and prior year's operating income divided by prior year's operating income
Operating cash flow (Cashflow)	Net cash flow from operating activities divided by total assets
Corporate social wealth creativity (*TobinQ*)	(Market value of outstanding shares + number of non-marketable shares × net assets per share + book value of liabilities)/total assets
Proportion of shares held by institutional investors (*INST*)	Total number of shares held by institutional investors divided by the outstanding share capital
Local municipality economic development level (G_GDP)	GDP growth rate at the local and municipal level
Local municipality size (*Pop*)	Natural logarithm of the total population at the local and municipal levels

Table 1 Summary statistics

The descriptive statistics for the variables utilized in the analysis are shown in this table. The appendix contains a list of the variables' definitions.

Variable	Obs	Mean	SD	Min	Median	Max
NCSKEW	23593	-0.322	0.701	-2.428	-0.281	1.619
DUVOL	23593	-0.220	0.471	-1.381	-0.218	0.981
Fintech	23593	3.593	2.592	0.000	3.135	10.302
Size	23593	22.100	1.274	19.838	21.909	26.135
ListAge	23593	2.205	0.672	0.693	2.303	3.258
Lev	23593	0.452	0.202	0.060	0.454	0.888
ROA	23593	0.039	0.061	-0.226	0.036	0.211
Growth	23593	0.166	0.373	-0.531	0.109	2.253
Cashflow	23593	0.049	0.071	-0.159	0.048	0.248
TobinQ	23593	1.949	1.188	0.878	1.551	7.682
INST	23593	0.372	0.243	0.000	0.372	0.879
G_GDP	23593	9.756	3.263	3.210	8.950	17.810
Pop	23593	6.414	0.695	4.307	6.482	8.111

Table 2 Baseline regression

The impact of the FinTech sector's level of development on the risk of a crash in listed companies' stock prices is reported in this table using regression analysis. The *NCSKEW* and *DUVOL* definitions refer to equations (4) and (5) in the text, and the appendix contains definitions for all other variables. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1) *NCSKEW*	(2) *DUVOL*
Fintech	-0.0072***	-0.0044***
	(-2.8487)	(-2.5982)
Size	0.0086	-0.0056
	(1.5506)	(-1.4861)
Lev	-0.0057	0.0037
	(-0.1810)	(0.1749)
ROA	-0.0049	-0.0200
	(-0.0478)	(-0.2991)
Growth	-0.0260**	-0.0324***
	(-1.9872)	(-3.7961)
Cashflow	0.0192	0.0266
	(0.2709)	(0.5587)
TobinQ	0.0009	-0.0089**
	(0.1779)	(-2.4952)
INST	0.1460***	0.1169***
	(6.1158)	(7.3579)
ListAge	-0.0398***	-0.0197***
	(-5.0304)	(-3.7088)
G_GDP	-0.0016	-0.0028*
	(-0.6955)	(-1.7447)
Pop	0.0129*	0.0099*
	(1.6823)	(1.9158)
Constant	-0.5163***	-0.0976
	(-4.0559)	(-1.1382)
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
N	23592	23592
R^2	0.0540	0.0543

Table 3 Robustness tests: excluding the effect of omitted variables

Panel A: Permutation tests

The results of the permutation test are presented in this table. *Ture_beta* is the regression coefficient from the baseline regression; *Test< Ture* is the proportion of 1000 simulated regressions in which the regression coefficient is smaller than the true regression coefficient and is consistent with the baseline regression; *Ind FE(1)* is the control for broad industry categories, and *Ind FE(3)* is a classification by three-digit industry code. The baseline regression controls for industry and year fixed effects.

	(1) *NCSKEW*	(2) *DUVOL*	(3) *NCSKEW*	(4) *DUVOL*
Ture_Beta	-0.0082***	-0.0052***	-0.0072***	-0.0044***
Test< Ture	4	7	11	15
Year FE	YES	YES	YES	YES
Ind FE(1)	YES	YES	NO	NO
Ind FE(3)	NO	NO	YES	YES

Panel B: Oster tests

The Oster test results are presented in this table. *Uncontrolled* and *Uncontrolled R2* are the respective regression coefficients without control variables and R^2, whereas *Controlled* and *Controlled R2* are the respective regression coefficients with control factors included. The last line "δ for β=0" indicates that the number of times the omitted variable should be as important as the current control variables so that the true value of β is equal to zero.

	(1) *NCSKEW*	(2) *DUVOL*	(3) *NCSKEW*	(4) *DUVOL*
Uncontrolled β	-0.0075 ***	-0.0030 **	-0.0075 ***	-0.0030 **
Uncontrolled R^2	0.001	0.000	0.001	0.000
Controlled β	-0.0082 ***	-0.0052***	-0.0072***	-0.0044***
Controlled R^2	0.047	0.048	0.054	0.054
99.5% CI	[-0.015, -0.001]	[-0.001, -0.001]	[-0.014, -0.000]	[-0.010, 0.000]
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Ind FE(1)	YES	YES	NO	NO
Ind FE(3)	NO	NO	YES	YES
"Ture"β	-0.0088	-0.0072	-0.0069	-0.0058
δ *for* β*=0*	3.7471	20.8118	2.5807	6.8342

Table 4 Robustness tests: Instrumental variables method

The results of the two-stage regression utilizing the instrumental variables approach are presented in this table. The share shift method instrumental variable, *ivFin*, uses the natural logarithm to simulate estimates of the rate of regional FinTech development over time. It does this by multiplying the growth rate of the number of national FinTech companies by the number of regional FinTech companies lagged by one order. The number of people who have local or municipal access to the Internet is known as *Internet*. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1) Fintech	(2) NCSKEW	(3) DUVOL	(4) Fintech	(5) NCSKEW	(6) DUVOL
IVFin	1.087***					
	(653.43)					
Internet				1.617***		
				(113.00)		
Fintech		-0.007***	-0.004**		-0.426*	-0.381**
		(-2.70)	(-2.56)		(-1.66)	(-2.17)
Controls	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
N	11182	4787	8009	7960	8009	7960
First-stage F		424219			16089.3	
Partial R^2		0.9511			0.3544	

Table 5 Robustness tests: Alternative variable measurement

Panel A: Alternative measures of stock price crash risk

The results of the regressions with the explained variables replaced are presented in this table. The explained variables in the regressions are dummy variables, and the unique weekly return $W_{i,t}$ of a company's stock for a week in a year is taken as 1 if it is 3.09 standard deviations below the mean of its distribution; if this criterium is not met, it is taken as 0. The fixed effects model, logit model, and probit model are used in columns (1) through (3), respectively. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1) *Crash*	(2) *Crash*	(3) *Crash*
Fintech	-0.0019*	-0.0209*	-0.0107*
	(-1.7480)	(-1.7705)	(-1.7349)
Controls	YES	YES	YES
Year fixed effects	YES	YES	YES
Industry fixed effects	YES	YES	YES
N	23593	23591	23591
R^2	0.0235	0.0387	0.0388

Panel B: Alternative measures of FinTech development

The results of the regressions with no explanatory variables are presented in this table. The Peking University Digital Inclusion Index's composite index is represented in columns (1) and (2), and its separate indices for the index's breadth of coverage are represented in columns (3) and (4). The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1) *NCSKEW*	(2) *DUVOL*	(3) *NCSKEW*	(4) *DUVOL*
Coverage	-0.0780**	-0.0486**		
	(-2.1947)	(-2.0642)		
Index			-0.0857*	-0.0572*
			(-1.6972)	(-1.7153)
Controls	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
N	17147	17147	17147	17147
R^2	0.0318	0.0299	0.0317	0.0298

Table 6 Tests of possible mechanism

The regression results of the mechanism test are presented in this table. Columns (1) through (3) are direct tests using the logit model, where *CRASH_BREAK_STRING1* is assigned a value of 1 if the firm experienced a stock price crash in the year and the firm's earnings decreased in the year but increased in the previous year; similarly, *CRASH_BREAK_STRING2* is assigned a value of 1 if the firm's earnings decreased in the year of the stock price crash but increased in the previous two years. In addition, we calculate a company's "windfall" as the change in income before extraordinary items in years t and t-1 divided by the market value of equity in year t-1. If a company's windfall is in the bottom decile in year t and non-negative in year t-1, then *SURP_UE* is assigned a value of 1. Columns (4) through (6) are indirect tests where the accrued surplus manipulation (*DA*) is calculated by the modified Jones' model, where financial restatement (*Restate*) is a dummy variable that takes the value of 1 if the company makes a financial restatement in the current year, and the information transparency indicator *ASY* is extracted from the liquidity ratio LR, non-liquidity ratio ILL, and return ratio ILL by referring to the method of Bharath et al. (2009). The first principal component of the liquidity ratio ILL and the yield reversal indicator GAM are extracted to construct a comprehensive indicator of information transparency *ASY*, where a larger value means lower information transparency. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRASH_BREAK_STRING1	*CRASH_BREAK_STRING2*	*SURP_UE*	*DA*	*Restate*	*ASY*
Fintech	-0.0485**	-0.0462*	-0.0440**	-0.0011***	-0.0219**	-0.0027***
	(-2.4301)	(-1.7193)	(-2.2913)	(-7.6095)	(-2.1763)	(-3.9597)
Size	0.0900*	0.2588***	0.3599***	0.0044***	-0.0705***	-0.2129***
	(1.8413)	(4.1733)	(8.9864)	(13.4374)	(-3.1197)	(-139.6261)
Lev	-0.5182**	-0.8430**	-0.0307	-0.0093***	0.3413***	0.1720***
	(-2.0867)	(-2.4105)	(-0.1425)	(-5.1423)	(2.8500)	(20.4353)
ROA	-3.1218***	0.4440	-11.2536***	0.9939***	-1.6250***	-0.3321***
	(-4.5950)	(0.3977)	(-18.9718)	(179.3795)	(-4.5009)	(-12.8710)
Growth	-1.4684***	-1.7544***	-2.6301***	-0.0212***	0.2239***	0.0146***
	(-6.9761)	(-5.4669)	(-14.9536)	(-28.5393)	(4.7906)	(4.2473)
Cashflow	-1.9462***	-1.5741*	-1.0209*	-1.0246***	-0.3357	-0.0379**
	(-3.2729)	(-1.8332)	(-1.8974)	(-247.9715)	(-1.2052)	(-1.9631)
TobinQ	-0.0303	-0.0346	-0.3104***	-0.0005*	0.0023	-0.1013***
	(-0.5864)	(-0.6132)	(-4.9873)	(-1.6977)	(0.1128)	(-74.1908)
INST	-0.4504**	-0.3258	-0.9729***	0.0041***	-0.2798***	0.2732***
	(-2.2375)	(-1.1856)	(-5.6259)	(3.0205)	(-3.0168)	(43.2596)
ListAge	-0.3602***	0.0029	-0.7872***	-0.0007	-0.0071	-0.0258***
	(-5.7629)	(0.0376)	(-13.0592)	(-1.4852)	(-0.2270)	(-12.1372)
G_GDP	-0.0007	0.0155	-0.0026	-0.0002	0.0202**	-0.0032***
	(-0.0376)	(0.5744)	(-0.1642)	(-1.1970)	(2.1154)	(-4.8525)
Pop	0.1494**	0.2357***	0.0371	0.0002	-0.0483	0.0129***
	(2.2865)	(2.8501)	(0.6574)	(0.4710)	(-1.5759)	(6.0770)
Constant	-4.7431***	-9.7005***	-9.8969***	-0.0672***	0.2909	4.7470***
	(-4.1173)	(-6.3370)	(-9.5933)	(-8.9301)	(0.5074)	(135.6091)
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
N	23553	23160	23372	23067	23568	21633
R^2	0.0794	0.0843	0.2032	0.7749	0.0336	0.6933

Table 7 Tests of cross-sectional heterogeneity

Panel A: Company characteristics

The regression results of the impact of FinTech on the risk of stock price collapse are presented in this table. Columns (1) through (4) compare the impact of FinTech on state-owned and non-state-owned firms, where the explained variable in columns (1) and (2) is *NCSKEW* and in columns (3) and (4) *DUVOL*; columns (5) through (8) compare the impact of FinTech on firms with high and low internal control quality, where we define a firm as a firm with high internal control quality when its internal control index score is higher than the median value of total assets for the corresponding year and industry; if this criterium is not met, the firm is classified as a firm with low internal control quality, where the explained variable in columns (5) and (6) is *NCSKEW* and in columns (7) and (8) *DUVOL*. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SOEs	*non-SOEs*	*SOEs*	*non-SOEs*	*High IC index*	*Low IC index*	*High IC index*	*Low IC index*
Fintech	-0.0032	-0.0083**	-0.0026	-0.0046*	-0.0022	-0.0119***	-0.0006	-0.0082***
	(-0.8769)	(-2.3261)	(-1.0604)	(-1.9592)	(-0.6698)	(-3.0670)	(-0.2500)	(-3.2625)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	10919	12669	10919	12669	12036	11546	12036	11546
R^2	0.0731	0.0488	0.0738	0.0485	0.0713	0.0539	0.0700	0.0549
Chow-Test	1.43***		1.48***		2.17***		2.08***	
(p-value)	0.0038		0.0015		0.0000		0.0000	

Panel B: Information environment

The regression results of the impact of FinTech on the risk of stock price collapse are presented in this table. Columns (1) through (4) compare the impact of FinTech on firms with more analyst tracking and firms with less analyst tracking, where the explained variable in columns (1) and (2) is *NCSKEW* and in columns (3) and (4) *DUVOL*; columns (5) through (8) compare the impact of FinTech on firms with more research report tracking and firms with less research report tracking, where the explained variable in columns (5) and (6) is *NCSKEW* and in columns (7) and (8) *DUVOL*; the grouping criteria are the number of analysts tracked and the annual median number of research reports tracked by firms. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High- tracking	*Low-tracking*	*High- tracking*	*Low-tracking*	*High- reports*	*Low-reports*	*High- reports*	*Low-reports*
Fintech	-0.0035	-0.0107***	-0.0024	-0.0058**	-0.0009	-0.0137***	-0.0012	-0.0072***
	(-1.0674)	(-2.7528)	(-1.0495)	(-2.2923)	(-0.2768)	(-3.4883)	(-0.5150)	(-2.8383)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	11253	12332	11253	12332	11572	12013	11572	12013
R^2	0.0742	0.0616	0.0759	0.0622	0.0708	0.0627	0.0730	0.0640
Chow-Test	4.40***		3.97***		4.54***		4.15***	
(p-value)	0.0000		0.0000		0.0000		0.0000	

Panel C: Agency issues

The regression results of the impact of FinTech on the risk of stock price collapse are presented in this table. Columns (1) through (4) compare the impact of FinTech on firms with high and low management expenses, where the explained variable in columns (1) and (2) is *NCSKEW* and in columns (3) and (4) *DUVOL*; columns (5) through (8) compare the impact of FinTech on firms with high and low management ownership, where the explained variable in columns (5) and (6) is *NCSKEW* and in columns (7) and (8) *DUVOL*; the grouping criteria are the annual median of the firms' management expenses and management ownership. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-fee	*Low-fee*	*High-fee*	*Low-fee*	*High-shareholder*	*Low- shareholder*	*High-shareholder*	*Low- shareholder*
Fintech	-0.0124***	-0.0010	-0.0087***	0.0009	-0.0050	-0.0099***	-0.0025	-0.0064***
	(-3.4100)	(-0.2866)	(-3.5978)	(0.3785)	(-1.4074)	(-2.7281)	(-1.0575)	(-2.6420)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	11514	12074	11514	12074	11917	11670	11917	11670
R^2	0.0584	0.0615	0.0576	0.0629	0.0549	0.0665	0.0573	0.0653
Chow-Test	1.67***		1.65***		1.90***		1.82***	
(p-value)	0.0000		0.0001		0.0000		0.0000	

Panel D: Industry and regional effects

The regression results of the impact of FinTech on the risk of stock price collapse are presented in this table. Columns (1) through (4) compare the impact of FinTech on firms in highly competitive industries and firms in less competitive industries, where the explained variable in columns (1) and (2) is *NCSKEW* and in columns (3) and (4) *DUVOL*; columns (5) through (8) compare the impact of FinTech on firms in areas with high marketization and firms with low marketization, where the explained variable in columns (5) and (6) is *NCSKEW* and in column (7) and (8) *DUVOL*. The grouping criteria are the annual median of the Lerner index of the firm's industry and the marketization index of the firm's region. The t-statistics under robust standard errors are displayed in parentheses. Significance is denoted by the symbols *, **, and *** at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-competition	*Low-competition*	*High-competition*	*Low-competition*	*High- market*	*Low- market*	*High-market*	*Low-market*
Fintech	-0.0139***	-0.0006	-0.0072***	-0.0015	-0.0179***	0.0005	-0.0111***	0.0013
	(-3.6632)	(-0.1745)	(-2.8457)	(-0.6533)	(-4.4728)	(0.1372)	(-4.0986)	(0.5611)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	11757	11834	11757	11834	11295	12294	11295	12294
R^2	0.0566	0.0660	0.0571	0.0649	0.0598	0.0578	0.0633	0.0560
Chow-Test	1.97***		1.76***		1.25**		1.40***	
(p-value)	0.0000		0.0000		0.0499		0.0056	

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