J. Account. Public Policy 40 (2021) 106874

Contents lists available at ScienceDirect

J. Account. Public Policy

journal homepage: www.elsevier.com/locate/jaccpubpol

Stock market openness and analyst forecast bias

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A R T I C L E I N F O

Article history:
Available online 22 June 2021

Keywords:
Equity market liberalization
Shanghai-Hong Kong connect
Forecast quality
Analyst forecast bias

A B S T R A C T

Biases in analysts' forecasts can be reduced not only through regulation but also through market mechanisms. In 2014, China launched the Shanghai-Hong Kong Connect program, which opened part of its domestic equity market to foreign investors. The implementation of this program provides a quasi-natural experimental setting to explore whether stock market openness plays a governance role in brokerage firms and minimizes their affiliated analysts' forecast biases. We find that the participation of foreign institutional investors mitigates the forecast biases of affiliated analysts. We also show that these analysts exert more significant effort by conducting more site visits. Our findings suggest that market liberalization can help improving the quality of analysts' forecasts.

1. Introduction

Financial analysts' conflicts of interest are a significant concern for investors, regulators, and other stakeholders, such as corporations, investment banks, brokers, and researchers. As major information providers to the financial market, financial analysts must provide objective and unbiased opinions on the future performance of the firms they follow. However, analysts tend to issue overly optimistic research to appeal to investment banks' existing and potential clients (Mehran and Stulz, 2007; Corwin, Larocque, and Stegemoller, 2017). In recent years, many internal and external mechanisms have been implemented to mitigate such conflicts of interest. In addition to disciplinary actions taken by self-regulatory organizations,[1] such as the Financial Industry Regulatory Authority, many external regulatory efforts have been made to mitigate these conflicts of interest, including the Sarbanes-Oxley Act of 2002 and the Global Analyst Research Settlement in 2003.

However, very little research has been conducted on how financial market liberalization may affect analysts' behavior. In the U.S., we have seen the adoption of Regulation Fair Disclosure of 2000[2], which significantly improves information transparency in the market. Another major step of market liberalization was the repeal of the Glass-Steagall Act in 1999[3], and it was found to significantly influence the analyst forecast quality (Chen and Martin, 2011).

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[1] See https://www.sec.gov/news/press/2003–89.htm.

[2] Regulation Fair Disclosure requires that when an issuer discloses material nonpublic information to certain individuals, the issuer must also make public disclosure of that information.See https://www.investor.gov/introduction-investing/investing-basics/glossary/fair-disclosure-regulation-fd

[3] Glass-Steagall Act was passed in 1933 in response to bank failures during the great depression. It separated investment banking from retail banking. It was repealed when Congress passed the Financial Service Modernization Act in 1999. Commercial banks are now allowed to engage in investment banking and securities trading.See https://www.federalreservehistory.org/essays/gramm-leach-bliley-act

https://doi.org/10.1016/j.jaccpubpol.2021.106874
0278-4254/

Market liberalization is more common in emerging countries in recent decades, and it often includes the opening of their stock markets to foreign investors. Previous studies show that stock market liberalization reduces the cost of capital (Bekaert and Campbell, 1995; Henry, 2000; Gupta and Yuan, 2009), improves market liquidity and financial development (Bekaert, Campbell, and Lumsdaine, 2002), improves company information environment and efficiency (Bae, Bailey, and Mao, 2006), and promotes innovation (Hsu, Tian, and Xu, 2014). China is the world's largest emerging and transitional economy, and market liberalization plays an important role in developing its capital market. We examine how stock market openness in China can mitigate conflicts of interest and lead to greater forecast accuracy and less forecast bias. Previous studies show that Chinese financial analysts devote less effort in information production and monitoring, but exhibit herding behaviors, and they tend to cater to client firms (Gu, Li, and Yang, 2013; Xu, Jiang, Chan, Wu, 2017; Matsumoto, Zhang, and Zheng, 2020). In this study, we argue that opening the stock market to more sophisticated foreign investors can also have a disciplinary effect on brokerage firms, resulting in better quality analysts' forecasts.

In 2014, China implemented the Shanghai-Hong Kong Connect (SHKC) program, allowing investors from Hong Kong to invest in Chinese mainland stocks. The SHKC program designated 568 stocks as SHKC firms and effectively opened the domestic Chinese equity market to foreign investors. Ten of the stocks included in the initial SHKC program are publicly traded brokerage firms (hereafter referred to as "SHKC brokerages") that employ 1024 financial analysts, covering 1452 firms. Although analysts, in addition to issuing forecasts, also perform other functions, such as advising, raising capital, securing new business, and conducting equity research,[4] the positive effect of analyst coverage on firms mainly stems from their roles as information distributors and external monitors (To, Navone, and Wu, 2018). We expect foreign institutions that invest in SHKC brokerage firms (hereafter referred to as "SHKC investors") to put pressure on the analysts employed by these SHKC brokerages (hereafter referred to as "SHKC analysts") to become better information providers and external monitors.

Using a sample of Chinese listed firms between 2012 and 2016, we document that the exogenous entry of foreign investors caused by the implementation of the SHKC program significantly increases the forecast quality of SHKC analysts. We also find evidence of more company site visits by SHKC analysts. Additionally, we find the disciplinary effect of the SHKC program to be more prominent for male analysts and more experienced analysts, and when other governance mechanisms (analyst competition in industry or firm) are less effective. To rule out the possibility that the improved forecast quality of SHKC analysts is mainly driven by the improved disclosure quality of SHKC firms, we show that our findings also hold for a sample of firms not in the SHKC program.

We contribute to the literature in several ways. First, we contribute to the broad literature on the conflicts of interest of financial analysts. Previous studies have investigated the disciplinary mechanisms that can mitigate the adverse impact of conflicts of interest, such as reputation (Mehran and Stulz, 2007), labor market (Hong and Kubik, 2003), and new rules and regulations (Kadan, Madureira, Wang, and Zach, 2009). We also explore how capital market openness can serve as an important market-based mechanism for disciplining brokerage firms and mitigating analyst biases.

Second, although recent studies investigate the disciplinary role of foreign institutional investors (Gillan and Starks, 2003; Bae, Ozoguz, Tan, and Wirjanto, 2012), many of them are unable to disentangle the endogeneity issues between institutional ownership and forecast quality. Using a series of staggered events, we are able to treat SHKC as an exogenous shock and apply a difference-in-difference (DiD) approach to better identify the disciplinary role of foreign institutional investors on analysts' incentives and behaviors. Previous studies tend to present market liberalization as market-wide events that simultaneously change the information environment, market liquidity, and institutional monitoring. It would be inappropriate to argue that changes in forecast quality stem from a single source. However, our setting presents a unique opportunity to separate these effects, as the SHKC program does not include all firms in the market, and we can easily tease out the information component using various constructs.

Third, this study is related to a series of papers on the consequences of capital market openness. Although prior studies have found a decrease in the cost of borrowing and an increase in the corporate governance quality (Li, Morck, Yang, and Yeung, 2004; Bae and Goyal, 2010; Balakrishnan, Vashishtha, and Verrecchia, 2019) after market liberalization, there has been no study on how it affects brokerage firms and their analysts. Our findings suggest that financial market liberalization improves forecast quality and enhances the information environment. We shed light on a specific channel through which capital market openness may improve capital market efficiency.

The rest of this paper is organized as follows. Section 2 gives the institutional background of the SHKC program. Section 3 provides the literature review and hypothesis. The data and variable descriptions are presented in Section 4. Section 5 reports the model and empirical findings. Section 6 presents the robustness checks and additional tests. Finally, Section 7 concludes the paper.

2. Institutional background of the SHKC program and brokerage industry in China

2.1. SHKC program

China's stock market had approximately 3600 listed firms and $6.31 trillion in market capitalization in December 2018, representing nearly 10% of the global stock market. In recent decades, the Chinese government has made a series of policies

[4] See the Corporate Finance Institute description at http://www.corporatefinanceinstitute.com.

to open its capital market to foreign investors hoping that foreign investors will improve the efficiency of the Chinese capital market. The SHKC program was not the first market liberalization program that allowed foreigners to acquire A-share stocks.[5] The China Securities Regulatory Commission (CSRC) approved the Qualified Foreign Institutional Investors (QFII) program in 2002, which allowed certain foreign institutional investors to invest in China.[6] By 2014, the QFII quota had expanded from the initial $4 billion to $52 billion in investments, distributed among 279 foreign institutional investors. Furthermore, these investors were allowed to invest in A-share equities and bonds, warrants, fixed income products, futures, IPO subscriptions, and convertible bonds. As the QFII program is heavily regulated and stocks are one of many instruments available through it, it is not surprising that the QFII program does not have a significant effect on the stock market. For example, it does not lower the cost or risk premium of equity capital (Chan and Yu, 2003; Tam, Li, Zhang, and Yu, 2010).

In 2014, the SHKC program offered an unprecedented opportunity for international investors to access the historically closed Chinese capital market. On April 10, 2014, Chinese Premier Li Keqiang announced the SHKC program as the "first of a new round" of liberalizations.[7] The China Security Regulatory Commission and the Hong Kong Stock Exchange made a joint announcement about adopting the SHKC pilot program. The SHKC program was implemented on November 17, 2014. It is touted as the first tangible advancement in China's capital market liberalization during the post-2008 financial crisis period. SHKC stocks are chosen based on a combination of market cap, turnover, industry characteristics, sales growth, and return on assets. Specifically, they are the constituent stocks of the Shanghai Stock Exchange (SSE) 180 Index and SSE 380 Index and SSE-listed A-shares with corresponding H-shares listed in Hong Kong. The SHKC program initially selected 568 stocks, including 10 SHKC brokerages.

Under the SHKC program, foreign investors are permitted to trade on any of the SHKC firms as long as they do not collectively exceed the daily quota of RMB52 billion (changed from RMB13 billion on May 1, 2018). Although before the implementation of the SHKC program, overseas institutional investors could invest in stocks listed on the Shanghai Stock Exchange (SSE) by acquiring QFII licenses and quotas, the SHKC program offers much greater freedom for international investors in China. Instead of purchasing ETF products that invest in Chinese securities or investing in mutual funds via their brokers, the SHKC program allows foreign investors to select and hold SHKC stocks listed on the SSE directly.

The implementation of the SHKC program allowed foreign investors to trade shares of SHKC brokerages, but it did not directly affect non-SHKC brokerages. This provides a natural treatment group and control group for researchers. Even more importantly, the adoption of the SHKC program is not known ex-ante[8]. The assistant director of the Stock Exchange's Capital Markets Institute noted the following:

The list of eligible firms and size of the liberalization was a surprise. Even our team that oversaw the facilitation of SHKC was notified of the regulation details on the day of Premier Li's speech. (May 15, 2017)

Thus, the adoption of the SHKC program provides an ideal quasi-natural experiment to examine foreign investors' disciplinary influence on brokerage firms, specifically on the forecast behavior of their affiliated analysts.

We note that SHKC stocks are not randomly assigned. According to China Securities Index Co. Ltd (the sponsor of SSE180 and SSE380), industry representation, market capitalization, and trading value are considered when determining whether to include a stock in SHKC[9]. Chan and Kwok (2017) analyze the determinants of SHKC program inclusion and find firm size to be a major determinant. Hence, the main identification challenge is not self-selection but the systemic differences between SHKC and non-SHKC stocks. In our regressions, we control for all observable differences to ensure that they do not drive any differences in analyst forecasts.

2.2. Brokerage industry in China

Brokerage firms emerged in China in 1991, when China launched the Shanghai and Shenzhen stock exchanges. Initially, these brokerage firms were controlled by either large state-owned banks or state-owned enterprises. In November 2001, non-state-owned enterprises were allowed to gain control or invest in brokerage firms. In 2002, Minsheng Securities was the first non-state-owned enterprise to obtain a brokerage license. Since then, the Chinese brokerage industry has grown steadily. According to the Securities Association of China, by the end of 2016, 129 brokerage firms employing more than 2350 financial analysts provided research reports and earnings forecasts. Many of these analysts are highly educated, and the industry practice is heavily influenced by practices in the U.S. market. Sell-side analysts in China face a similar set of incentives to sell-side analysts in the U.S. when issuing stock recommendations (Liu and Zhang, 2008; Wang, 2009). These incentives have led to generally optimistic analyst forecasts. For example, Chan, Jiang, Wu, Xu, and Zeng (2020) find that

[5] A share class initially created for trading by domestic investors.

[6] In the SHKC program, all Hong Kong and overseas investors can trade the eligible stocks of firms included in the SHKC program. In the QFII program, only selected institutional investors are able to trade RMB denominated products approved by the CSRC.

[7] See http://www.china.org.cn/business/2014–04/11/content_32062531.htm

[8] Firms are included in the SHKC program over time. The first batch of SHKC firms was announced together with the selection criteria, so the market was not given any early notice about which firms were on the list. After the initiation of SHKC, it would still be difficult for firms to know if they were chosen as SHKC firms, because many of the criteria were based on firm ranking in the market. It is difficult for a firm to precisely predict its ranking ahead of time without exact information about its peers.

[9] One of the potential shortcomings in our analysis is that the inclusion of a firm in the SHKC program is not entirely unexpected. Although the exact list of the firms is unknown ahead of time, sophisticated investors can still reasonably forecast the firms that are likely to be included in the SHKC program.

affiliated analysts' recommendations are more optimistic when a firm's large shareholders plan to sell their shares after China's split-share reform.

3. Literature review and hypothesis development

Foreign institutions have international experience and expertise in searching and processing information (Chakravarty, 2001; Hartzell and Starks, 2003; Aslan, Easley, Hvidkjaer, and O'Hara, 2011). They also improve stock price efficiency (Bae, Ozoguz, Tan, and Wirjanto, 2012). Thus, more sophisticated foreign institutions are more likely to undercover the optimistic biases in analysts' research reports and discipline brokers whose analysts show systemic biases. Under these circumstances, analysts are under more pressure to issue unbiased forecasts. For example, Ljungqvist, Marston, Starks, Wei, and Yan (2007) find that the presence of institutional investors is associated with more accurate earnings forecasts because the cost of publishing biased and misleading research is high for stocks that are highly visible to institutional investors. Similarly, Mola and Guidolin (2009) find that analyst recommendations on stocks that are highly visible to institutional investors are less likely to be influenced by family pressure.

Analysts might also exercise more effort when they are under pressure. A primary and necessary condition for improving forecast accuracy is that analysts devote the effort required to properly understand the business before forecasting its earnings. Jacob, Lys, and Neale (1999) find that the amount of effort an analyst devotes to following a company is as important as her past experience for explaining future accuracy. Harford, Jiang, Wang, and Xie (2017) demonstrate that analysts strategically allocate more effort to portfolio firms that are more important for their careers, leading to greater forecast accuracy for these firms. Merkley, Michaely, and Pacelli (2017) argue that increased competition at the industry level can potentially enhance the quality of analyst reports within an industry by increasing analyst effort and thus information quality. Site visits are an important part of analysts' efforts to gather information. During a visit, analysts can engage in face-to-face talks with Investor Relation managers and divisional managers and then tour firms' operating and production activities. Even more importantly, site visits allow analysts to better understand firms' production processes, corporate culture, and employee morale, potentially leading to better quality research reports. Cheng, Du, Wang, and Wang (2016) find that analysts who conduct visits show higher forecast accuracy than analysts who do not conduct visits. Han, Kong, and Liu (2018) also find that company visits enhance forecast accuracy and facilitate information acquisition. If analysts are motivated to conduct site visits to discover new information or better interpret available information, the quality of their research reports is improved. We expect SHKC analysts to respond to the entry of foreign investors by conducting more corporate site visits than non-affiliated analysts, leading to fewer forecast errors.

Consequently, we propose the following hypothesis:

H1: The entry of foreign investors into the Chinese market due to equity market liberalization improves the forecast accuracy of SHKC analysts.

4. Sample selection, variable definitions, and summary statistics

4.1. Sample selection

We use data from the China Stock Market & Accounting Research (CSMAR) database to construct our analyst forecast accuracy and control variables. First, we delete firms in the financial services and utility industries because disclosure requirements and accounting rules are significantly different for these regulated industries. Next, we exclude samples with missing values for the dependent or control variables. Finally, we require all sample firms to be active both before and after SHKC program adoption to ensure that we capture changes in analyst forecast accuracy for the same set of firms. To mitigate the effect of outliers, all of the continuous variables are winsorized at the 1% level. Our final sample includes 75,384 firm-year-analyst observations between 2012 and 2016.

4.2. Identification strategy, variable definitions, and empirical models

We use the adoption of the SHKC program as a quasi-natural experiment to investigate foreign investors' disciplinary role in brokerage firms. We examine foreign investors' disciplinary pressure by focusing on how SHKC analysts may have different levels of forecast accuracy than non-SHKC analysts. This identification strategy is similar to that used by Kedia, Rajgopal, and Zhou (2017), who study how large shareholders affect credit ratings at the rating agency level. We do not compare analyst forecasts of SHKC stocks with analyst forecasts of non-SHKC stocks, as the differences in analysts' incentives and firm-specific factors may complicate the interpretation of the results. By analyzing data at the brokerage level, we can better isolate the changes in analyst behavior caused by the entry of foreign investors. The pilot brokerages in the designated list of the SHKC program (i.e., SHKC brokerages) are classified as the treated brokerages, and their affiliated analysts (i.e., SHKC analysts) are regarded as treated analysts. The SHKC program was implemented on November 17, 2014. The 10 SHKC brokerage firms included in the SHKC program are Citic Securities, Sinolink Securities, Northeast Securities, Haitong Securities, Merchants Securities, Industrial Securities, Soochow Securities, Founder Securities, Pacific Securities, and Huatai Securities. In

2015, another four brokerages, Orient Securities, Dongxing Securities, Guotai Junan Securities, and Everbright Securities, were added. In total, there are 1380 SHKC financial analysts employed by these SHCK brokerage firms across 1548 firms.

The SHKC program in the Chinese stock market creates an ideal setting to examine the effect of foreign investors on analyst forecast behavior. The most interesting feature of this experiment is that the list of SHKC brokerages included in the SHKC program changes over time, creating samples for both time-series and cross-sectional analyses. In other words, the "events" we use here are staggered over time. A key advantage of a multi-period natural experiment is that multiple shocks affect different firms exogenously at different times. Such a setting removes a common identification difficulty faced by studies with a single shock, namely the existence of potential omitted variables that coincide with the shock that directly affects analyst forecast accuracy. Furthermore, the staggered inclusion of firms in the SHKC program implies that the control group is not restricted to non-SHKC brokerage firms that do not have any foreign investment, which helps alleviate the concern that differences between SHKC and non-SHKC brokerages drive the results. Following Bertrand and Mullainathan (2003), we adopt the difference-in-differences (DiD) approach as follows:

$$\begin{aligned} AnalystForecastBias_{ijt} = \beta_0 + \beta_1 SHK_{ijt} + \sum_{b=2}^{n} \beta_b Control\ Variables_{it} + Firmfixedeffect \\ + Analystfixedeffect + Yearfixedeffect + \varepsilon \end{aligned} \tag{1}$$

where *Analyst Forecast Bias*$_{ijt}$ is analyst *j*'s forecast bias for firm *i* in year *t*. Our proxy for forecast bias is the signed forecast error (*FB*). Following prior studies, we also use absolute forecast error (*FE*). To construct FB_{ijt} (FE_{ijt}), for each year, we compute signed forecast errors (unsigned) for each firm-analyst as the difference between analyst *j*'s most recent earnings per share (EPS) forecast and the actual EPS for firm *i* in year *t*, and then scale it by the stock price at the end of the previous fiscal year. SHK_{ijt} is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by an SHKC brokerage and 0 otherwise. Following previous studies (Green, Jame, Markov, and Subasi, 2014; Cheng, Du, Wang, and Wang, 2016; Bradley, Gokkaya, and Liu, 2017), we control for a vector of firm and brokerage characteristics that may affect analyst forecast accuracy in our analysis. We compute all of the variables for firm *i* over its fiscal year *t*. Our control variables include firm size (*SIZE*), leverage (*LEV*), firm value (*Tobin's Q*), profitability (*ROA*), R&D expense (*R&D*), stock volatility (*Volatility*), firm age (*AGE*), the ownership of the controlling shareholder (*SOE*), board size (*DSIZE*), the proportion of independent directors (*INDPR*), the duality of CEO and chairman positions (*CEOD*), and audit firm (*BIG4*). We also control for such characteristics as brokerage size (*BSIZE*), brokerage growth (*BGROWTH*), brokerage age (*BAGE*), whether the brokerage is public or private (*BLIST*), and the total number of research reports issued by the brokerage in one year (*BFNUM*). The detailed variable definitions are given in the Appendix.

Firm fixed effects and *analyst fixed effects* are used to control for time-invariant omitted firm and analyst characteristics. Their inclusion ensures that estimates of β_1 reflect the average within-firm-analyst change in analyst forecast accuracy over time rather than simple cross-sectional correlations. *Year fixed effects* account for nation-wide factors, such as macroeconomic conditions, that might simultaneously affect analyst forecast accuracy and the likelihood that a brokerage is selected to be in the pilot group. The coefficient of interest in this model is β_1. As Imbens and Wooldridge (2009) explain, with the fixed effects, β_1 represents the within-analyst differences before and after SHKC program adoption. Similar DiD models are also used by Bertrand and Mullainathan (2003), Chang, Chen, Wang, Zhang, and Zhang (2019), and Rauter (2020).

4.3. Summary statistics

Panel A of Table 1 presents the descriptive statistics of the main variables. The means (medians) of forecast bias *FB* and forecast error *FE* are 0.008 (0.003) and 0.011 (0.005), respectively. The mean and median of *SHKC* are 20.3% and 0.0%, respectively, and the 75th percentile is 0.0%, indicating that the treatment group is rather small compared with the control group. For the control variables, the mean values of *SIZE, LEV,* and *ROA* are 22.636, 0.425, and 0.116, respectively. On average, our sample firms have been listed on the stock exchange for 9 years. The mean value of *SOE* is 0.371, indicating that state-owned enterprises represent approximately 37.1% of our sample. In China, most firms hire domestic accounting firms to provide auditing services, whereas approximately only 10% of companies hire international Big 4 audit firms.

Panel B presents the summary statistics for the SHKC and non-SHKC firms. On average, the SHKC firms demonstrate higher profitability, greater growth opportunity, higher R&D expenditure, higher liquidity, and more listed years. They do not differ much in size, leverage, or other governance qualities.

5. Empirical results

5.1. Baseline DiD results for analyst forecast optimism

In this section, we first compare the forecast optimism of SHKC analysts with that of non-SHKC analysts. We test the hypothesis that forecasts issued by the treated analysts are less biased (more accurate). The regression results estimating Eq. (1) are reported in Table 2. The dependent variable in Panel A is analyst forecast bias *FB*. In columns (1) and (2), the coefficients of *SHKC* are statistically and economically significant. For example, the results given in column (2) suggest that relative to the unconditional mean of the dependent variable, this effect represents a change of approximately 12.5% (0.001/0.008). We further examine the effect of the SHKC program on upward and downward bias. The results in columns

Table 1
Summary statistics.

Panel A: Summary Statistics for Main Variables at the Firm-year-analyst Level								
Variable	N	Mean	Median	SD	Min	Q1	Q3	Max
FB	75,384	0.008	0.003	0.017	−0.029	0.000	0.012	0.090
FE	75,384	0.011	0.005	0.016	0.000	0.002	0.014	0.092
SHKC	75,384	0.203	0.000	0.402	0.000	0.000	0.000	1.000
SIZE	75,384	22.636	22.372	1.384	20.320	21.627	23.394	26.895
LEV	75,384	0.425	0.417	0.203	0.054	0.257	0.587	0.847
ROA	75,384	0.116	0.095	0.103	−0.155	0.046	0.163	0.477
TOBIN'S Q	75,384	2.184	1.778	1.262	0.908	1.320	2.623	7.534
R&D	75,384	15.461	17.837	6.606	0.000	16.583	18.838	22.304
VOLATILITY	75,384	0.135	0.123	0.057	0.051	0.097	0.157	0.363
AGE	75,384	2.214	2.197	0.620	1.099	1.792	2.833	3.178
SOE	75,384	0.371	0.000	0.483	0.000	0.000	1.000	1.000
BIG4	75,384	0.100	0.000	0.300	0.000	0.000	0.000	1.000
DSIZE	75,384	2.166	2.197	0.197	1.609	2.079	2.197	2.708
INDPR	75,384	0.374	0.333	0.055	0.333	0.333	0.429	0.571
CEOD	75,384	0.257	0.000	0.437	0.000	0.000	1.000	1.000
BSIZE	75,384	15.523	15.657	1.208	12.528	14.760	16.314	17.695
BGROWTH	75,384	0.297	0.153	0.507	−0.496	−0.051	0.561	1.723
BAGE	75,384	2.676	2.890	0.736	0.000	2.398	3.178	3.367
BLIST	75,384	0.531	1.000	0.499	0.000	0.000	1.000	1.000
BFNUM	75,384	6.661	6.810	0.821	3.526	6.335	7.246	7.788
SHORT	75,384	0.065	0.000	0.247	0.000	0.000	0.000	1.000

Panel B: Summary Statistics for SHKC Firms and Non-SHKC Firms							
Variable	SHKC=1 (N=3,232)			SHKC=0 (N=4,715)			Mean Diff Test
	Mean	Median	SD	Mean	Median	SD	
SIZE	22.354	22.135	1.281	22.316	22.105	1.311	0.038
LEV	0.430	0.422	0.205	0.428	0.421	0.213	0.002
ROA	0.097	0.077	0.108	0.090	0.071	0.105	0.007***
TOBIN'S Q	2.209	1.787	1.316	2.104	1.676	1.250	0.105***
R&D	15.081	17.494	6.543	14.526	17.453	7.012	0.555***
VOLATILITY	0.145	0.131	0.064	0.142	0.128	0.060	0.003**
AGE	2.279	2.303	0.619	2.236	2.197	0.630	0.043***
SOE	0.383	0.000	0.486	0.379	0.000	0.485	0.004
DSIZE	2.154	2.197	0.197	2.151	2.197	0.198	0.003
INDPR	0.373	0.333	0.053	0.374	0.333	0.054	−0.001
CEOD	0.249	0.000	0.433	0.263	0.000	0.440	−0.014
BIG4	0.074	0.000	0.262	0.066	0.000	0.249	0.008

This table presents the summary statistics for our main variables. To mitigate the effect of outliers, all of the continuous variables are winsorized at the 1% and 99% levels. Detailed definitions of all of the variables are provided in the Appendix.

(3) to (6) indicate that the SHKC program reduces the forecast optimism of analysts in SHKC brokerages while having no effect on forecast pessimism. These results are consistent with our predictions.

Panel B of Table 2 reports the results for the forecast errors *FE*. Without the control variables, the DiD estimator in column (1), which is the coefficient estimate on *SHKC*, is −0.001 and significant at the 1% level, suggesting that the earnings forecasts issued by SHKC analysts are relatively more accurate than those issued by non-SHKC analysts not faced with the disciplinary effect of foreign investors. After controlling for firm and brokerage characteristics, the coefficient estimate on *SHKC* in column (2) is negative and significant at the 1% level. This difference represents approximately 9.1% (0.001/0.011) of the average change in *FE* for our full sample (0.011).

Overall, the results in Table 2 indicate that the adoption of the SHKC program mitigates analysts' forecast optimism and errors.

5.2. Addressing endogeneity concerns

There may be concerns regarding whether our findings are endogenous. For example, brokerages listed on the Shanghai Stock Exchange must meet certain criteria, such as turnover and market capitalization, to be included in the pilot list. Unobservable brokerage firm heterogeneity correlated with both inclusion in the list and forecast accuracy may bias our results. We use two methods to address these endogeneity concerns.

The first is to introduce a propensity score matching (PSM) procedure. The purpose of matching is to reduce sample selection bias by pairing each SHKC brokerage firm with a non-SHKC brokerage firm with similar fundamentals in year *t*. To eliminate the order effect, the observations are randomly ordered before matching (Dehejia and Wahba, 2002). We estimate the propensity score using a logistic regression model to regress *SHKC* on brokerage size, brokerage growth, brokerage age, the

Table 2
Effect of the SHKC Program on analyst forecasts.

Panel A: SHKC and analyst forecast bias

	FB		FB > 0		FB < 0	
	(1)	(2)	(3)	(4)	(5)	(6)
SHKC	**−0.001***** **(-3.62)**	**−0.001***** **(-3.57)**	**−0.001***** **(-2.73)**	**−0.001***** **(-2.60)**	**−0.000** **(-0.22)**	**0.000** **(0.52)**
SIZE		0.002** (2.30)		0.001 (1.31)		0.000 (0.18)
LEV		−0.006*** (-2.75)		−0.002 (-0.95)		−0.003 (-1.54)
ROA		−0.099*** (-17.51)		−0.084*** (-14.29)		−0.029*** (-6.46)
TOBIN'S Q		0.000 (0.83)		−0.000 (-1.01)		0.001** (2.56)
R&D		−0.000 (-1.27)		−0.000 (-1.49)		0.000 (0.31)
VOLATILITY		0.002 (0.44)		0.008* (1.89)		−0.005 (-1.59)
AGE		−0.004* (-1.81)		−0.002 (-0.84)		−0.004*** (-2.64)
SOE		−0.002 (-1.18)		−0.001 (-0.76)		0.001 (0.52)
DSIZE		0.004 (1.55)		0.003 (1.25)		−0.000 (-0.08)
INDPR		0.017** (2.42)		0.009 (1.29)		0.008* (1.75)
CEOD		0.001 (1.36)		0.001 (0.93)		0.000 (0.03)
BIG4		−0.003 (-1.40)		−0.001 (-0.65)		0.001 (0.74)
BSIZE		0.000 (1.37)		0.001* (1.67)		0.000 (0.48)
BGROWTH		0.000 (0.85)		0.000 (0.26)		−0.000 (-0.36)
BAGE		−0.001*** (-3.60)		−0.001*** (-4.05)		0.000 (1.13)
BLIST		−0.000 (-0.72)		−0.001 (-1.30)		−0.000 (-1.10)
BFNUM		−0.001** (-2.20)		−0.001** (-2.31)		0.000 (0.39)
SHORT		0.001** (2.45)		0.001*** (2.63)		−0.001* (-1.84)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
N	75,384	75,384	54,289	54,289	19,056	19,056
Adj. R^2	0.281	0.342	0.386	0.432	0.434	0.450

Panel B: SHKC and Analyst Forecast Error

	FE	
	(1)	(2)
SHKC	**−0.001***** **(-2.74)**	**−0.001***** **(-2.86)**
SIZE		0.001 (1.45)
LEV		−0.002 (-0.93)
ROA		−0.066*** (-12.58)
TOBIN'S Q		−0.000 (-1.30)
R&D		−0.000 (-0.47)
VOLATILITY		0.007** (2.08)
AGE		0.000 (0.27)
SOE		−0.002

(*continued on next page*)

Table 2 (*continued*)

Panel B: SHKC and Analyst Forecast Error

	FE	
	(1)	(2)
		(-0.94)
DSIZE		0.002
		(0.79)
INDPR		0.008
		(1.39)
CEOD		0.001
		(0.96)
BIG4		−0.002
		(-1.24)
BSIZE		0.000
		(1.51)
BGROWTH		0.000
		(0.79)
BAGE		−0.001***
		(-4.86)
BLIST		−0.000
		(-0.36)
BFNUM		−0.000*
		(-1.79)
SHORT		0.001***
		(3.41)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
N	75,384	75,384
Adj. R^2	0.337	0.371

This table reports DiD test results of how the SHKC program affects analyst forecast quality. The dependent variables in Panels A and B are forecast bias *(FB)* and forecast error *(FE)*, respectively. *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

number of research reports issued by the brokerage in one year, and then use nearest-neighbor matching to specify a new control group. A good matching effect requires well-balanced covariates. Imbalances across experimental conditions yield biased treatment effects, thereby preventing causal inferences from being made. Thus, to ensure good matching, we first implement a matching balance test.

Panel A of Table 3 presents the results of the covariate balancing tests after matching. They show that the mean differences in the given covariates are insignificant at the conventional p-value level with the matched samples. The absolute value of the standardized mean differences is below 0.25, indicating well-balanced covariates (Rubin, 2001; Stuart, 2010). Furthermore, the bias ratio of the covariates decreases from the unmatched samples to the matched samples and shows a noticeable improvement in balance after matching. These results suggest the reasonable success of the proposed specification of the propensity score in terms of balancing the distribution of covariates between the two groups. In other words, our findings are not biased by the differences between SHKC and non-SHKC brokerages.

After confirming the covariate balance between the treatment and control groups, we rerun the DiD regressions using the propensity score matching sample. Standard matching estimators in combination with the DiD methodology not only significantly improve the quality of non-experimental evaluation results (Blundell and Costa Dias, 2000) but also eliminate unobserved time-invariant differences by controlling for the differences in analyst forecasts between SHKC and non-SHKC brokerages that standard matching estimators fail to eliminate (Smith and Todd, 2005). The results in Panel B of Table 3 show that the coefficients on *SHKC* are significantly negative, consistent with our baseline findings.

The second strategy is to conduct a placebo test using the fictional adoption of the SHKC program. We conduct this placebo test as follows. For SHKC brokerages, we create a fictional inclusion that occurs three years before their actual inclusion in the SHKC program while maintaining the same treatment and control group assignments. If the baseline results are driven by inherent and unobservable differences between the treatment and control groups, the results should be unchanged when we use the fictional deregulation date. However, if the baseline results are not the same in the placebo tests, we can argue that our findings are not driven by omitted variable bias. Panel C of Table 3 presents the results, which show that the coefficients on *SHKC* are insignificant and even positive, which is different from the baseline results.

Table 3
Addressing Endogeneity Concerns.

Panel A: Covariate Balance After Matching

	SHKC = 1		SHKC = 0		T-Value	Std. Mean Diff	V(T)/V(C)	Change in Balance (%)
	Mean	SD	Mean	SD				
BSIZE	2.844	0.362	2.768	0.393	0.458	0.199	0.88	19.6
BGROWTH	6.318	1.125	6.142	1.210	0.601	0.151	0.60	92.8
BAGE	15.599	0.866	15.393	0.925	0.194	0.229	1.34	94.3
BFNUM	0.361	0.522	0.339	0.482	0.517	0.044	1.02	12.5
MALER	0.723	0.098	0.739	0.096	0.746	−0.165	1.27	94.2
HEDUR	0.898	0.067	0.869	0.094	0.300	0.230	0.52	49.4
EXPERR	7.294	1.813	7.481	2.656	0.954	−0.082	0.59	49.1

Panel B: Regression Results Using the PSM Matched Sample

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**−0.002*****	**(-4.17)**	**−0.002*****	**(-3.98)**
SIZE	0.002**	(2.28)	0.001	(1.35)
LEV	−0.007***	(-2.74)	−0.002	(-1.03)
ROA	−0.100***	(-16.62)	−0.066***	(-11.49)
TOBIN'S Q	0.000	(0.81)	−0.000	(-1.44)
R&D	−0.000	(-1.26)	−0.000	(-0.33)
VOLATILITY	0.001	(0.18)	0.007*	(1.83)
AGE	−0.003	(-1.46)	0.002	(1.05)
SOE	−0.002	(-1.19)	−0.002	(-1.05)
DSIZE	0.005*	(1.89)	0.002	(1.11)
INDPR	0.020***	(2.70)	0.010*	(1.69)
CEOD	0.001	(1.55)	0.001	(0.96)
BIG4	−0.003	(-1.42)	−0.002	(-0.97)
BSIZE	0.001**	(2.32)	0.001*	(1.75)
BGROWTH	0.001**	(2.42)	0.001***	(2.96)
BAGE	−0.001**	(-2.12)	−0.001***	(-3.46)
BLIST	−0.000	(-0.06)	0.000	(0.59)
BFNUM	0.000	(1.04)	0.001*	(1.85)
SHORT	0.001***	(2.78)	0.001***	(3.69)
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	57,083		57,083	
Adj. R^2	0.337		0.365	

Panel C: Placebo Tests

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**0.001**	**(0.86)**	**0.001**	**(1.28)**
SIZE	0.004*	(1.78)	−0.003	(-1.59)
LEV	−0.030***	(-4.46)	−0.001	(-0.25)
ROA	−0.134***	(-11.47)	−0.051***	(-5.00)
TOBIN'S Q	0.001**	(2.51)	0.000	(1.50)
R&D	0.000	(0.61)	−0.000	(-0.38)
VOLATILITY	0.020	(1.55)	0.040***	(4.09)
AGE	−0.001	(-0.31)	0.002	(0.72)
SOE	0.004	(1.56)	0.006***	(2.83)
DSIZE	0.002	(0.38)	−0.006	(-1.62)
INDPR	−0.009	(-0.75)	−0.015	(-1.53)
CEOD	−0.001	(-0.43)	0.001	(0.97)
BIG4	−0.001	(-0.42)	−0.003	(-1.33)
BSIZE	0.001**	(2.11)	0.001**	(2.22)
BGROWTH	0.002	(1.46)	0.003	(1.40)
BAGE	0.001*	(1.70)	0.001	(0.96)
BLIST	−0.002	(-1.63)	−0.002**	(-2.28)

(*continued on next page*)

Table 3 (*continued*)

Panel C: Placebo Tests				
	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
BFNUM	−0.000	(-0.08)	−0.000	(-0.14)
SHORT	−0.081	(-1.58)	0.075*	(1.73)
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	18,183		18,183	
Adj. R^2	0.314		0.345	

This table presents test results addressing endogeneity concerns. Panel A presents the summary statistics of the brokerage characteristics after matching. Panel B re-runs the regressions after introducing a propensity score matching procedure. Panel C reports the regression results after using fictional deregulation dates of 4 years before the actual adoption. The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.3. Increased effort by SHKC analysts

As discussed previously, one of the mechanisms through which the SHKC program affects the quality of analyst reports is its effect on analyst effort. We consider two measures of analyst effort: site visits and the number of published research reports.

We first examine how the SHKC program affects analysts' site visits. An analyst can obtain more detailed and contextual information about public announcements and better understand a firm's strategy and position through site visits. Site visits require time, energy, and financial resources (Cheng, Du, Wang, and Wang, 2016). In this sense, site visits represent a significant effort to search for additional information to complement public disclosures. In the U.S. and Europe, firms either do not maintain archival records of site visits or prohibit the distribution of such information. In China, however, the data on analysts' corporate site visits are available starting from 2009.[10]

Using this unique data, we perform a DiD regression similar to the original analysis but replace the dependent variable, *FE* or *FB*, with site visits, *DVISIT* or *LNVISIT*. *DVISIT* equals 1 if an analyst from brokerage *k* visits firm *i* in year *t* and 0 otherwise. *LNVISIT* is the natural log of 1 plus the number of site visits conducted by brokerage *j* for firm *i* in a year. In this test, the observations are at the brokerage-year level. In columns (1) and (2) of Table 4, the coefficients of *SHKC* are significantly positive, suggesting that SHKC analysts are more likely to conduct site visits than non-SHKC analysts. We also examine the effect on the frequency of site visits; the coefficients of *SHKC* in columns (3) and (4) remain positive and significant at the 1% level, indicating that SHKC analysts also conduct more site visits than non-SHKC analysts. Han, Kong, and Liu (2017) show that analysts gain an informational advantage by visiting listed companies, and site visits significantly improve analysts' forecast accuracy. However, site visits incur costs. Cheng, Du, Wang, and Wang (2016) find that analysts are less likely to visit firms located farther away due to the higher time and financial commitments required to do so. Our findings highlight how external pressure from SHKC investors may increase analysts' incentive to conduct site visits.

Second, following Jacob, Lys, and Neale (1999), we measure analyst effort by the number of researches reports they provide to market participants. Specifically, *FREQUENCY* is defined as the natural log of the number of reports issued by analyst *j* for firm *i* each year. We expect the adoption of the SHKC program to positively affect the amount of information analysts provide to capital markets. As shown in columns (5) and (6), analysts in SHKC brokerages produce more reports after adopting the SHKC program.

5.4. Governance role of SHKC investors

This section presents additional evidence to strengthen our conjecture that pressure from SHKC investors causes SHKC analysts to improve their forecast quality.

To this end, we first examine whether the baseline results are more pronounced in subsample firms with higher SHKC investors' ownership. We construct a dummy variable *HIGH_HOLD* that equals 1 if SHKC investors' ownership in an SHKC brokerage is above the sample median and 0 otherwise.[11] Table 5 shows that the interaction term between *SHKC* and

[10] To address the concern regarding fair disclosure, the SZSE Information Fair Disclosure Guidelines require firms to report to the CSRC two working days before site visits.

[11] We collect the ownership data for SHKC investors from the WIND database (https://www.wind.com.cn/) and Eastmoney website (https://www.eastmoney.com/). WIND databases pairs over 1.3 million macroeconomic and industry time series with data analysis tools. It is the most comprehensive database covering the Chinese market. It also provides company-level information such as ownership information. East Money Information Co., Ltd., is a Chinese financial and stock information website provider. It provides current and historical firm-level information, including ownership information by SHKC investors.

Table 4
Effect of the SHKC Program on Analyst Effort.

	DVISIT		LNVISIT		FREQUENCY	
	(1)	(2)	(3)	(4)	(5)	(6)
SHKC	**0.029***** **(4.74)**	**0.024***** **(3.62)**	**0.033***** **(5.74)**	**0.030***** **(4.63)**	**0.021**** **(2.18)**	**0.020**** **(2.00)**
SIZE		−0.017** (-2.22)		−0.006 (-0.81)		0.062*** (6.45)
LEV		−0.034 (-1.30)		−0.029 (-1.18)		0.046 (1.53)
ROA		0.170*** (4.83)		0.167*** (5.08)		0.389*** (9.38)
TOBIN'S Q		0.006** (2.00)		0.007*** (2.72)		0.021*** (6.25)
R&D		0.000 (0.27)		−0.000 (-0.10)		0.001 (1.06)
VOLATILITY		0.011 (0.27)		0.025 (0.64)		0.150*** (3.05)
AGE		0.077*** (4.90)		0.083*** (5.69)		0.027 (1.17)
SOE		−0.001 (-0.09)		−0.008 (-0.55)		−0.010 (-0.50)
DSIZE		0.014 (0.62)		−0.004 (-0.18)		0.022 (0.72)
INDPR		0.027 (0.44)		0.031 (0.53)		0.037 (0.47)
CEOD		0.015* (1.88)		0.008 (1.12)		0.001 (0.10)
BIG4		0.029 (1.59)		0.033** (2.01)		0.028 (1.29)
BSIZE		0.034*** (3.34)		0.037*** (3.92)		−0.027*** (-2.83)
BGROWTH		0.006 (0.94)		0.011* (1.91)		0.017** (2.43)
BAGE		0.010 (1.16)		0.009 (1.15)		−0.000 (-0.05)
BLIST		−0.009 (-1.26)		−0.009 (-1.34)		−0.017 (-1.48)
BFNUM		0.007 (1.60)		0.008** (2.11)		0.111*** (19.87)
SHORT		0.004 (0.48)		−0.002 (-0.32)		−0.015 (-1.52)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
N	60,288	60,288	60,288	60,288	75,384	75,384
Adj. R^2	0.325	0.325	0.327	0.329	0.213	0.222

This table reports the DiD test results of how the adoption of the SHKC program affects analyst effort. The dependent variables are site visits and forecast frequency, *DVISIT*, *LNVISIT*, and *FREQUENCY*. *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

HIGH_HOLD is significantly negative, suggesting that higher ownership by SHKC investors improves the forecast quality of SHKC analysts. These results provide collaborative evidence that monitoring effects are prominent in SHKC brokerages with high foreign investor holdings.

We further examine whether the effect of the SHKC program on analyst forecast varies with the monitoring threat of SHKC investors. From the WIND database, we retrieve the top 10 stocks traded by SHKC investors. If a brokerage firm is highly traded by SHKC investors (one of the top 10 stocks), we define the dummy variable *HIGH_TRADE* as 1 and 0 otherwise. Table 6 shows that the interaction term between *SHKC* and *HIGH_TRADE* is significantly negative, suggesting that the treatment effect is more pronounced for brokerage firms heavily traded by SHKC investors. These firms are presumably subject to more monitoring pressure, and the negative coefficient is consistent with our prediction.

To provide additional evidence of how SHKC may put more pressure on SHKC brokerages, we follow Grullon, Michenaud, and Weston (2015) and confirm that the stock prices of SHKC brokerages are more sensitive to bad news. We examine both the SHKC and non-SHKC brokerages' daily returns during bearish and bullish stock market days. The objective of this test is to provide evidence that SHKC brokerages experience an asymmetric shock to stock price risk. We test the brokerages' stock price reactions to market-wide bad news. Specifically, to test whether SHKC firms' returns become more negative on very

Table 5
Governance effect of the SHKC Program: SHKC investors' ownership.

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	−0.000	(-0.83)	−0.000	(-0.40)
HIGH_HOLD	−0.001	(-0.78)	−0.001	(-1.38)
SHKC × HIGH_HOLD	−0.003***	(-3.62)	−0.002***	(-3.07)
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	75,384		75,384	
Adj. R^2	0.342		0.371	

This table reports DiD test results of how SHKC investors' ownership affects the SHKC program's effect on forecast quality. The dependent variables are forecast bias *(FB)* and forecast error *(FE)*. *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Governance effect of the SHKC program: trading activities.

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	−0.001**	(-1.99)	−0.001	(-1.30)
HIGH_TRADE	−0.001	(-0.64)	−0.002*	(-1.76)
SHKC × HIGH_ TRADE	−**0.002****	**(-2.16)**	−**0.001***	**(-1.95)**
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	75,384		75,384	
Adj. R^2	0.344		0.374	

This table reports DiD test results of how trading activities by SHKC investors affect the SHKC program's effect on forecast quality. The dependent variables are forecast bias *(FB)* and forecast error *(FE)*. *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Governance effect of the SHKC program: sensitivity to daily market return.

	Before			After			DiD
Buckets	Treat	Control	Diff	Treat	Control	Diff	
1 (Lowest)	−0.002	−0.002	0.000	−0.004	0.000	−0.004**	−0.004*
2	0.000	0.001	−0.001	−0.001	−0.001	0.000	0.001
3	−0.001	−0.002	0.001	0.001	0.001	0.000	−0.001
4	−0.001	0.000	−0.001	0.004	0.005	−0.001	0.000
5	0.001	0.001	0.000	0.001	0.001	0.000	0.000
6	0.005	0.005	0.000	0.001	0.001	0.000	0.000
7 (Highest)	0.007	0.007	0.000	0.002	0.001	0.001	0.001

This table presents the mean daily raw returns for SHKC brokerages and non-SHKC brokerages. We sort the observations into seven buckets based on the value-weighted daily market returns (from the CSMAR database) and then compute the average daily market returns for the SHKC brokerages and the non-SHKC brokerages for each bucket. Bucket 1 of the value-weighted daily market returns is the lowest bucket of market daily returns, and bucket 7 is the largest. The DiD approach measures the change in the mean daily returns after the announcement of the SHKC program for the treatment group relative to the control group.

bad market days (top 1/7 market returns) after they become SHKC firms, we conduct DiD analyses and sort daily market-wide returns into seven buckets. Table 7 reports the results of this analysis. The two groups of firms do not display different patterns of returns on bad market days before the introduction of SHKC program. However, the SHKC brokerages experience more severe negative returns than the non-SHKC control brokerages after the introduction of the SHKC program. The DiD coefficient is statistically significant at the 10% level. The results show that SHKC brokerages are exposed to more downside risk after SHKC adoption. This supports the potential governance role of SHKC investors.

Collectively, these tests are consistent with our argument that the baseline result is driven by direct governance functions of foreign investors after the openness of the SHKC program.

5.5. Cross-sectional analyses

When alternative governance mechanisms can discipline brokerage firms and minimize analyst forecast bias, the marginal benefit of the SHKC program is expected to decrease. Hong and Kacperczyk (2010) argue that the information produced by analysts and the competition between them is related to the number of analysts in an industry or a firm. Merkley, Michaely, and Pacelli (2017) demonstrate that the changes in the number of analysts covering an industry affect analyst competition and have significant spillover effects on other analysts' efforts, and in turn, on forecast accuracy and bias. Therefore, we expect the treatment effect to be more pronounced in an industry with less competition among analysts during the pre-SHKC program period. To test this conjecture, we use the number of analysts covering an industry and the number of analysts covering a firm to measure analyst competition at the industry and firm levels, respectively (Merkley, Michaely, and Pacelli, 2017). Specifically, we set a dummy variable, *LC_IND (LC_FIRM*), which equals 1 if the average number of analysts covering an industry (a firm) is below the sample median (industry median) of the pre-event period. The results reported in Table 8 show that the coefficients of the interaction term between the SHKC program and analyst competition are significantly negative, suggesting that the SHKC program has a greater impact on analysts facing less competition from peers. The results in Table 8 are consistent with the findings of Merkley, Michaely, and Pacelli (2017), who argue that competition between analysts is an important governance factor in disciplining them and mitigating biases in their behavior. They find that a single-unit decrease in the number of analysts in an industry decreases average earnings forecast accuracy by approximately 2.6% and increases optimistic forecast bias by approximately 5.5%. We confirm that analyst competition serves as a governance mechanism and contributes to higher forecast quality. Our findings also suggest that market openness can be an effective governance mechanism when analyst competition is weak.

We also examine whether the treatment effect varies with analyst characteristics. Within the context of analysts' forecasting, experience is a key factor in forecast accuracy. Cowen, Groysberg, and Healy (2006) suggest that analyst experience is likely to be related to forecast optimism because of either selection bias or lack of objectivity. We further consider analyst gender. Kumar (2010) and Li, Sullivan, Xu, and Gao (2013) suggest that male analysts are more optimistic than female analysts. Female analysts are more conservative and provide more accurate earnings forecasts than male analysts. Hence, we expect the presence of SHKC investors to mitigate such biases and to have a more (less) significant impact on more (less) experienced analysts and male (female) analysts.

To test these predictions, we create two dummy variables, *HEXP* and *MALE.* Specifically, *HEXP* is set to 1 if an analyst has more years of experience than the sample median and 0 otherwise. *MALE* is set to 1 if the research report is issued by a male analyst and 0 otherwise. Table 9 reports the results. The coefficients on the interaction between the adoption of the SHKC program and analyst experience are negative and significant at the 1% level, as shown in columns (1) and (2). The coefficients on the interaction between the adoption of the SHKC program and male analysts are negative and significant, as shown in

Table 8
Cross-sectional test: disciplinary effect of analyst competition.

	FB		FE	
	(1)	(2)	(3)	(4)
SHKC × LC_IND	**−0.002***** **(-2.78)**		**−0.001**** **(-2.13)**	
LC_IND	**0.000** **(0.50)**		**0.000** **(0.51)**	
SHKC × LC_FIRM		**−0.001**** **(-2.48)**		**−0.001*** **(-1.92)**
LC_FIRM		**0.000** **(0.82)**		**0.001***** **(2.96)**
SHKC	−0.001** (-2.31)	−0.001* (-1.75)	−0.001* (-1.82)	−0.001* (-1.86)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
N	75,384	75,384	75,384	75,384
Adj. R^2	0.322	0.149	0.337	0.174

This table reports DiD test results of how the SHKC program's effect on analyst forecast quality varies with the competitive pressure faced by analysts. The dependent variables are forecast bias (*FB*) and forecast error (*FE*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels. T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Cross-sectional test: characteristics of analyst.

	(1) FB	(2) FE	(3) FB	(4) FE
SHKC × HEXP	**−0.003***** **(-4.35)**		**−0.003***** **(-5.62)**	
HEXP	**0.005***** **(7.64)**		**0.007***** **(10.78)**	
SHKC × MALE		**−0.003***** **(-6.61)**		**−0.003***** **(-7.10)**
MALE		**0.001***** **(4.61)**		**0.001***** **(4.61)**
SHKC	0.000	0.001**	0.001*	0.002***
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
N	75,384	75,384	75,384	75,384
Adj. R^2	0.342	0.342	0.372	0.371

This table reports DiD test results of how an analyst's experience (*HEXP*) and gender (*MALE*) moderate the effect of the SHKC program on forecast quality. The dependent variables are forecast bias (*FB*) and forecast error (*FE*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

columns (3) and (4). These findings suggest that the adoption of the SHKC program has a greater effect on the forecast quality of both more experienced analysts and male analysts.

6. Additional tests

6.1. Examining the parallel trend condition

The validity of the DiD estimates depends on the parallel trend assumption that in the absence of the treatment, the average change in analyst forecast accuracy would have parallel trends in both groups. More specifically, the parallel trend assumption does not require the level of forecast accuracy to be identical in the treatment and control groups in the pre-event period because any distinctions are differenced out in the estimation. It does require similar pre-event trends in the forecast variables in both the treatment and control groups. We first check whether the parallel trend assumption holds in our treatment (SHKC) and control (non-SHKC) groups. We perform two diagnostic tests and present evidence to show that the parallel trend assumption is not violated. The first test estimates the pre-event difference in forecast accuracy between the two groups. The multivariate regressions, presented in Panel A of Table 10, show no significant differences in the dependent variables in the two groups during the pre-SHKC program period.

The second test examines the timing of the changes in forecast accuracy around the adoption of the SHKC program. Specifically, we replace *SHKC* in Equation (1) with the following dummy variables: *SHKC (-1)*, *SHKC (0)*, and *SHKC (>=1). SHKC (-1)* is a dummy variable that equals 1 if the year of observation is 1 year before the firm's inclusion in the SHKC program and 0 otherwise. *SHKC (0)* equals 1 if the year of observation is the year when the broker is included in the SHKC program and 0 otherwise. Finally, *SHKC (>=1)* equals 1 if the year of observation is after the firm's inclusion in the SHKC program and 0 otherwise. The results are presented in Panel B of Table 10. We find that the coefficients of *SHKC (-1)* are very small and statistically insignificant, which suggests that there is no pre-event trend suggesting a difference between the two groups in terms of the originality and generality of analyst forecast accuracy. The coefficients of *SHKC (0)* are also insignificant, indicating that forecast accuracy is not affected in the event year. These results are reasonable, given the adoption of the SHKC program in November 2014. However, the coefficients of *SHKC (>=1)* are negative and significant, suggesting that the differences in forecast accuracy between the two groups are significant in the liberalization period. Overall, these findings support the parallel trend assumption.

6.2. Ruling out alternative explanations

6.2.1. Change in forecast quality caused by overall market conditions

One may argue that the observed effect of the SHKC program on analyst forecasts is driven by the overall improvement in market quality caused by market liberalization rather than the governance effect of SHKC investors. To rule out this explanation, we focus on the sample of non-SHKC firms that are not allowed to be traded by SHKC foreign investors. As they would not benefit from market liberalization, we can attribute the improved forecast quality to improved analyst behavior. Thus, if the baseline results continue to hold for the non-SHKC firms, we could argue that the improved forecast quality is consistent with the fact that foreign institutions put more pressure on analysts.

Table 10
Parallel trend test.

Panel A: Subsample before opening the SHKC program				
	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**0.008**	**(0.98)**	**0.005**	**(0.61)**
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	32,236		32,236	
Adj. R^2	0.475		0.484	
Panel B: Time Trend Analysis				
	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC (-1)	**−0.000**	**(-0.45)**	**−0.000**	**(-1.42)**
SHKC (0)	**−0.000**	**(-0.13)**	**0.000**	**(0.16)**
SHKC (>=1)	**−0.002*****	**(-4.21)**	**−0.002*****	**(-4.40)**
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	75,384		75,384	
Adj. R^2	0.342		0.371	

This table presents the test results of the parallel trend assumption. Panel A presents the regression results of the differences in the forecast quality of the firms in the treatment and control groups before 2014. Panel B presents the results of the timing of the changes in forecast quality. The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11
Effects of the SHKC Program on Non-SHKC Firms.

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**−0.001****	**(-2.25)**	**−0.001****	**(-2.52)**
SIZE	0.002**	(2.42)	0.003***	(2.94)
LEV	−0.002	(-1.05)	−0.004	(-1.62)
ROA	−0.070***	(-12.59)	−0.091***	(-14.55)
TOBIN'S Q	−0.000	(-0.20)	0.000	(0.63)
R&D	−0.000*	(-1.67)	−0.000*	(-1.93)
VOLATILITY	0.006	(1.58)	0.002	(0.48)
AGE	0.000	(0.16)	−0.004	(-1.59)
SOE	−0.001	(-0.72)	−0.003	(-1.51)
DSIZE	0.003	(1.10)	0.005*	(1.79)
INDPR	0.005	(0.65)	0.010	(1.25)
CEOD	0.000	(0.26)	0.001	(0.97)
BIG4	0.000	(0.37)	−0.000	(-0.13)
BAGE	−0.001***	(-3.41)	−0.001***	(-2.63)
BSIZE	0.000	(0.39)	0.000	(0.89)
BGROWTH	−0.000	(-0.75)	−0.000	(-1.01)
BLIST	−0.000	(-0.13)	−0.000	(-0.27)
BFNUM	−0.000**	(-2.03)	−0.001*	(-1.88)
SHORT	0.001***	(3.24)	0.001***	(2.59)
LNVISIT	−0.001***	(-3.44)	−0.001***	(-2.67)
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	51,333		51,333	
Adj. R^2	0.345		0.380	

The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12
Regression results for the subsample covered by both SHKC brokerages and non-SHKC brokerages.

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**−0.001*****	**(-3.07)**	**−0.001****	**(-2.51)**
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	52,919		52,919	
Adj. R^2	0.344		0.373	

This table presents the test results of the alternative explanation of our baseline results (i.e., that they are driven by improvement in the firm's information environment). The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by an SHKC brokerage and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

To ensure the robustness of our results, we must also control for the difference between SHKC and non-SHKC firms. We check the sample firms in the SHKC program versus those not in the SHKC program and find no significant difference in the distribution by industry between these two subsamples. The SHKC firms demonstrate higher profitability, greater growth opportunity, higher R&D expenditure, and higher liquidity (Panel B of Table 1). We then control for these variables when examining the analyst forecast quality of non-SHKC firms. In Table 11, we run the main regression (model 1) using only the non-SHKC firm sample. We see that SHKC analysts significantly decrease the forecast errors and forecasts biases for non-SHKC firms, consistent with the main results.

6.2.2. Client firms' informational environments

One may argue that changes in analysts' forecasts are driven by the informational environment of the covered firms. For example, Beuselinck, Blanco, and Garcia Lara (2017) find that increases in foreign ownership lead to increases in financial reporting quality. Yoon (2017) demonstrates that firms increase voluntary disclosure after the adoption of the SHKC program. Thus, it is possible that the increase in forecast accuracy is driven by more disclosure and higher quality disclosure by pilot firms rather than the disciplinary role of pilot brokerages. We conduct two sets of tests to rule out this alternative explanation.

First, we construct a sample of firms that are followed by both SHKC and non-SHKC analysts and then compare the SHKC and non-SHKC analysts' forecasts for the same set of client firms. As both the SHKC and non-SHKC analysts make forecasts about the same firm, we remove any differences caused by variations in the firms' informational environments. As shown in Table 12, the coefficients for SHKC are consistent with our main findings.

Second, we better control for information transparency in our models. Following the literature, we measure a firm's information asymmetry in two ways (Harford, Jiang, Wang, and Xie, 2017; Balakrishnan et al., 2019). First, we compute a stock's bid-ask spread as a percentage of the stock price. A lower bid-ask spread implies lower information asymmetry. Second, we compute the Amihud (2002) stock illiquidity measure, which is the natural log of 1 plus the ratio of the absolute stock return to the dollar trading volume and scaled by 1 million. Table 13 shows that the coefficients for *SHKC* remain significantly negative after controlling for these additional variables.

Overall, these tests largely control for changes in the informational environments faced by analysts, thus ruling out the alternative argument that the informational environments of the covered firms drive the change in analyst forecasts.[12]

6.3. Self-selection bias of SHKC brokerage firms

Another concern is that market liberalization may systemically change the analyst composition within a brokerage firm, systemically affecting forecast quality. For example, large brokerage firms may be inclined to hire experienced analysts around the program date, which may improve the broker's average earnings forecast accuracy. To address this concern, we first examine the analyst composition of SHKC brokerages in the pre-and-post-SHKC program periods. The results in Panel A of Table 14 indicate that the mean differences in SHKC analysts' educational background, work experience, and workload are insignificant over the SHKC event period. Next, we rerun our tests using a subsample that includes only analysts that remained in the same position before and after SHKC program adoption. As reported in Panel B, the results are consistent with those reported previously using this subsample.

[12] We also examine whether SHKC investors' ownership is related to our findings. We find that higher SHKC investor ownership leads to better SHKC analyst forecast quality. Detailed results are available upon request.

Table 13
Effect of the SHKC Program on Analyst Forecasts After Controlling for Firms' Information Environment.

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**−0.001*****	**(-3.66)**	**−0.001*****	**(-2.91)**
SIZE	0.001	(1.14)	0.000	(0.66)
LEV	−0.005**	(-2.42)	−0.001	(-0.68)
ROA	−0.100***	(-18.09)	−0.067***	(-12.76)
TOBIN'S Q	−0.000	(-0.91)	−0.001**	(-2.39)
R&D	−0.000	(-1.35)	−0.000	(-0.48)
VOLATILITY	−0.046***	(-7.41)	−0.025***	(-5.18)
AGE	−0.003	(-1.27)	0.001	(0.90)
SOE	−0.002	(-1.21)	−0.002	(-0.95)
DSIZE	0.003	(1.17)	0.001	(0.48)
INDPR	0.017**	(2.42)	0.008	(1.40)
CEOD	0.001	(1.10)	0.001	(0.75)
BIG4	−0.002	(-1.13)	−0.002	(-1.02)
BAGE	−0.001***	(-3.40)	−0.001***	(-4.72)
BSIZE	−0.000	(-0.72)	−0.000	(-0.37)
BGROWTH	−0.001**	(-2.37)	−0.000*	(-1.89)
BLIST	0.001**	(2.26)	0.001***	(3.26)
BFNUM	0.001	(1.53)	0.000	(1.59)
SHORT	0.000	(0.88)	0.000	(0.79)
SPREAD	0.090***	(11.42)	0.059***	(9.13)
ILLIQUIDITY	−0.006	(-0.70)	0.011	(1.39)
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	75,384		75,384	
Adj. R^2	0.351		0.376	

This table presents the test results of the alternative explanation of our baseline results (i.e., that they are driven by improvement in the firms' information environment). The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14
Analyst composition of SHKC brokerages in the pre- and post-SHKC program periods.

Panel A: Summary Statistics for the Analyst Composition of SHKC Brokerages Before and After SHKC Program Adoption

Characteristics		Before (Mean)	After (Mean)	Difference(T-Value)
Gender	Male	0.729	0.718	−0.011 (t = 0.46)
Educational Background	≤ High school	0.001	0.004	0.003 (t = 1.46)
	Undergraduate degree	0.111	0.090	−0.021 (t = 1.12)
	≥ Master's degree	0.888	0.906	0.018 (t = 1.34)
Work Experience	Average # of years as an analyst	6.885	7.301	0.416 (t = 1.14)
Work Load	Average # of firms following each year	8.687	9.364	0.676 (t = 0.67)
	Average # of research reports issued each year	16.799	19.152	2.354 (t = 1.08)

Panel B: Regression Results for the Subsample Covered by Analysts Who Do Not Experience a Job Change Between the Pre- and Post-SHKC Program Periods

	(1) FB		(2) FE	
	Coefficient	T-Value	Coefficient	T-Value
SHKC	**−0.001****	**(-2.56)**	**−0.001***	**(-1.95)**
Control Variables	Yes		Yes	
Year FE	Yes		Yes	
Firm FE	Yes		Yes	
Analyst FE	Yes		Yes	
N	60,198		60,198	
Adj. R^2	0.342		0.344	

This table presents the test results controlling for the analyst composition in brokerage firms. Panel A presents the summary statistics for the analyst composition of SHKC brokerages before and after SHKC program adoption. Panel B presents the DiD test results using the subsample, which only includes the forecasts issued by analysts who do not experience a job change during the sample period. The dependent variables are forecast error (*FE*) and forecast bias (*FB*). *SHKC* is a dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm and 0 otherwise. Detailed definitions of all of the variables are provided in the Appendix. Each regression includes firm fixed effects, analyst fixed effects, and year fixed effects. Standard errors are heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Petersen, 2009). T-values are displayed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Conclusion

In addition to regulatory efforts, market forces can also improve analyst forecast quality. Using a sample of Chinese listed firms from 2012 to 2016, we document that the exogenous entry of foreign investors caused by the adoption of the SHKC program was an effective market mechanism for decreasing analysts' forecast biases. We also find supporting evidence that the disciplinary role of equity market liberalization is accompanied by an increase in analyst effort. Analysts employed by brokerage firms included in the SHKC program conduct significantly more site visits than analysts affiliated with non-pilot brokerages. Additionally, we find that the disciplinary effect of the SHKC program is greater when other governance mechanisms (analyst competition at the industry or firm level) are less effective.

Many recent studies show how equity market liberalization can function as a governance mechanism in mitigating the agency problem between managers and shareholders in non-financial firms (Stulz, 2005; Bae, Bailey, and Mao, 2006; Bae and Goyal, 2010). We extend this line of the literature and show that it can also improve the governance of financial intermediaries (i.e., brokerage firms), leading to higher quality analyst forecasts. Our findings add to the discussion of the effects of market liberalization on corporate governance and enrich the literature on the market mechanisms of corporate governance and their interaction with financial analysts' forecasts.

Acknowledgment

Chen acknowledges funding for project 71572087 from the China National Natural Science Foundation. Lu acknowledges funding for project 71872192 from the China National Natural Science Foundation. Ma acknowledges funding for project 2020M681404 from the China Postdoctoral Science Foundation.

Appendix. Variable definitions

Variable	Definition
FB	Analyst forecast bias, defined as the value of analyst forecast error (signed), calculated as an analyst's most recent forecast EPS for firm *i* minus its actual EPS, deflated by the stock price at the end of the previous fiscal year.
FE	Analyst forecast error, defined as the absolute value of analyst forecast error (unsigned), calculated as an analyst's most recent forecast EPS for firm *i* minus its actual EPS, deflated by the stock price at the end of the previous fiscal year.
DVISIT	Dummy variable that equals 1 if the brokerage visits the client's site in year *t*, and 0 otherwise.
LNVISIT	Natural logarithm of 1 plus the number of site visits the brokerage conducts for firm *i* in year *t*.
FREQUENCY	Natural logarithm of the number of research reports issued by analyst *j* for firm *i* every year.
SHKC	Dummy variable that equals 1 if analyst *j* of firm *i* in year *t* is employed by a pilot brokerage firm, and 0 otherwise.
SIZE	Natural logarithm of total assets.
LEV	Ratio of total debt to total assets.
ROA	Ratio of earnings to total assets.
TOBIN'S Q	Ratio of the market value of total assets to the book value of total assets.
R&D	Natural logarithm of 1 plus the R&D expense.
VOLATILITY	Standard deviation of the monthly stock return.
AGE	Natural logarithm of 1 plus the number of years since the firm was listed on the exchange.
SOE	Dummy variable that equals 1 if the firm is state-owned, and 0 otherwise.
DSIZE	Natural logarithm of the number of directors on the board.
INDPR	Proportion of independent directors on the board.
CEOD	Dummy variable that equals 1 if the CEO also serves as the chairman, and 0 otherwise.
BIG4	Dummy variable that equals 1 if the firm is audited by a Big 4 audit firm, and 0 otherwise.
BSIZE	Natural logarithm of the total sales of the brokerage.
BGROWTH	Sales growth of the brokerage.
BAGE	Natural logarithm of 1 plus the number of years since the brokerage was listed on the exchange.
BLIST	Dummy variable that equals 1 if the brokerage is listed on the exchange, and 0 otherwise.
BFNUM	Natural logarithm of the number of research reports issued by brokerages every year.
SHORT	Dummy variable that equals 1 if the brokerage can be shorted, and 0 otherwise.
HIGH_HOLD	Dummy variable that equals 1 if SHKC investors' ownership in an SHKC brokerage is above the sample median, and 0 otherwise.

Appendix (*continued*)

Variable	Definition
HIGH_TRADE	Dummy variable that equals 1 if the brokerage firm is a highly traded SHKC security, and 0 otherwise.
LC_IND	Dummy variable that equals 1 if the average number of analysts covering an industry is below the sample median, and 0 otherwise.
LC_FIRM	Dummy variable that equals 1 if the average number of analysts covering a firm is below the industry median, and 0 otherwise.
HEXP	Dummy variable that equals 1 if the number of years of experience as an analyst is above the sample median, and 0 otherwise.
MALE	Dummy variable that equals 1 if the analyst is male, and 0 otherwise.

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