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Abstract

During times when the Chinese government wished to prop up the market, sell-side analysts from brokerages with significant government ownership issued relatively less pessimistic (or more optimistic) earnings forecasts, earnings-forecast revisions, and stock recommendations; they were also slower to revise. Although less accurate, these forecasts significantly influenced investors' beliefs. Overall, the evidence is consistent with analysts' temporary compliance with government incentives, especially those with more expertise or fewer outside options. Our findings highlight the dual-role of sell-side analysts in emerging market contexts and how their information production may be compromised at times of economic uncertainty.

Keywords: Sell-Side Analysts; Forecast Optimism; Forecast Accuracy; Government Incentives; Emerging Markets; Coordinated Economies

JEL: G14, G24, G28, O16

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1 Introduction

The development of robust market institutions is crucial in emerging markets (Khanna and Palepu, 2010). The quality of these institutions can determine the risks faced by capital providers and contribute to capital formation and economic growth (Chow, 1993; Boskin and Lau, 1990). In emerging markets, the government typically plays an instrumental role in cultivating market institutions; one reason is that the strength of markets can be a source of the government's power (e.g., Tullock, 1987). However, the government may also at times have incentives to compromise the credibility of its institutions, for example due to its desire to manage market outcomes or preserve social stability.

This paper studies the implications of these conflicting incentives for the functioning of a crucial market institution—sell-side analysts—and addresses two research questions. First, how do government's incentives influence analysts' information production in emerging market contexts? Second, what are the consequences of such influence for capital markets? Sell-side analysts are broadly perceived to be "the preeminent market information intermediaries" (Bradshaw, 2011): they extract information from managers; process and distill complex economic, financial, and strategic information; and produce analyses, forecasts, and recommendations about firms. Thus their information output can critically influence market participants' beliefs (e.g., So, 2013). Despite analysts' importance as a market institution, little is known about their behavior in emerging markets, specifically how the government influences their information production. Answers to these research questions therefore fill an important void in the literature.

To answer these questions, we examine the behavior of Chinese sell-side analysts vis-a-vis the Chinese central government's incentives. China is a natural setting to study these questions not only because it is one of the world's most important emerging markets where the government plays a central role in the development of market institutions, but also because it is a setting in which the government's conflicting incentives are well known. Indeed, developing strong capital markets and institutions is viewed by Chinese policy makers as a crucial component to the country's competitiveness (Qi, 2008). Nevertheless, the Chinese central government at times exerts influence on market institutions, such as financial intermediaries, which can serve to undermine their credibility.[1] For example, the government at times has strong incentives to stabilize or prop up the stock market: in China, where by 2018 retail investors numbered 135 million and accounted for 85 percent of trades, a stable stock market is likely to contribute significantly to maintaining social stability and the government's power (e.g., Tullock, 1987; Piotroski, Wong, and Zhang, 2015).

In particular, analysts play an important and growing role in China's financial markets. The government fostered and monitored the growth of this industry in the early 2000s, and, by the end of 2017, the number of sell-side analysts had increased threefold over the preceding 15 years.[2] Sell-side analysts' research and recommendations are relied on by a significant proportion of retail investors (Gu, Li, and Yang, 2013; Shenzhen Stock Exchange (SSE), 2017), and they directly influence nearly 1,000 institutions with assets under management exceeding 70 trillion RMB. Critically, anecdotal evidence suggests that the government perceives sell-side analysts to be impactful and wishes to influence their information production. For example, Bloomberg reported in late 2018 that the Chinese Securities Regulatory Commission had warned representatives of more than 30 brokerage firms that their analysts should "strive for higher-level thinking and take into account the interests of the Party and the country when publishing research." As such, examining the influence of Chinese government's incentives on sell-side research affords a window into how central government's conflicting incentives affects the functioning of capital market institutions in emerging market contexts.

Ex ante, it is unclear how analysts would respond to external pressures on the information and analyses they produce. Analysts' reputational concerns may counterbalance the influence of

[1] For example, Bloomberg reported in 2017, shortly before the 19th National Congress of the Communist Party of China (CPC), that "As China's most important political event in years draws nearer, regulations have made it clear to the nation's top financiers that they don't want to see any major turbulence." Similarly, the *Wall Street Journal* reported in mid-2018 that "traders and brokers say regulators are increasingly stepping in to influence trades and make China's market appear less volatile, especially when Beijing wants to project stability."

[2] This estimate appeared in the 2017 annual report on sell-side analysts in China issued by *New Fortune*, which selects "star" analysts annually by surveying institutional investors, as *Institutional Investor* does in the United States. The report can be accessed via `http://www.xcf.cn/article/4cf22130b18211e8a3350242ac110003.html`.

external parties' incentives and pressures; on the other hand, concern for their career trajectories at the brokerage firm, which may (implicitly) depend on the central government's influence, could magnify analysts' responsiveness to the government's incentives. The degree to which sell-side analysts' information production is "captured" by the government is thus likely to depend on how analysts trade off these two conflicting forces (Jackson and Moerke, 2005; Cowen, Groysberg, and Healy, 2006).

We hypothesize that analysts who work at brokerage firms with significant government-brokerage ownership will be more likely to respond to government incentives than analysts employed at brokerage firms without government-brokerage ownership. State-owned brokerages are likely to be more sensitive to political influence because (i) the government is the controlling shareholder and thus a strong voice at the brokerage firm; (ii) their senior managers' appointments and promotions are likely to depend on government guidance; and (iii) they tend to be larger and thus to have greater market influence and greater potential as policy tools.

To empirically test these hypotheses, we examine variation in analysts' information production during periods when the central government had especially strong incentives to influence the stock market. We identify six such event periods between 2005 and 2015: four market-rescue attempts and the 17^{th} and 18^{th} National Congress Meetings of the Communist Party of China in 2007 and 2012 (see Table A1 for details). During these periods, the central government had especially strong incentives to limit the extent of market panic (in the case of the four financial-market rescue events) and to manage external perceptions of China (in the case of the National Congress Meetings). Consequently, the government would also have been especially likely to exert influence through market-information intermediaries, such as sell-side analysts.

By leveraging these economic shocks and the expected differences in incentives between analysts at state-owned brokerage firms (treatment) and at non-state-owned brokerage firms (control), we document the following main findings. First, during government intervention periods, analysts at state-owned brokerage firms issue forecasts that are relatively more optimistic than those of their counterparts at non-state-owned firms, although such relative optimism does not exist in non-intervention periods. For example, during market-rescue periods non-government-brokerage analysts issue lower earnings forecasts, consistent with the declining fundamentals. Relative to this baseline, government-brokerage analysts' forecasts during market-rescue periods undo about 26% of this decline.

We provide a variety of evidence that government-brokerage analysts' relative optimism is a consequence of compliance with government incentives during intervention periods. In particular, we show that relative optimism is more pronounced among those government-brokerage analysts who are more likely to be pressured (those who are specialists on the firms they forecast about and thus more credible) and among those more likely to be concerned about their internal career prospects (those who are generally less experienced). Optimism is also more pronounced in the case of forecasts for firms that the government has the strongest incentives to prop up: larger firms, firms in industries supported by the government's Five-Year Plan, and state-owned enterprises (SOEs). Finally, using a novel hand-collected dataset on brokerage firm manager backgrounds, we show that the forecast optimism exhibited by analysts is more pronounced in brokerage firms where the senior managers have close ties with the CSRC, consistent with the compliance hypothesis.

We also show how the relative optimism of government-brokerage analysts during government intervention periods is manifested in other aspects of their information production. During government intervention periods, government-brokerage analysts issue relatively more optimistic stock recommendations; they also comply with the government's incentives at least in part by delaying issuance of new forecasts (and revisions) during economic downturns. And when government-brokerage analysts revise downward during economic downturns, they do so less severely than non-government-brokerage analysts. During market-rescue periods, for example, the (downward) revisions of government-brokerage analysts are 15% less severe than those of non-government brokerage analysts.

Furthermore, we show that the relatively optimistic earnings forecasts of government-brokerage analysts during government intervention periods are less accurate. This finding rules out the possibility that these analysts' relative optimism was due to access to better information. Again, this evidence is consistent with government brokerage analysts' relative optimism being response to government incentives.

Finally, we show that the relative optimism of government-brokerage analysts probably influenced market participants' beliefs about firms' future prospects. By examining the drift in stock prices after earnings announcements, we show that market participants are slower to adjust to bad news when government-brokerage analysts play a more important role in firms' information environment (i.e., when they constitute a larger percentage of the firms' analyst coverage).

Our evidence contributes novel evidence on the role of government incentives on the functioning of market institutions in emerging market contexts. We also contribute to the literature on state-owned and private enterprises (e.g., Megginson, 2016; Fan and Wong, 2002; Faccio, Masulis, and McConnell, 2006; Hung, Wong, and Zhang, 2012). Prior studies argue that the inefficiency of state-owned enterprises is accounted for by their pursuit of social objectives instead of profit maximization (Aharoni and Ronen, 1989; Chen, Ljungqvist, Jiang, Lu, and Zhou, 2017; Toninelli, 2000). We draw attention to a novel channel—information production by stated-owned brokerage analysts—whereby governmental objectives, such as stabilizing capital markets, can be fulfilled. Our findings also highlight the dual roles of state-owned capital-market institutions in China: serving as information intermediaries and (implicitly) executing governmental policies (Hope, Li, Liu, and Wu, 2019; Wong, 2014).

Moreover, we contribute to research on analysts' informational role in capital markets and on how their incentives shape the information they produce (Bradshaw, 2011). The effects of U.S. analysts' incentives on their earnings forecasts have been exhaustively studied: for example, this literature has shown that analysts issue more optimistic reports to obtain or maintain access to management (Francis and Philbrick, 1993; Bradshaw, Lee, and Peterson, 2016; Chen and Matsumoto, 2006), and to generate investment-banking business (Dugar and Nathan, 1995; Michaely and Womack, 1999) or trading business for their firms (Hayes, 1998; Irvine, 2001; Jackson and Moerke, 2005; Firth, Lin, Liu, and Xuan, 2013; Gu et al., 2013). By contrast, relatively little attention has been paid to analysts' incentives in emerging-market or coordinated-economy contexts, where the central government often wield significant influence over capital-market institutions. Our paper suggests that government incentives can influence the properties of analysts' forecasts. Our evidence also contributes to the nascent literature on the role and importance of sell-side research at times of elevated economic uncertainty. Prior research (Loh and Stulz, 2018) suggests that, during bad times, market participants place greater weight on sell-side analysts' information, which is particularly useful when firms' economic prospects are less certain. We show that, in emerging-economy contexts, the information produced by sell-side analysts may be less reliable precisely at times of economic uncertainty.

Finally, our evidence contributes to the growing literature on the role of the central government in shaping China's information environment. Prior literature has investigated how China's institutional environment shapes listed firms' reporting incentives, both via formal rules set by regulators, which can affect firms' earnings-management behavior (e.g., Chen and Yuan, 2004; Haw, Qi, Wu, and Wu, 2005), and via the government's political influence on affiliated firms, which can affect the timing of negative news releases (e.g., Piotroski et al., 2015). Most closely related to our work is the burgeoning stream of literature that examines how the government intervenes in financial intermediaries' information production. Several papers have examined how the government's influence affects the timing and quality of information produced by various news media (e.g., Piotroski, Wong, and Zhang, 2017; Hope et al., 2019). Although other scholars (Piotroski, Wong, and Wu, 2012) have examined the government's role in the structure and competitive landscape of the brokerage industry, we are the first to document the impact of government incentives on the forecasts and recommendations of government-brokerage sell-side analysts.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on the brokerage industry in China. Section 3 presents our main empirical analysis. Section 4 presents the results of robustness tests. Section 5 assesses the market impact of government-brokerage analysts' relative optimism. Section 6 concludes.

2 Background and Hypothesis Development

This section traces the development of the Chinese brokerage industry. We explain how the industry is regulated and the channels through which the central government can exert influence. Finally, we present hypotheses on how the government's incentives are likely to affect the incentives of different groups of sell-side analysts.

2.1 The Brokerage Industry in China

In response to the 1991 formal opening of China's two stock exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange, financial institutions obtained licenses to engage in securities trading and underwriting; thus a brokerage industry emerged in China. These brokerage firms were all controlled either by large state-owned banks or by state-owned enterprises. For instance, Huaxia Securities, one of the largest securities brokerages in the 1990s, was owned by the Industrial and Commercial Bank of China.

Over the ensuing decade the Chinese stock market grew rapidly, and in 2001 the China Securities Regulatory Commission (CSRC) issued a notice permitting non-state-owned enterprises to invest in or control brokerage firms.[3] Minsheng Securities was the first non-state-owned enterprise to obtain a brokerage license, in 2002; the company's larger shareholders included such well-established non-state-owned enterprises as China Oceanwide, New Hope Group, and Fosun International. By the end of 2002, non-state-owned brokerage firms numbered about 20.

The prosperity of non-state-owned brokerage firms during the 2002–2003 market decline at-

[3]The CSRC, established in 1992, is the main regulator of China's securities markets, comparable to the U.S. Securities and Exchange Commission. The CSRC's main responsibilities include enacting and enforcing policies, laws, and regulations concerning securities markets; supervising securities issuers and financial institutions; and imposing penalties for misconduct or violations of rules or laws related to securities and futures.

tracted the attention of regulatory agencies. In 2003, the CSRC re-emphasized that brokerage firms were strictly prohibited from using trading-settlement funds, entrusted assets, and customers' entrusted bonds for other purposes. Over the next five years the CSRC imposed severe sanctions, including revocation of business licenses, on non-compliant brokerage firms: most of the approximately 30 firms sanctioned during this period were non-state-owned. Since then, the Chinese brokerage industry has grown steadily. By the end of 2015, approximately 15% of all brokerage firms were non-state-owned.

2.2 Government Influence on China's Brokerage Industry

In many respects, the operations and performance of Chinese brokerage firms depend on the CSRC. First, they must be licensed by the CSRC to engage in securities trading or underwriting. Further, every prospective IPO firm requires the approval of the CSRC before it can be listed on an exchange. Thus the underwriting fees earned by brokerage firms, which account for a significant portion of their total revenues, depend to some extent on the CSRC. Permission is also necessary when brokerage firms wish to pursue new businesses, such as margin trading and issuance of asset-backed securities. Furthermore, the CSRC oversees the activities of brokerage firms by investigating misconduct and enforcing sanctions. Jointly, its formal powers constitute a formidable mechanism through which the central government exerts influence on brokerage firms' behavior.

Alongside formal regulatory channels, the CSRC can also influence brokerage firms via an informal and frequently employed mechanism known as *window guidance*. A phenomenon that originated in Japan in the 1950s, window guidance is a method by which regulatory agencies communicate their agendas to the directors of financial institutions privately, via phone calls or private meetings. By contrast to formal mechanisms, window guidance is non-mandatory and less rigid, but can entail an implicit threat: potential retribution for non-compliance via the formal powers of the regulator. To the extent that such an implicit threat could incentivize top managers of brokerage firms, window guidance could serve as an effective instrument for enforcing compliance with government incentives.

For example, in an effort to stabilize the stock market, the CSRC met with 21 brokerage firms on July 4, 2015. Immediately after the meeting, the participating firms jointly announced that they would invest no less than 120 billion RMB in blue-chip ETFs and would not sell stock holdings as long as the Shanghai Composite index remained below 4,500 points. In the ensuing months, however, CITIC Securities, China's largest investment bank and a state-owned enterprise, was suspected of short-selling while the "national team" of state financial institutions injected cash into the market. That September the company's president, Boming Cheng, was arrested for bribery and eventually sentenced to more than three years in prison.

2.3 Hypothesis Development

Though the entire Chinese brokerage industry, and its analysts, could have been subject to CSRC influence and pressure, state-owned firms are likely to have been especially sensitive to government incentives. First, state-owned brokerage firms were ultimately controlled by the central government or by local government, whose incentives could have directly shaped these firms' behavior. Second, the senior managers of state-owned brokerage firms were appointed (and could be dismissed) by the government, and their promotions (or demotions) probably depended in part on government guidance. The motivations of these firms' management teams were therefore much more likely than non-state-owned firms' to be aligned with those of the government. Finally, state-owned firms were typically larger and more influential in capital markets than their non-state-owned counterparts. To the extent that the Chinese government pursued policy objectives by influencing the brokerage industry, therefore, it was more likely to target state-owned brokerages. For these reasons we hypothesize that, to the extent that government incentives are embodied in information production at brokerage firms, they are apt to be reflected in information produced by government-owned firms and their analysts.

Nevertheless, it is *ex ante* unclear how compliantly government-brokerage analysts would respond to government incentives. We hypothesize that certain analysts at state-owned brokerage firms, due to their expertise or credibility, would have faced greater pressures to comply. Thus, holding all else equal, relative optimism during government intervention periods should be more pronounced among such analysts.

To the extent that analysts' career trajectories at government-owned brokerage firms depended on their level of compliance, they faced a tradeoff between their external reputations and career opportunities on the one hand and internal career prospects on the other (Jackson and Moerke, 2005; Cowen et al., 2006). We hypothesize that, all else equal, those government-brokerage analysts likely to be particularly preoccupied with their internal career prospects would have been more responsive to government incentives. If so, we would also expect relative optimism during government intervention periods to be more pronounced among such analysts.

3 Main Empirical Results

This section presents the results of empirical analyses of differences in the earnings forecasts of government-brokerage analysts and non-government-brokerage analysts during periods when the Chinese government could plausibly have had stronger incentives to prop up the stock market. Following a description of our sample construction and research design, we report our analyses and interpretation of the results.

3.1 Sample Selection and Research Design

Our sample consists of annual earnings forecasts from 2005 through 2015. Because no single database in China provides full coverage of analysts' forecast data, we construct a comprehensive dataset by combining data from five vendors. We begin with earnings-forecast data from the China Stock Market & Accounting Research (CSMAR) database, to which we add any new forecasts found in the following data sources: CBAS, the Wind Financial database, the RESSET financial research database, and HIBOR.[4] We assign a unique code to each analyst, whom we identify by name across the various datasets. For a new forecast to be included in our sample, it must (i) be issued by a different analyst, (ii) be issued on a different date, or (iii) pertain to a different firm. Following prior literature (e.g., Clement and Tse, 2005), we include only one-year-ahead earnings forecasts issued between the prior and current fiscal-year earnings announcements. We merge in information about the brokerage, the analyst, and the covered firm, and eliminate observations about which we lack necessary information on brokerage ownership (i.e., state-owned or private) or analyst characteristics.

Our overall sample consists of 234,328 earnings forecasts for 2,112 unique listed firms between 2005 and 2015. These forecasts were issued by 5,056 analysts at 94 distinct brokerage firms; around 80% were state-owned and 20% non-state-owned.[5] A state-owned brokerage firm typically employed an average of 30 analysts each year; a non-state-owned brokerage firm typically employed about 20 analysts per year. Overall, about 14% of the annual earnings forecasts in our sample were issued by analysts at non-state-owned brokerages.

Our main outcome of interest is the observed optimism of an analyst's forecast of a firm's annual earnings. To measure this outcome, we follow prior literature (i.e., Clement and Tse, 2005; Clement and Law, 2014) and normalize an analyst's *Raw Optimism*—the one-year-ahead earnings-per-share (EPS) forecast for a given firm minus the firm's actual EPS—to range from 0 to 1. That is, the main dependent variable in our study is defined as

$$Optimism_{ij\tau T} = \frac{Raw\ Optimism_{ij\tau T} - \min_{jT}\left(Raw\ Optimism_{ij\tau T}\right)}{\max_{jT}\left(Raw\ Optimism_{ij\tau T}\right) - \min_{jT}\left(Raw\ Optimism_{ij\tau T}\right)}, \tag{1}$$

where $Optimism_{ij\tau T}$ is the normalized optimism of analyst i's forecast of firm j's annual earnings issued at date τ in year T; $\min_{jT}\left(Raw\ Optimism_{ij\tau T}\right)$ and $\max_{jT}\left(Raw\ Optimism_{ij\tau T}\right)$ are the

[4] Over 80% of the forecasts included in our final sample are from CSMAR. Our results are robust to using only data from CSMAR.

[5] In untabulated results, we find that government-brokerage analysts and non-government-brokerage analysts cover similar firms. We do not find that the firms covered by these analysts exhibit significantly different firm characteristics, including firm size, book-to-market ratio, leverage, ROA, market beta, and sales growth.

sample minimum and maximum of $Raw\ Optimism_{ij\tau T}$ for all the forecasts issued for firm j in year T (i.e., varying at the firm-year level).

As explained in Clement and Tse (2005) and Clement and Law (2014), this normalization facilitates the interpretation and comparison of regression coefficients while conserving the relative distance between forecasts issued for the same firm and the same year. Since variation in this optimism measure, by construction, captures the relative optimism of forecasts issued for the same firm, this normalization also has the advantage of neutralizing the effect of firm-level factors at a particular time.[6] In other words, our effects are mainly identified by within-firm and across-analyst variation in $Optimism_{ij\tau T}$.[7] Thus our empirical tests will control for the effects on forecast optimism arising from differences in analyst characteristics.

To examine how analysts employed at state-owned brokerage firms respond to government incentives, we study how their forecasts differ from those issued by analysts at non-state-owned brokerage firms during periods when the central government aimed to prop up the stock market (government intervention periods).[8] We identify six such periods between 2005 and 2015 (see Table A1 for details): four market-rescue attempts and the six-month periods surrounding the 17th and 18th National Congress meetings of the Communist Party of China. To account for the possibility of baseline differences between the forecasts of analysts employed at state-owned and non-state-owned brokerages, we benchmark and compare their intervention-period differences in optimism against non-intervention-period differences.[9]

Thus, our main tests estimate variations of the following difference-in-difference (DID) specifi-

[6]Clement and Law (2014) explain that "this [scaled optimism] metric is conditional on the same firm-year ... [and thus] this adjustment is identical to controlling for firm-year fixed effects."

[7]Though this normalization is a standard in the literature on analysts' forecast properties, we verified in untabulated results that our main findings are robust to alternative normalizations. For example, when we scale *Raw Optimism* by price per share, government-brokerage analysts' relative optimism during government intervention period is positive and significant, with the baseline effect being about 12.5% of the mean. Relative to the decrease in optimism of non-government-brokerage analysts during intervention periods, government-brokerage analysts' forecasts undo about 10% of this decline.

[8]It is possible that the government may also have incentives to influence the market during periods of relatively high investor sentiment; however, government influence at these times is much more difficult to identify empirically.

[9]Our results are robust to changing the definition of the intervention periods for the National Congress meetings to the interval beginning three months before the meetings began and ending one month after their conclusion.

cation:

$$
\begin{aligned}
Optimism_{ij\tau T} &= \beta_0 + \beta_1 Intervention_{\tau T} \times Govbro_{i\tau T} + \beta_2 Intervention_{\tau T} \\
&+ \beta_3 GovBro_{i\tau T} + \gamma' X_{i\tau T} + f_T + \xi_{ij\tau T},
\end{aligned} \tag{2}
$$

where $Intervention_{\tau T}$ is an indicator variable that takes a value of 1 if the earnings forecast is issued on a date and year that falls within a government intervention period and 0 otherwise; $GovBro_{i\tau T}$ is an indicator variable that takes a value of 1 if the earnings forecast is issued by an analyst employed (at the time of the forecast) by a state-owned brokerage firm and 0 otherwise; and $X_{i\tau T}$ is a set of analyst characteristics observed as of the date of the earnings forecast.

A brokerage firm is classified as state-owned ($GovBro_{i\tau T} = 1$) when we determine its ultimate controller to be a government entity. Following prior literature (La Porta, Lopez-De-Silanes, and Shleifer, 1999; Fan and Wong, 2002; Claessens, Djankov, Fan, and Lang, 2002), we define the ultimate controller as the shareholder that possesses determining controlling rights in the company and is not controlled by another entity. To identify the ultimate controller, we track each firm's ownership pyramid and find the ultimate owners of all shareholders whose ownership stake in a brokerage firm is greater than 10%. Whether the brokerage firm is state-owned is then determined by the identity of its largest ultimate owner.[10] In our sample, all of the largest ultimate owners possessed more than 20% of a given brokerage firm's shares.

To account for analyst characteristics ($X_{i\tau T}$) that could explain variation in *Optimism*, we control for the effect of the analyst's firm-specific experience (*Firmexp*), defined as the number of years that an analyst has issued forecasts at the firm; the analyst's general experience (*Genexp*), defined as the number of years that the analyst has issued forecasts included in the database; the analyst's forecasting frequency at the firm in the current year (*Frequency*); the number of companies the analyst follows (*Companies*); the number of industries the analyst follows (*Industries*); elapsed

[10] Many state-owned brokerage firms are ultimately owned by local State-owned Assets Supervision and Administration Commission of the State Council.

time from the date of the forecast to the end of the fiscal year (*Horizon*); and the number of unique analysts employed by the brokerage firm (*Brokersize*). Following Clement and Tse (2005), all analyst-level controls are normalized to range from 0 to 1, like the normalization of *Raw Optimism* to create the Optimism variable. Definitions of these regression controls appear in Table A2; their distributional summary statistics are reported in Table 1, Panel A.

The main coefficient of interest in Eq., (2) is β_1 (i.e., the "DID coefficient"), which compares the average differences in earnings forecast optimism between state-owned and non-state-owned brokerage analysts during intervention-event periods to the average differences in earnings forecast optimism between the two types of analysts during non-event periods. In keeping with our hypothesis that analysts at state-owned brokerages were more likely to respond to the government's incentives to prop up the stock market during government intervention periods, we expect a positive and significant β_1.

3.2 Earnings-Forecast Optimism during Government Intervention Periods

We begin by examining how government-brokerage analysts' forecast optimism differs from that of analysts at non-state-owned brokerages during government intervention periods. We then provide additional tests to examine whether the main effects are attributable to analysts' responsiveness to government incentives or to alternative causes. We also examine how analysts' responses to government incentives were manifested in other aspects of their information production, including stock recommendations and forecast revisions. Finally, we explore the extent to which the relative optimism of government-brokerage analysts during government intervention periods influenced market participants' beliefs about firms' future prospects.

Table 1, Panel A, provides descriptive statistics on the variables in our main sample. All the forecast-related variables are normalized to range from 0 to 1, following the approach of Clement and Tse (2005) and as described in Eq., (1). The mean of *GovBro* is 0.862, indicating that 86% of the forecasts included in our sample were issued by government-brokerage analysts; about 26% of forecasts were issued during government intervention periods.

Table 1, Panel B, provides a univariate summary of *Optimism* for government-brokerage and non-government-brokerage analysts. It shows that, during intervention periods, *Optimism* declines overall by about 10% (from 0.4662 to 0.4203). This pattern reflects the fact that the majority of the intervention periods we consider—the four market-rescue periods—were characterized by significant market declines, during which the fundamentals of China's economy were anticipated to decline. Given the general decline in *Optimism* in the forecasts of both government-brokerage and non-government-brokerage analysts, the state-owned-brokerage analysts were relatively more optimistic (i.e., the decline in optimism was less pronounced).

In Table 2 we examine whether these univariate results are robust to controlling for analyst and brokerage characteristics. This table reports DID regression estimates, following Eq., (2), of how government incentives during intervention periods affect government-brokerage analysts' *Optimism*. Columns 1-2 examine the two types of event respectively, the four market-rescue events (*Rescue*) and the two National Congress meetings (*Meeting*); column 3 pools all the events (*Event*).

The multivariate tests of Table 2 are consistent with the univariate analyses. In each specification, we find a DID coefficient that is positive and statistically significant (at the 5% level), consistent with government-brokerage analysts having issued relatively more optimistic earnings forecasts during government intervention periods than non-government-brokerage analysts.

These findings are consistent with the idea that analysts at government-owned brokerage firms attempt to strike a balance between two conflicting considerations: their external reputations and their internal promotional prospects (Jackson and Moerke, 2005; Cowen et al., 2006). During market-rescue periods, in particular, government-brokerage analysts on average revised downward (i.e., the sum of the coefficients on $GovBro \times Rescue$ and $Rescue$ is negative and significant at the 1% level), in keeping with the declining fundamentals, a pattern that suggests that they cared about preserving credibility in the marketplace. But our DID estimates also show that these analysts' forecasts were relatively more optimistic—they revised less severely than did non-government-brokerage analysts during economic downturns—which suggests a degree of compliance with the government's incentives.

One way to interpret the magnitude of the effect is to assess how much of the decline in *Optimism* during intervention periods is "un-done" by government-brokerage analysts. Interpreting the coefficients in column 1, we find that *Optimism* on the part of non-government-brokerage analysts declines on average by 0.046 during the market rescue periods (the coefficient on *Rescue*), consistent with analysts' expectations of deteriorating fundamentals during these times; relative to this baseline, government-brokerage analysts' forecasts undo about 26% of this decline in *Optimism*.

3.3 Heterogeneity by Analyst Characteristics

Next, we provide further evidence that the observed patterns in *Optimism* could be due to analysts' responsiveness to government incentives, rather than a consequence of an alternative mechanism. In particular, we examine how the baseline effects documented in Table 2 vary with analysts' likelihood of facing pressure to respond to government incentives as well as their sensitivity to such pressures.

As noted above, analysts whose forecasts are perceived to be more credible, such as specialists on the firms for which they forecast, are, all else equal, more likely to face pressure to comply with government incentives; their compliance is more important for achieving the government's objectives. Thus we expect relative optimism among government-brokerage analysts to be more pronounced in forecasts issued by these analysts.[11] Also, because analysts at government-owned brokerage firms face a tradeoff between their external reputations and their internal promotional prospects (Jackson and Moerke, 2005; Cowen et al., 2006), we hypothesize that, all else equal, analysts with relatively less general experience, and thus less attractive outside options, will be more preoccupied with internal career prospects. Thus less experienced analysts at government brokerage firms will be more responsive to government incentives during intervention periods.

[11] In untabulated tests, we verified that forecast revisions by analysts who had covered a firm longer produced a significantly stronger reaction from market participants.

We estimate difference-in-difference-in-differences (DDD) specifications to examine the differential relative optimism of government-brokerage analysts' forecasts for firms with and without certain characteristics:

$$\begin{aligned} Optimism_{ij\tau T} &= \beta_0 + \beta_1 GovBro_{i\tau T} \times Intervention_{\tau T} \times Characteristic_{ij\tau T} \\ &+ \beta_2 GovBro_{i\tau T} \times Characteristic_{ij\tau T} + \beta_3 GovBro_{i\tau T} \times Intervention_{\tau T} \\ &+ \beta_4 Characteristic_{ij\tau T} \times Intervention_{\tau T} + \beta_5 GovBro_{i\tau T} \\ &+ \beta_6 Intervention_{\tau T} + \beta_7 Characteristic_{ij\tau T} + \gamma X_{i\tau T} + f_T + \epsilon_{ij\tau T}. \end{aligned} \tag{3}$$

Here, $Characteristic_{ij\tau T}$ is an indicator that takes a value of 1 if a forecast issued by analyst i at time τ for firm j's time-T earnings exhibits a particular characteristic and 0 otherwise. All other variables are as defined in Eq., (2). If the forecasts of government-brokerage analysts with certain characteristics exhibit relatively greater optimism, we should expect β_1 to be positive and statistically significant.

Table 3 reports DDD coefficients using various analyst characteristics of interest. As in Table 2, we report results for each type of intervention separately: market rescues in column 1, National Congress meetings in column 2, and all intervention events pooled in column 3. Table 3, Panel A, compares the relative optimism of government-brokerage analysts who are specialists in particular firms ($Firmexp > .5$) with that of non-specialists ($Firmexp < .5$). Consistent with a likelihood that specialists face greater pressures to comply, we find relative optimism among government-brokerage analysts to be more pronounced among firm specialists in all three specifications. Each specification produces a positive and statistically significant (at the 5% level) DDD coefficient.

Table 3, Panel B, compares the relative optimism of government-brokerage analysts who are generally inexperienced ($Genexp < .5$) with that of experienced analysts ($Genexp > .5$).[12] During market-rescue periods (column 1), the relative-optimism effect is especially pronounced among

[12] Our indicator for firm specialists exhibits a negative correlation of 37% with our indicator for generally inexperienced analysts.

inexperienced government-brokerage analysts: we report a positive and significant (at the 5% level) DDD coefficient. We do not find any significant results associated with National Congress meetings (column 2) or in the pooled event specification (column 3), suggesting that relatively inexperienced analysts are most likely to respond during market-downturn periods.

Based on the intuition established above, we also compare the relative-optimism effect between inexperienced specialists to that of experienced non-specialists. We expect the former group to be more sensitive to internal career concerns *and* to face greater pressure to comply with government incentives; we expect the latter group to be less sensitive to internal career concerns *and* to face less pressure to comply. Under the compliance hypothesis, therefore, we expect the relative-optimism effect to be especially pronounced in this comparison. Consistent with these expectations, Table 3, Panel C, shows the relative-optimism effect to be significantly greater among generally less experienced firm specialists than among more experienced non-specialists. In all three specifications we find a positive and significant DDD coefficient; moreover, the magnitudes of the coefficients are substantially larger than those of the previously examined specifications.

We also compare the relative-optimism effect between analysts designated as "stars" by *New Fortune* versus non-star analysts. Ex ante, we made no clear prediction. On the one hand, star analysts are likely to exert greater influence on markets, and thus may face greater pressure to comply with government incentives. On the other hand, star analysts may enjoy better outside options and thus be less responsive to pressure to comply with government incentives. Table 3, Panel D, shows that the relative-optimism effect does not differ between star and non-star analysts. In all three specifications, we obtain DDD coefficients that are not statistically significant at the 10% level.

3.4 Heterogeneity by Forecast-Target Characteristics

Analysts at government brokerage firms may also face stronger pressures to issue optimistic forecasts for particular firms. To minimize market panic (in the case of the four financial-market rescue events), or to create an impression of robust financial markets (in the cases of the National Congress meetings), the government may want to prop up the prices of larger firms, firms in supported industries explicitly identified by the prevailing Five-Year plan, or SOEs.

To test these hypotheses, we again estimate the DDD specification of Eq., (3), but use sample splits based on target-firm characteristics. To sharpen our tests, we examine how different target-firm characteristics influence relative optimism among the analysts most likely to be targeted and most likely to be responsive, namely firm experts and inexperienced firm experts.

We begin by identifying a firm's importance to the overall stock market; firms with larger market capitalization wield greater weight in (and thus greater influence on) the major stock indexes. We create an indicator for firms above the median in market capitalization in the cross-section (*Large Market Cap*). Table 4, Panel A1, shows that, among firm-expert analysts, the relative-optimism effect is significantly greater in the case of larger-market-capitalization firms. In each of the three specifications, we find a positive and significant DDD coefficient (at the 5% level in columns 1 and 3 and at the 10% level in column 2); the coefficient magnitudes are also large relative to our baseline results. Panel A2 estimates the same specification but uses the significantly smaller subsample of less experienced firm experts; we find similar results using this sample of the most responsive analysts.

Next we examine how the relative-optimism effect differs in forecasts about target firms in a Five-Year-Plan-supported industry versus other target firms. In Panel B1, using the subsample of firm-specialist analysts, we find positive DDD coefficients in all three specifications; for the National Congress Meetings, we find a DDD coefficient that is statistically significant at the 1% level. In Panel B2, using the subsample of most responsive analysts, we find consistently positive coefficients that are generally larger in magnitude (i.e., column 3) but do not obtain significance. This result could be explained by the fact that few firms belong to supported industries (about 22% of our sample) and very few analysts are inexperienced firm experts (about 10% of our sample), resulting in a low-powered test.

Finally, we examine the relative-optimism effect in the case of SOE and non-SOEs firms. In Panel C1, using the subsample of firm-specialist analysts, we find positive DDD coefficients in all three specifications. For the National Congress Meetings (column 2) and the pooled event specification (column 3), we find DDD coefficients that are statistically significant at the 10% level. In Panel C2, using the subsample of most responsive analysts, we again find consistently positive coefficients that are generally larger in magnitude; statistical significance is eroded by the substantially smaller sample, but we still obtain a statistically significant (at the 10% level) DDD coefficient for the National Congress meetings.

4 Robustness Tests

This section presents several robustness tests to provide further evidence that (i) government-brokerage analysts produced relatively more optimistic information during intervention periods, and (ii) these analysts' behavior is attributable to compliance with government incentives.

4.1 Forecast Optimism and CSRC-Connected Managers

To validate whether our results could be driven by analysts' forecast optimism during intervention periods could be a result of their compliance with government incentives, we consider the influence of senior managers and exploit an alternative "treatment" based on analysts' senior managers' types.

Our hypothesis is that senior managers with stronger ties to the CSRC may be more likely to exert pressure on analysts to comply with government incentives. To test such a hypothesis, we manually collected data on the senior managers of all the brokerage firms in our sample using information disclosed in brokerage firms' annual reports. We identify a brokerage firm as having a CSRC-connected senior manager (*CSRC Manager*) if one of its senior managers had prior work experience in the headquarter or local office of CSRC.

Table 5 reports the results of our empirical tests of the influence of having CSRC-connected senior managers at brokerage firms. We begin in column 1 by estimating the baseline DID specification of Eq., (2) on the full sample and pooling all intervention events, but using *CSRC Manager* as the treatment variable of interest (instead of *GovBro*). We find a positive and statistically significant (at the 1% level) DID coefficient, suggesting that analysts working under CSRC-connected managers issue relatively more optimistic forecasts during intervention periods. We further estimate this specification separately for the subsample of government-brokerage analysts (in column 2) and for the subsample of non-government-brokerage analysts (in column 3). In both subsamples, we find a significant optimism effect associated with having a CSRC-connected manager. Interestingly, the magnitude of the effect is significantly larger for non-government-brokerage analysts—the DID coefficient is more than two times as large.

Together, these results are consistent with analysts' forecast optimism during government intervention periods being a response to government pressure. These findings also suggest that having a CSRC manager is a substitute for the other channels for influencing analysts' forecast behavior in government-brokerage firms. On the other hand, for analysts in non-government-brokerage firms, in which the central government has fewer channels through which it can exert influence, having a CSRC manager has a relatively larger effect on analysts' compliance of government incentives.

4.2 Optimism in Stock Recommendations

To the extent that the government's incentives influence certain sell-side analysts' information production, we may also expect to find relative optimism in the other information they produce. Stock recommendations are important, and frequently studied, summary statistics produced by analysts (Jegadeesh, Kim, Krische, and Lee, 2004; Barber, Lehavy, McNichols, and Trueman, 2005). As a robustness test, therefore, we examine how the stock recommendations of government-brokerage analysts and non-government brokerage analysts differ during intervention periods. In particular, if government-brokerage analysts were complying with government incentives to prop up the stock market, we would expect to see relative optimism in stock recommendations.

To test this hypothesis, we estimate the DID specifications presented in Table 2 using an alternative dependent variable *REC*, which assigns the recommendations "strong buy," "buy," "hold," "sell," and "strong sell" the respective numerical values 1, 0.75, 0.5, 0.25, and 0. The results, reported in Table 6, show that government-brokerage analysts on average made relatively optimistic stock recommendations during each of the intervention periods, corroborating our main results on earnings-forecast optimism.

4.3 Optimism in Earnings Forecast Revisions

To the extent that the government's incentives influence certain sell-side analysts' information production, we may also expect to find relative optimism in their forecast revisions (*Revision*). To examine whether the magnitude of revisions varied during intervention periods, we extract a subset from our sample consisting of earnings forecasts issued by the same analyst that differed from her prior forecast for the same period's earning and the same firm. This specification produce a sample of 61,938 one-year-ahead forecasts between 2005 and 2015.

Table 7 estimates the DID specifications of Table 2, but uses *Revision* as the dependent variable of interest. The results suggest that during market-rescue periods (column 1), non-government-brokerage analysts who revised tended to revise downward, consistent with deteriorating economic fundamentals. By contrast, the revisions of government brokerage analysts tended to be on average less severe: we obtain a positive and statistically significant DID coefficient (at the 10% level). Moreover, the economic magnitudes are significant: government-brokerage analysts' downward revisions at these times are less severe, on average, by about 15%. We do not find any differential patterns in forecast revisions during National Congress Meetings (column 2). Overall, pooling all events, we continue to find relatively optimistic forecast revisions during government intervention periods. In the pooled specification (column 3) we obtain a positive DID coefficient that is both statistically significant (at the 5% level) and economically significant.

4.4 Exploring Analysts' Earnings Forecast Lag

We further explore whether government incentives influence the time lag between the latest forecast and its most recent predecessor (*Forecast Gap*). Table 8 estimates the three specifications of Table 2 but uses *Forecast Gap* as the dependent variable of interest.

Table 8, column 1, suggests, that when government-brokerage analysts issue forecasts during market-rescue periods, they do so slowly (e.g., their revisions are less timely during these times). Interestingly, during non-event periods government-brokerage analysts tend to update more frequently—that is, the interval between forecasts tends to be shorter than non-government-brokerage analysts (i.e., the negative and statistically significant coefficient on *GovBro*). This comparative promptness disappears, however, during market downturns (i.e., the sum of the coefficients on *GovBro* $\times$ *Rescue* and *GovBro* is statistically no different from 0).

Column 2 suggests a relative delay in government-brokerage analysts' forecasts during the National Congress Meetings. However, this phenomenon appears to be driven by increased promptness on the part of non-government-brokerage analysts at these times (i.e., the negative and significant coefficient on *Meeting*). Specifically, in examining the behavior of government-brokerage analysts, we find no differential delay (i.e., the sum of the coefficients on *GovBro* $\times$ *Meeting* and *Meeting* is statistically no different from 0). Not surprisingly, when pooling all intervention event periods (column 3), we continue to find a significant relative delay (at the 1% level) in government-brokerage analysts' earnings forecasts.

The findings in Tables 7 and 8 suggest that government-brokerage analysts comply with the government's incentives at least in part by delaying forecasts (and revisions) during economic downturns. Moreover, when they revise downward during economic downturns, they do so less severely than non-government-brokerage analysts. Jointly, these findings are consistent with a pattern of balancing career incentives inside the brokerage firm against external reputational concerns.

4.5 Forecast Accuracy: Distinguishing the Compliance Hypothesis from the Information Hypothesis

Our overall evidence is consistent with the hypothesis that government-brokerage analysts communicate relatively optimistic information to market participants to comply with the government's incentives during intervention periods ("the compliance hypothesis"). But these results could also signify that government-brokerage analysts possess superior information about firms at these times ("the information hypothesis"). State-owned brokerage firms may be more capable of acquiring information about firms' future prospects during uncertain or bad times; in particular, they may be able to predict which firms will receive preferential treatment (e.g., a bailout) from the Chinese government. If so, our main results would reflect a differential information-quality effect rather than a differential optimism effect.

To ascertain whether the information hypothesis explains our main findings, we test whether earnings forecasts issued by government-brokerage analysts during intervention periods exhibit differential accuracy. Under the information hypothesis, we expect forecasts issued by government-brokerage analysts during the intervention periods to be relatively more accurate; under the compliance hypothesis, we expect the forecasts of government-brokerage analysts during intervention periods to be relatively less accurate.

Table 9 reports the results of this test for each event type and for both types jointly. We estimate the three DID specifications of Table 2, but use *Accuracy* as the dependent variable of interest. The results in Table 9 suggest that the forecasts issued by government-brokerage analysts during intervention periods are on average relatively *less* accurate: the coefficients on each of the three DID coefficients are negative and statistically significant at the 5% level. The analysis in Table 9 thus contradicts the information hypothesis and supports the compliance hypothesis.

5 Assessing Market Impact

Having established that our findings of relative optimism among government-brokerage analysts are consistent with the compliance hypothesis, we conclude the empirical analyses by assessing whether such optimism had an impact on market participants' beliefs. It is difficult to test directly how analysts' forecasts, recommendations, and general information production influence investors' beliefs, but we can make inferences based on the evolution of market prices after earnings announcements. In particular, to the extent that markets overweight the *general* relative optimism of government-brokerage analysts' information during times of economic downturn, we should expect to see more negative post-earnings-announcement drift in stock price (PEAD). This is the case because overreliance on government-brokerage analysts' optimism would lead market participants to be overly optimistic about future earnings, resulting in slow adjustment to bad news, persistently negative earnings surprises, and therefore a more negative PEAD (Cao and Narayanamoorthy, 2012).

We design a test to measure how PEAD varies depending on the composition of prior consensus earnings forecasts. To the extent that a firm is covered by more government-brokerage analysts, the consensus forecasts for the firm are more likely to be influenced by government-brokerage analysts' relative optimism during intervention periods. We construct a variable $GovBro\%$ that measures the percentage of analysts covering the firm employed at state-owned brokerage firms, and examine whether the market's reaction to earnings surprises during event periods differs when the consensus is subject to greater government-brokerage analysts' influence. We do so by estimating the following DDD specification:

$$\begin{aligned} CAR(3,90)_{jtT} &= \beta_0 + \beta_1 GovBro\%_{jtT} \times Surp_{jtT} \times Eventy_T + \beta_2 GovBro\%_{jtT} \times Surp_{jtT} \\ &+ \beta_3 Surp_{jtT} \times Eventy_T + \beta_4 GovBro\%_{jtT} \times Eventy_T \times + \beta_5 GovBro_{jtT} \\ &+ \beta_6 Surp_{itT} + \gamma X_{jtT} + f_T + \epsilon_{ij\tau T}, \end{aligned} \tag{4}$$

where $CAR(3,90)_{jtT}$ is the cumulative abnormal returns of firm j measured from three days to 90 days after the earnings announcement made on date t in year T; $Surp_{jtT}$ is the difference between firm j's actual fiscal-year earnings announced on date t in year T and the prior consensus earnings forecast for firm i, deflated by beginning-year stock price; and $Eventy$ is an event-year indicator variable. The main effect for $Eventy$ does not belong to the specification because it is absorbed by year-fixed effects (f_T). All other regressors are as defined in Eq., (2) and detailed in Table A2.

To the extent that market participants are influenced by the relative optimism of government-brokerage analysts, we would expect a positive and signficant β_1. This should be particularly true in bad times, since the market's overreliance on government-brokerage analysts' optimism would imply a slow adjustment to bad news.

Table 10, column 1, shows that, given a level of consensus earnings surprise, post-earnings-announcement drift is more pronounced when government-brokerage analysts constitute a greater percentage of the consensus. Columns 2 and 3 of Table 10 show that the greater PEAD is indeed concentrated in the subsample of firm-years when there was negative earnings surprise. That is, for a given level of negative earnings surprise, the PEAD in stock price is more negative when government-brokerage analysts constitute a greater percentage of the consensus. The DDD coefficient in column 3 is positive and significant at the 1% level, and suggests that, given the mean level of negative surprise (about -0.008), there is an additional downward three-month drift of 62 basis points in the stock returns of firms covered exclusively by government-brokerage analysts as compared to firms counterfactually covered exclusively by non-government-brokerage analysts. Thus the empirical evidence suggests that market participants appear to overweight the relatively optimistic information produced by government brokerage analysts during event periods.

6 Conclusion

In many countries the central government plays a critical role in coordinating capital-market institutions, and the government's incentives can influence the functioning of these institutions. This paper examines the Chinese setting; it studies how the central government's incentives influence the information production of sell-side analysts, who are among the most important information intermediaries in financial markets.

This paper shows that analysts influenced by government incentives are relatively more optimistic in the information that they produce about firms—earnings forecasts, forecast revisions, and stock recommendations—at times when the government has strong desires to prop up the stock market. This optimism is consistent with compliance with government incentives, and is not explained by an information advantage over non-government-brokerage analysts during intervention periods. In turn, market participants are slower to adjust to bad news when government-brokerage analysts play a more dominant role in firms' information environment, suggesting that relative optimism at these times is likely to affect investors' beliefs about firms' future prospects.

Despite a growing body of research on how the Chinese government influences financial-market institutions, our work is the first to examine how the government's incentives can influence the information production of sell-side analysts. Moreover, despite a sizeable body of work about sell-side analysts' incentives, and how these incentives affect analysts' forecasts and recommendations, our work is the first to examine how analysts' incentives align with the government's incentives in a coordinated-economy context. Finally, we contribute to understanding of analysts' informational role at times of economic uncertainty.

These findings provide novel evidence on the functioning of Chinese capital-market institutions, and also speak to the efficiency with which market participants understand the implications of institutional weaknesses. We hope that our work will advance academic knowledge about how capital markets function in coordinated-economy contexts, and contribute to strengthening these countries' institutions and markets in the future.

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Table A1. Government Intervention Events and Periods

This table reports the details of the two types of market intervention events used in the paper. We define market-rescue intervention periods as the time interval between the first and the last publicly identifiable dates in which notable market-rescue steps were taken by the Chinese government for each given episode. We define the intervention period for each National Congress of the Communist Party of China to be the time interval starting three months prior to the beginning of and ending three months after the conclusion the meeting.

Event	Intervention Period	Notes
Market Rescue		
1st	1/23/2005–6/5/2005	Notable market-rescue steps: • On January 23, 2005, the Ministry of Finance announced that the security-transaction tax rate would be lowered (from 0.2% to 0.1%). • On May 25, 2005, the CSRC froze IPOs. • On June 5, 2005, the CSRC called for a meeting with executives of fund companies, securities firms, and stock exchanges to discuss share-split structure reform. The CSRC asked fund companies to sell less to maintain the stability of the stock market. Meanwhile the CSRC would take steps to rescue the market, such as permitting new equity funds to invest in stock markets and decreasing the tax rate on dividends.
2nd	4/24/2008–10/30/2008	Notable market-rescue steps: • On April 24, 2008, the Ministry of Finance announced that the security-transaction tax rate would be lowered (from 0.3% to 0.1%). • After August 19, 2008, transaction taxes were levied only on stock sellers. Central Huijin Investment bought shares in three large stated-owned banks. State-owned Assets Supervision and Administration Commission (SASAC) encouraged large shareholders of SOEs to buy stocks. • On September 16, 2008, the CSRC froze IPOs. • On October 9, 2008, the Central Bank lowered interest rates and reserve requirements and waived interest taxes. On October 30, 2008, the Central Bank lowered interest rates again.
3rd	4/1/2012–12/4/2012	Notable market-rescue steps: • On April 30, 2012, the Shanghai Stock Exchange and the Shenzhen Stock Exchange announced that transaction fees would be lowered (by around 25%). • On October 10, 2012, Central Huijin Investment announced its intention to purchase shares in four state-owned banks. • On November 2, 2012, the CSRC announced that IPOs would be frozen.
4th	7/1/2015–12/31/2015	Notable market-rescue steps: • On July 1, 2015, the Shanghai Stock Exchange and the Shenzhen Stock Exchange announced that they would lower transaction fees (by around 30%). • Between July 2 and July 4, 2015, the CSRC announced investigations into market-manipulation activities; Central Huijin Investment Ltd. announced its intention to buy market ETFs; the CSRC announced that it would slow down IPOs; the CSRC called a meeting with 21 brokerage firms, after which the firms jointly announced that they would invest no less than 120 billion RMB in blue-chip ETFs and would not sell off these holdings as long as the Shanghai Composite index was below 4,500 points. • On July 8, 2015, the Central Bank announced its intention to provide unlimited liquidity to the China Securities Finance Corporation and to invest social-insurance funds in the market. More than 100 SOEs were prohibited from selling stocks and IPOs were frozen. • Until the end of 2015, China Securities Finance Corporation held shares in more than 1,000 listed firms.
National Congress of CPC		
17th	8/1/2007–1/31/2008	The meeting was held 10/15/2007–10/21/2007
18th	9/1/2012–2/28/2013	The meeting was held 11/8/2012–11/14/2012

Table A2. Definitions of Variables

This table details the definitions of variables used in this paper's empirical analyses.

Variable	Definition
Optimism	Forecast optimism (analyst EPS forecast minus actual EPS) for analyst i following firm j in year t minus the minimum forecast optimism for analysts who follow firm j in year t. This difference is scaled by the range of forecast optimism of analysts following firm j in year t.
Rescue	Equals 1 if forecasts are issued during a market-rescue period and 0 otherwise.
Meeting	Equals 1 if forecasts are issued within the six-month period surrounding a meeting of the National Congress of the Chinese Communist Party, and 0 otherwise.
Event	Equals 1 if *Rescue* equals 1 or *Meeting* equals 1, and 0 otherwise.
GovBro	Equals 1 if a brokerage is ultimately controlled by a state-owned enterprise or by the state-owned Assets Supervision and Administration Commission of the State Council, and 0 otherwise.
CSRC Manager	Equals 1 if any senior manager of a brokerage firm has work experience at the headquarters or a local branch of the CSRC and holds the title of Division Chief or above, and 0 otherwise.
Firmexp	The number of days of firm-specific experience for analyst i, who follows firm j in year t, minus the minimum number of days of firm-specific experience for analysts who follow firm j in year t. This difference is scaled by the range (in number of days) of firm-specific experience of analysts who follow firm j in year t.
Genexp	The number of days of general experience for analyst i, who follows firm j in year t, minus the minimum number of days of general experience for analysts who follow firm j in year t. This difference is scaled by the range (in number of days) of general experience of analysts who follow firm j in year t.
Industries	The difference between the number of industries (with the same two-digit CSRC industry code) followed by analyst i, who follows firm j in year t, and the minimum number of industries followed by analysts who follow firm j in year t. This difference is scaled by the range in the number of industries followed by analysts who follow firm j in year t.
Frequency	The number of firm-j forecasts made by analyst i, who follows firm j in year t, minus the minimum number of firm-j forecasts for analysts who follow firm j in year t. This difference is scaled by the range in the number of firm-j forecasts issued by analysts who follow firm j in year t.
Horizon	The difference between the number of days from the forecast date to fiscal year-end for analyst i, who follows firm j in year t, and the minimum number of days from the forecast date to fiscal year-end for analysts who follow firm j in year t. This difference is scaled by the range in the number of days from the forecast date to fiscal year-end for analysts who follow firm j in year t.
Brokersize	The difference between the number of analysts employed by the brokerage employing analyst i, who follows firm j in year t, and the minimal number of analysts employed by brokerages whose analysts follow firm j in year t, deflated by the range in the number of analysts employed by the brokerage whose analysts follow firm j in year t.
Faccuracy	The difference between maximum forecast error (the absolute value of the difference between EPS forecast and actual EPS) for analysts who follow firm j in year t and the forecast error for analyst i. This difference is scaled by the range in forecast error for analysts who follow firm j in year t.
FGAP	The difference between the number of days elapsed since the last forecast about the same firm by analyst i, who follows firm j in year t, and the minimum number of days elapsed since the last forecast about the same firm by analysts who follow firm j in year t. This difference is scaled by the range in the number of days elapsed since the last forecast about the same firm by analysts who follow firm j in year t.
REC	Equals 1 for strong buy, 0.75 for buy, 0.5 for neutral, 0.25 for sell, and 0 for strong sell.
CAR	Cumulative abnormal return calculated using a market model.

Table A2. Continued

Revision	The difference between the current EPS forecast (current forecast) and the most recent EPS forecast issued by the same analyst about the same firm for the same year (prior forecast), deflated by the prior forecast.
Govbro%	The proportion of government-brokerage analysts in the total cohort of analysts who follow a given firm.
Eventy	Equals 1 for a year when at least four of the six months before an earnings-announcement date fall into an event period, and 0 otherwise. In our sample period, it equals 1 for 2007 and 2012, and 0 for other years.
Surp	Earnings surprise (actual EPS minus analyst consensus forecast) deflated by stock price at the beginning of the year. Consensus forecast is calculated as the mean of the last forecast that each analyst issues within 180 days prior to the actual earnings announcement.
Size	Logarithm of market value of equity measured at the beginning of the earnings-announcement year.
MB	Market-to-book ratio measured at the beginning of the earnings-announcement year.
Turnover	Average daily turnover rate during the six months prior to the earnings-announcement date.
Institutional Ownership	Percentage of total shares owned by institutional investors at the beginning of the earnings-announcement year.
Momentum	Buy-and-hold return for the 180-day period before the earnings-announcement date.

Table 1.
Descriptive Statistics

Panel A provides descriptive statistics on the variables in our main sample, which consists of 234,328 one-year-ahead analysts' forecasts issued from 2005 to 2015. For each variable, the following pooled distributional summary statistics are reported: sample minimum (Min), 25^{th} percentile (P25), average (Mean), 50^{th} percentile (Median), 75^{th} percentile (P75), maximum (Max), and standard deviation (SD). Panel B reports the means of our main dependent variable of interest, *Optimism*, between the earnings forecasts issued by state-owned (*GovBro*=1) and non-state-owned (*GovBro*=0) brokerage firms, as well as their mean differences, and between the event (*Event*=1) and non-event (*Event*=0) periods, as well as their mean differences. The bottom row of the rightmost column reports the pooled difference-in-difference estimate. Robust standard errors are reported in parentheses, and significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. All variables are defined in Table A2.

Panel A: Distributional Summary Statistics

	Min	P25	Mean	Median	P75	Max	SD
Optimism	0	0.173	0.455	0.434	0.714	1	0.312
GovBro	0	1	0.862	1	1	1	0.345
Rescue	0	0	0.208	0	0	1	0.406
Meeting	0	0	0.084	0	0	1	0.277
Event	0	0	0.256	0	1	1	0.436
CSRC Manager	0	0	0.192	0	0	1	0.394
Firmexp	0	0.037	0.372	0.290	0.667	1	0.340
Genexp	0	0.251	0.516	0.522	0.799	1	0.314
Frequency	0	0.167	0.495	0.500	1	1	0.377
Companies	0	0.109	0.354	0.264	0.531	1	0.305
Industries	0	0.086	0.321	0.222	0.500	1	0.305
Horizon	0	0.330	0.568	0.571	0.890	1	0.322
Brokersize	0	0.258	0.502	0.477	0.761	1	0.313
Revision	-0.038	-0.002	-0.002	0	0	0.024	0.008
Faccuracy	0	0.389	0.641	0.739	0.929	1	0.325
Fgap	0	0	0.446	0.295	1	1	0.435
REC	0	0.750	0.819	0.750	1	1	0.167

Panel B: Earnings Forecast Optimism

		Optimism			
	N	Total Sample	*GovBro*=0	*GovBro*=1	*Diff(1-0)*
Event=0	175,204	0.4662***	0.4696***	0.4657***	-0.0039*
		(0.001)	(0.002)	(0.001)	(0.002)
Event=1	59,124	0.4203***	0.4065***	0.4228***	0.0163***
		(0.001)	(0.003)	(0.001)	(0.003)
Diff(1-0)	234,328	0.0459***	0.0632***	0.0429***	0.0202***
		(0.001)	(0.004)	(0.002)	(0.004)

Table 2.

Government Intervention Periods and Earnings-Forecast Optimism

This table reports the results of OLS regressions of *Optimism* on an event indicator, an indicator for a state-owned brokerage firm (*GovBro*), an interaction of the two indicators, and control variables. Column 1 examines differential forecast optimism during the market-rescue events (*Rescue*); column 2 examines differential forecast optimism during the National Congress meetings (*Meeting*); and column 3 examines differential forecast optimism during both types of events (*Event*). All specifications include year- and industry-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Optimism		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0119***		
	(0.003)		
Rescue	-0.0460***		
	(0.009)		
GovBro × *Meeting*		0.0263**	
		(0.010)	
Meeting		-0.0386	
		(0.027)	
GovBro × *Event*			0.0167***
			(0.003)
Event			-0.0360
			(0.024)
GovBro	-0.0056**	-0.0057*	-0.0075**
	(0.002)	(0.003)	(0.003)
Firmexp	-0.0018	-0.0014	-0.0016
	(0.004)	(0.003)	(0.004)
Genexp	-0.0046	-0.0042	-0.0044
	(0.004)	(0.005)	(0.005)
Frequency	0.0032***	0.0032***	0.0032***
	(0.001)	(0.001)	(0.001)
Companies	-0.0133*	-0.0144*	-0.0139*
	(0.007)	(0.007)	(0.007)
Industries	0.0270***	0.0272***	0.0270***
	(0.005)	(0.005)	(0.005)
Horizon	0.3068***	0.3069***	0.3056***
	(0.037)	(0.035)	(0.035)
Brokersize	0.0090**	0.0088**	0.0089**
	(0.004)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	234,328	234,328	234,328
Adj R^2	0.1105	0.1097	0.1099

Table 3.

Heterogeneous Effects on Earnings-Forecast Optimism by Analyst Type

This table reports the results of estimating the difference-in-difference-in-differences (DDD) specification of Eq., (3), using analyst "Characteristic" as the third differencing group. Our sample consists of 234,328 one-year-ahead forecasts issued from 2005 to 2015, as in Table 2. For brevity, only the coefficients on the triple interactions of *GovBro*, *Event* and *Characteristic* are reported. "Characteristic" denotes indicator variables for (A) "firm-specialist" forecasts, issued by analysts with more firm-specific experience (i.e., where *Firmexp* is greater than 0.5); (B) "inexperienced" forecasts, issued by analysts with less general experience (i.e., where *Genexp* is less than 0.5); (C) forecasts issued by analysts with more firm-specific experience but less general experience; and (D) forecasts issued by "star" analysts, as designated by *New Fortune* magazine. All specifications include full interactions, the analyst controls of Table 2, and industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. All variables are defined in Table A2.

	Rescue (1)	*Meeting* (2)	*Event* (3)
	A. Firm Specialist vs. Non-Firm-Specialist Analysts		
$Govbro \times Intervention \times Characteristic$	0.0243**	0.0558***	0.0347***
	(0.006)	(0.005)	(0.006)
	B. Inexperienced vs. Experienced Analysts		
$Govbro \times Intervention \times Characteristic$	0.0141**	-0.0054	0.0077
	(0.003)	(0.004)	(0.005)
	C. Inexperienced Firm Specialist vs. Experienced Non-Firm-Specialist Analysts		
$Govbro \times Intervention \times Characteristic$	0.0710**	0.0706***	0.0698**
	(0.019)	(0.015)	(0.021)
	D. Star vs. Non-Star Analysts		
$Govbro \times Intervention \times Characteristic$	-0.0129	0.0087	-0.0099
	(0.013)	(0.013)	(0.014)

Table 4.

Heterogeneous Effects on Earnings-Forecast Optimism by Covered-Firm Characteristics

This table reports the results of estimating the difference-in-difference-in-differences (DDD) specification of Eq., (3), using covered-firm "Characteristic" as the third differencing group. Our sample consists of 234,328 one-year-ahead forecasts issued from 2005 to 2015, as in Table 2. For brevity, only the coefficients on the triple interactions of *GovBro*, *Event*, and *Characteristic* are reported. "Characteristic" denotes indicator variables for (A) forecasts about firms with relatively large market capitalization (i.e., whose market capitalization at the beginning of the year is above the cross-sectional median); (B) forecasts about firms in an industry supported by a Five-Year Plan; and (C) forecasts about state-owned firms (SOE). The coefficients reported in A1, B1, and C1 are estimated using the sample of earnings forecasts issued by firm-specialists (i.e., where *Firmexp* is greater than 0.5); the coefficients reported in A2, B2, and C2 are estimated using the sample of earnings forecasts issued by firm-specialists who are also generally less experienced (i.e., where *Genexp* is less than 0.5). All specifications include full interactions, the analyst controls of Table 2, and industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. All variables are defined in Table A2.

	Rescue (1)	*Meeting* (2)	*Event* (3)
	A1. Large Market Cap vs. Small Market Cap Firms		
Govbro×Intervention×Characteristic	0.0628**	0.0728*	0.0732**
	(0.019)	(0.029)	(0.017)
	A2. Large Market Cap vs. Small Market Cap Firms		
Govbro×Intervention×Characteristic	0.1028***	0.0587	0.1048***
	(0.020)	(0.046)	(0.022)
	B1. Supported vs. Non-Supported Industries		
Govbro×Intervention×Characteristic	0.0051	0.0571***	0.0152
	(0.012)	(0.006)	(0.014)
	B2. Supported vs. Non-Supported Industries		
Govbro×Intervention×Characteristic	0.0421	0.0227	0.0340
	(0.021)	(0.012)	(0.020)
	C1. SOE vs. Non-SOE Firms		
Govbro×Intervention×Characteristic	0.0149	0.0467***	0.0231*
	(0.008)	(0.006)	(0.008)
	C2. SOE vs. Non-SOE Firms		
Govbro×Intervention×Characteristic	0.0416	0.0547*	0.0456
	(0.021)	(0.019)	(0.022)

Table 5.
Analysts' Earnings-Forecast Optimism and Managers' CSRC Affiliation

Our sample consists of 234,328 one-year-ahead analysts' forecasts issued from 2005 to 2015. This table reports OLS results of regressing forecast optimism on an event indicator (*Event*), an indicator for brokerage firm with CSRC afflicated senior managers (*CSRC Manager*), an interaction of *Event* and *CSRC Manager*, and control variables. Columns 1 examines differential forecast optimism during event periods (*Event*) for the full sample; columns 2 and 3 examines differential forecast optimism during event periods (*Event*) across state-owned brokerage firms and non-state-owned brokerage firms. All specifications include year-fixed effects and industry-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Optimism		
	(1) *Full Sample*	(2) *GovBro=1*	(3) *GovBro=0*
CSRC Manager × Event	0.0162***	0.0134**	0.0315***
	(0.004)	(0.004)	(0.005)
Event	-0.0246	-0.0211	-0.0482*
	(0.024)	(0.024)	(0.024)
CSRC Manager	-0.0009	0.0004	-0.0107
	(0.004)	(0.004)	(0.010)
Firmexp	-0.0016	-0.0005	-0.0069
	(0.004)	(0.003)	(0.013)
Genexp	-0.0046	-0.0048	-0.0016
	(0.005)	(0.005)	(0.008)
Frequency	0.0032***	0.0029***	0.0056**
	(0.001)	(0.001)	(0.002)
Companies	-0.0134*	-0.0166*	0.0086
	(0.007)	(0.008)	(0.007)
Industries	0.0269***	0.0265***	0.0257***
	(0.005)	(0.005)	(0.007)
Horizon	0.3058***	0.3005***	0.3379***
	(0.036)	(0.036)	(0.029)
Brokersize	0.0088**	0.0091*	0.0050
	(0.004)	(0.004)	(0.015)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	234,328	202,051	32,277
Adj R^2	0.1099	0.1060	0.1411

Table 6.
Stock-Recommendation Optimism

This table reports the results of OLS regressions of analysts' recommendations (*REC*) on an event indicator (*Event*), an indicator for a state-owned brokerage firm (*GovBro*), an interaction of *Event* and *GovBro*, and control variables. The dependent variable *REC* assigns the recommendations "strong buy," "buy," "hold," "sell," and "strong sell" the numerical values of 1, 0.75, 0.5, 0.25, and 0 respectively. Column 1 examines differential recommendations during market-rescue events (*Rescue*); column 2 examines differential recommendations during the National Congress meetings (*Meeting*); and column 3 examines differential recommendations during both types of events (*Event*). All specifications include industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Recommendation Optimism		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0090**		
	(0.003)		
Rescue	-0.0106		
	(0.011)		
GovBro × *Meeting*		0.0100*	
		(0.005)	
Meeting		-0.0158*	
		(0.007)	
GovBro × *Event*			0.0091**
			(0.004)
Event			-0.0085
			(0.008)
GovBro	-0.0250***	-0.0241***	-0.0254***
	(0.004)	(0.004)	(0.004)
Firmexp	0.0018	0.0019	0.0018
	(0.003)	(0.003)	(0.003)
Genexp	-0.0027	-0.0028	-0.0027
	(0.005)	(0.005)	(0.005)
Frequency	0.0556***	0.0555***	0.0556***
	(0.005)	(0.005)	(0.005)
Companies	-0.0499***	-0.0500***	-0.0498***
	(0.007)	(0.007)	(0.007)
Industries	-0.0013	-0.0014	-0.0014
	(0.005)	(0.005)	(0.005)
Horizon	-0.0154**	-0.0168**	-0.0155**
	(0.005)	(0.006)	(0.005)
Brokersize	0.0108	0.0107	0.0108
	(0.009)	(0.009)	(0.009)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	291,090	291,090	291,090
Adj R^2	0.0796	0.0797	0.0796

Table 7.
Earnings-Forecast Revision

This table reports the results of OLS regressions of earnings-forecast revisions (*Revisions*) on an event indicator, an indicator for a state-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables. Column 1 examines differential revision magnitudes during the market-rescue events (*Rescue*); column 2 examines differential accuracy during the National Congress meetings (*Meeting*); and column 3 examines differential accuracy during all intervention event periods (*Event*). All specifications include industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Forecast Revisions		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0005*		
	(0.000)		
Rescue	-0.0033***		
	(0.000)		
GovBro × *Meeting*		-0.0000	
		(0.000)	
Meeting		0.0036***	
		(0.001)	
GovBro × *Event*			0.0005**
			(0.000)
Event			-0.0020**
			(0.001)
GovBro	-0.0001	-0.0000	-0.0002
	(0.000)	(0.000)	(0.000)
Firmexp	-0.0017***	-0.0016***	-0.0017***
	(0.000)	(0.000)	(0.000)
Genexp	0.0006***	0.0007***	0.0006***
	(0.000)	(0.000)	(0.000)
Frequency	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)
Companies	-0.0002	-0.0002	-0.0002
	(0.000)	(0.000)	(0.000)
Industries	0.0001	0.0001	0.0001
	(0.000)	(0.000)	(0.000)
Horizon	-0.0006	0.0004	-0.0008
	(0.001)	(0.001)	(0.001)
Brokersize	-0.0002	-0.0002	-0.0002
	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	61,938	61,938	61,938
Adj R^2	0.0452	0.0452	0.0414

Table 8.

Days Elapsed since Last Forecast

This table reports the results from OLS regressions of the number of days elapsed since the prior forecast (*FGAP*) on an event indicator, an indicator for a state-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables. Column 1 examines differential days elapsed during the market-rescue events (*Rescue*); column 2 examines differential days elapsed during the National Congress meetings (*Meeting*); and column 3 examines differential days elapsed during all intervention events (*Event*). All specifications include industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Forecast Gap		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0134***		
	(0.004)		
Rescue	-0.0547		
	(0.043)		
GovBro × *Meeting*		0.0128**	
		(0.006)	
Meeting		-0.0804***	
		(0.017)	
GovBro × *Event*			0.0138***
			(0.004)
Event			-0.0461
			(0.048)
GovBro	-0.0109***	-0.0096***	-0.0117***
	(0.002)	(0.002)	(0.003)
Firmexp	-0.0190***	-0.0182***	-0.0188***
	(0.003)	(0.003)	(0.003)
Genexp	-0.0130**	-0.0133**	-0.0131**
	(0.004)	(0.005)	(0.004)
Companies	0.0049*	0.0029	0.0042*
	(0.002)	(0.002)	(0.002)
Industries	0.0057*	0.0059*	0.0057*
	(0.003)	(0.003)	(0.003)
Horizon	-0.0330***	-0.0433**	-0.0364**
	(0.009)	(0.018)	(0.012)
Brokersize	0.0065*	0.0067*	0.0066*
	(0.003)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	136,032	136,032	136,032
Adj R^2	0.0031	0.0035	0.0028

Table 9.

Earnings-Forecast Accuracy

This table reports the results of OLS regressions of forecast accuracy (*Accuracy*) on an event indicator, an indicator for a state-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables. Column 1 examines differential accuracy during the market-rescue events (*Rescue*); column 2 examines differential accuracy during the National Congress meetings (*Meeting*); and column 3 examines differential accuracy of forecasts issued during all intervention event periods (*Event*). All specifications include industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Table A2.

	Forecast Accuracy		
	(1)	(2)	(3)
GovBro × *Rescue*	-0.0081***		
	(0.002)		
Rescue	0.0163		
	(0.014)		
GovBro × *Meeting*		-0.0089**	
		(0.004)	
Meeting		0.0351	
		(0.019)	
GovBro × *Event*			-0.0085**
			(0.003)
Event			0.0140
			(0.022)
GovBro	0.0028	0.0021	0.0033
	(0.003)	(0.003)	(0.003)
Firmexp	-0.0033	-0.0035	-0.0033
	(0.003)	(0.002)	(0.003)
Genexp	0.0115**	0.0115**	0.0115**
	(0.004)	(0.004)	(0.004)
Frequency	0.0036***	0.0035***	0.0036***
	(0.001)	(0.001)	(0.001)
Companies	-0.0073	-0.0067	-0.0072
	(0.007)	(0.007)	(0.007)
Industries	-0.0325***	-0.0325***	-0.0325***
	(0.007)	(0.007)	(0.007)
Horizon	-0.4529***	-0.4483***	-0.4523***
	(0.023)	(0.020)	(0.021)
Brokersize	-0.0035	-0.0035	-0.0035
	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	234,328	234,328	234,328
Adj R^2	0.2161	0.2164	0.2161

Table 10.

Post Earnings Announcement Drift

This table reports OLS results of regressing cumulative abnormal returns following the announcements of fiscal-year earnings on the following explanatory variables: earnings surprise (*Surp*), proportion of analysts covering the firm employed by government brokerage firms (*GovBro%*), the indicator of event year (*Eventy*), and all interactions of these three variables. Main effects for *Eventy* are not reported because they are absorbed by year-fixed effects. We also include in each specification the following controls: firm size (*Size*), market-to-book multiple (*MB*), share turnover (*Turnover*), institutional ownership (*Institution Ownership*), and stock return momentum (*Momentum*). We examine cumulative abnormal returns from 3 days to 90 days after earnings announcements. Column 1 is estimated on the full sample, column 2 is estimated on the subsample of "good news" earnings announcements (positive earning surprises), and column 3 is estimated on the subsample of "bad news" earnings announcements (negative earning surprises). Our sample consists of 9,522 firm-year observations from 2005 to 2015. All specifications include industry- and year-fixed effects. Standard errors, reported in parentheses, are two-way-cluster robust, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. All variables are defined in Table A2.

	(1) *Full Sample*	(2) *Good News*	(3) *Bad News*
GovBro% × *Surp* × *Eventy*	0.8507*	-0.5315	0.7760***
	(0.418)	(2.958)	(0.166)
GovBro% × *Surp*	-0.0663**	0.1299	-0.0549*
	(0.023)	(0.749)	(0.030)
Surp × *Eventy*	-0.6004	-1.5231	-0.4213
	(0.471)	(1.945)	(0.272)
GovBro% × *Eventy*	-0.0073	0.0103	-0.0101
	(0.021)	(0.038)	(0.015)
GovBro%	0.0027	-0.0255	0.0174
	(0.012)	(0.024)	(0.015)
Surp	0.5150**	0.1678	0.2709
	(0.197)	(0.969)	(0.255)
Size	-0.0249*	-0.0239**	-0.0258
	(0.013)	(0.010)	(0.015)
MB	0.0014	0.0020	0.0012
	(0.001)	(0.002)	(0.001)
Turnover	-0.8907*	-1.1184**	-0.7821
	(0.472)	(0.446)	(0.554)
Institution Ownership	-0.0005*	-0.0005*	-0.0006*
	(0.000)	(0.000)	(0.000)
Momentum	-0.0354	-0.0300	-0.0449
	(0.035)	(0.040)	(0.034)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	9,522	3,161	6,359
Adj R^2	0.1259	0.1332	0.1364