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Abstract

We show analysts at government-controlled brokerage firms serve as a market stabilization tool in China. Using earnings forecasts from 2005–2019, we find government-brokerage analysts issue relatively more optimistic—yet less accurate and timely—forecasts during market rescue periods, supporting stock prices. During market booms, they issue comparatively pessimistic but more accurate and timely forecasts, tempering excessive optimism. We show that these patterns are consistent with market stabilization incentives, and their impact is substantial: stocks with greater government-brokerage coverage experience higher liquidity during downturns but lower liquidity during hot markets, with corresponding post-earnings price adjustments. Our findings validate Brunnermeier, Sockin, and Xiong (RES 2022)'s theoretical predictions: state interventions can erode information efficiency under intensive intervention while maintaining it under a moderate level of intervention. Collectively, these results underscore that analysts can serve a dual role—as information providers and policy instruments shaping market expectations and stability—in a coordinated economy.

Keywords: Sell-side analysts; Market stabilization; Forecast optimism; Forecast accuracy; Government ownership; Coordinated economies

JEL: G14, G24, G28, O16

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1 Introduction

Analysts rank among the most influential informational intermediaries in modern capital markets. As "the preeminent market information intermediaries" (Bradshaw, 2011), brokerage firm (sell-side) analysts play a crucial role in the functioning of capital markets. An extensive literature—primarily examining developed, free-market settings such as the United States—has explored how these intermediaries operate and how various economic forces, from investment banking relationships to institutional investor pressures, influence both the content of their research (e.g., Michaely and Womack, 1999; Jackson, 2005; Cowen et al., 2006) and their broader impact on market outcomes (e.g., Loh and Stulz, 2018; Amiram et al., 2018). More recently, scholars have turned their attention to understanding how the institution of sell-side research operates in emerging markets and coordinated market economies, especially how political incentives distort analysts' informational roles (e.g., Kong et al., 2025; Pittman et al., 2024), given the prevalence of government influence (e.g., La Porta et al., 2002; Barth et al., 2013).

In this paper, we investigate how the government can shape analyst behavior and information production to achieve market stabilization objectives. Although the academic evidence on this channel is sparse, the use of financial intermediaries as policy tools has historical precedent. In Japan, for instance, regulators extensively used "window guidance" — informal directives communicated through private meetings — to influence financial institutions' behavior throughout the post-war period. Similar informal regulatory guidance is prevalent in other coordinated markets.

Recent theoretical work by Brunnermeier et al. (2022) provides a framework for understanding how such government intervention in financial markets could optimally function. Their model yields a paradoxical insight: while intensive state intervention can stabilize markets at the cost of reduced information efficiency, under other conditions, more modest intervention can stabilize markets yet not undermine information efficiency. Thus, in periods where market instability poses a significant risk, heavy intervention may be optimal even if it sacrifices some informational efficiency to boost prices, whereas moderate interventions under calmer conditions can still promote information aggregation and price efficiency. These findings are particularly relevant for emerging economies where financial markets are dominated by retail investors, prone to noise-trader-driven volatility, and where government involvement in financial institutions is prevalent and used as a tool for achieving broader state objectives (Gerschenkron, 1962; Tullock, 1987; Shleifer and Vishny, 1994).

Our research setting focuses on brokerage analysts in China, the world's largest coordinated economy, where sell-side analysts are highly influential, retail investors are prevalent, and the government actively manages market outcomes. Sell-side analysts' research and recommendations are widely consumed by retail investors (Gu et al., 2013; New Fortune, 2022) in China; they also directly influence nearly 1,000 institutions with assets under management exceeding 90 trillion RMB at the end of 2022. Anecdotal evidence suggests that Chinese market regulators regularly attempt to influence analysts to help stabilize financial markets: with retail investors contributing the vast majority of trades, a stable stock market is viewed as integral to maintaining social stability and consolidating government authority (e.g., Tullock, 1987; Piotroski et al., 2015). For example, Bloomberg reported in late 2018 that the China Securities Regulatory Commission (CSRC), aiming to counter slower economic growth and a weakening market, advised representatives of more than 30 brokerage firms that their analysts should strive for higher-level thinking and take into account the interests of the country when publishing research. Moreover, in its 2024 annual meeting, the Security Analyst Association of China—the regulatory body of analysts in China—listed market expectation management as a key agenda item.

We hypothesize that analysts at government-controlled brokerages ("government-brokerage analysts") are more likely than their private-sector counterparts to respond to market stabilization incentives. Specifically, we predict that during market rescue periods—when states intervene more intensively to support market prices and avoid social disruption—government-brokerage analysts will issue comparatively more optimistic forecasts that prove less informative. Conversely, during times of market exuberance, which warrant more modest interventions to temper sentiment, government-brokerage analysts will issue relatively less optimistic forecasts that provide greater information content. This behavioral pattern aligns with theoretical predictions on optimal government intervention in financial markets within coordinated economies.

To empirically test these hypotheses, we collect a comprehensive dataset of annual earnings forecasts covering the period from 2005 to 2019. Our sample primarily comprises Chinese-listed firms for which we can identify brokerage affiliation and ownership information, allowing us to distinguish government-controlled ("government-brokerage") institutions from private ones. We further identify "market rescue" periods using publicly documented government interventions—intervals during which authorities deploy aggressive measures, such as capital injections or trading restrictions, to support declining markets—and "hot" periods using market indicators such as turnover ratios, which signal times of exuberance and rapid price increases. These distinct regimes enable us to capture the differential intensity of state intervention: rescue periods reflect urgent, heavy-handed stabilization efforts, whereas hot periods are characterized by more modest interventions aimed at tempering excessive optimism. For each firm-year forecast, we measure both the level of forecast optimism and its accuracy relative to realized earnings, along with several timing metrics to gauge the speed of information updates. This setup enables us to compare how government-brokerage analysts and their private-sector peers adjust forecasts across different market regimes—namely, rescue versus hot periods—while controlling for firm characteristics, analyst attributes, and broader economic conditions.

We first document several findings that support our hypotheses about government-brokerage analysts' responsiveness to market stabilization incentives. We find that government-brokerage analysts issue forecasts that are notably more optimistic during official market rescue periods, while the same analysts provide comparatively pessimistic forecasts during hot market periods. The economic magnitude of these effects is substantial—during market rescue periods, government—brokerage analysts' forecast optimism experience a 15% smaller decline, helping to moderate market panic. Conversely, during hot market periods, their forecast optimism increases are on average 41%

smaller, helping to moderate market exuberance. Together, these empirical results are consistent with government-brokerage analysts being more responsive to the government's market stabilization objectives.

The pattern of government-brokerage analysts' relative responsiveness extends beyond forecast optimism: we observe similar results in forecast recommendations and revisions. Moreover, the patterns in forecast optimism are more pronounced at brokerages with deeper government ties, such as those with higher levels of government ownership or with senior managers previously employed at regulatory agencies, and at more influential brokerage firms, such as the large ones. They are also stronger in contexts where market stabilization incentives are likely more salient: state-owned enterprises, large market capitalization firms, and industry leaders, whose stock prices often have outsized effects on market indexes and the market sentiment. Together, these empirical results are consistent with government-brokerage analysts being more responsive to the government's market stabilization objectives.

Next, we document the findings that support the theoretical predictions of Brunnermeier et al. (2022) on how different types of government intervention in the markets can generate different levels of information efficiency. Specifically, we find that during market rescue periods, which involve more aggressive interventions, government-brokerage analysts' more optimistic forecasts are 20% less accurate and 21% less timely than those of non-government-brokerage analysts, consistent with sacrificing some informational efficiency to support prices during market stress. In contrast, their relatively pessimistic forecasts during hot market periods demonstrate greater accuracy (by 29%) and faster incorporation of news (by 59%), suggesting that more modest intervention during market strength can enhance the quality of information production.

Importantly, these analyst forecast properties are associated with market outcomes that align with government stabilization objectives: stocks with greater coverage by government-brokerage analysts experience relatively higher liquidity during market rescue periods but relatively lower liquidity during hot periods. We also detect stronger post-earnings announcement drift following negative earnings surprises for firms with higher government-brokerage coverage during rescue periods—indicating market underreaction to bad news—whereas price adjustments to such news in the same firms are more rapid during hot periods. These market effects are consistent with government-brokerage analysts' forecasts effectively serving as a market stabilization mechanism. These findings also support the theoretical predictions regarding the relation between government intervention intensity and market efficiency.

Our study makes several distinct contributions to the literature. First, we extend research on how government incentives shape analyst behavior by uncovering a novel market stabilization channel. Prior research on political influence in China has mainly shown that government or political ties can bias analysts toward optimistic forecasts or compromised accuracy (e.g., He and Ma, 2019; Kong et al., 2025; Pittman et al., 2024). By contrast, we highlight a distinct market-stabilization role of sell-side analysts at government-owned brokerages, which leads them to vary their optimism, accuracy, and timeliness in market busts versus booms. In doing so, our findings offer a more nuanced perspective on how government influence shapes sell-side research quality, underscoring the countercyclical adjustments analysts make to meet broader stabilization objectives.

Second, our study broadens the literature on government intervention in financial markets by identifying this under-explored "informational" channel through which authorities in coordinated economies can maintain orderly markets. Whereas prior work has focused on formal intervention tools, such as IPO supply control (Shi et al., 2018), transaction tax change (Deng et al., 2018), and direct fund injection (e.g., Dang et al., 2023; Huang et al., 2019; Cheng et al., 2022; Jin et al., 2023), we uncover how governments can indirectly influence analyst forecasts via ownership ties. Crucially, this influence does not uniformly suppress negative information (e.g., Piotroski et al., 2017; Hope et al., 2021; Luo, 2021); rather, it alternates between relatively bullish and bearish biases in a manner consistent with market stabilization at both ends of the market cycle. Hence, our results highlight a subtler, yet potent, policy tool for coordinating market outcomes beyond direct interventions.

Third, we provide the first empirical validation of the theoretical predictions of Brunnermeier et al. (2022) regarding the trade-off between market stability and information efficiency under varying government intervention intensities. Their model suggests that heavy state intervention, while stabilizing markets, may reduce information efficiency, whereas more modest interventions can stabilize markets without undermining the quality of information production. Our analysis of government-brokerage analysts' information quality during "market rescue" versus "hot" periods demonstrates this trade-off, offering direct evidence that the impact of government intervention on information efficiency hinges on the intensity of the intervention.

Finally, our paper revisits the role of sell-side research under heightened economic uncertainty by situating it in a coordinated economy context. Unlike in the U.S., where analysts' research is generally more valued during during turbulent times (e.g., Loh and Stulz, 2018; Amiram et al., 2018), we find that Chinese government-brokerage analysts produce less reliable forecasts in crisis periods yet become more informative in overheated markets. Consequently, we show that the informational reliability of analyst research in coordinated markets is contingent on whether and which stabilization objective (propping up prices or tempering exuberance) dominates at a given time.

2 Background and Hypothesis Development

This section describes the institutional background underlying government market stabilization policies in China and develops our main hypotheses regarding how these interventions affect the properties of sell-side analysts' forecasts.

2.1 Background: Formal and Informal Market Stabilization Tools

The Chinese approach to managing financial markets differs fundamentally from the Western approach, where price discovery is primarily driven by market forces. In China, the government frequently intervenes to mitigate stock market volatility and stabilize share prices during both market booms and busts. Given that retail investors, who account for approximately 80% of total trades and can fuel both market booms and busts (Bian et al., 2018), are a dominant force, ensuring financial market stability is viewed as integral not only to maintaining investor confidence but also to preserving social stability and government authority (Piotroski et al., 2015).

The China Securities Regulatory Commission (CSRC), established in 1992, serves as the primary regulator of China's financial markets. One of its key tools in stabilizing financial markets is IPO supply control, which was particularly powerful under China's approval-based IPO system, where all prospective listings required CSRC approval, a system that prevailed until 2019 when a registration-based IPO system was introduced on the STAR market. Between 1994 and 2016, the CSRC suspended IPOs nine times during market downturns to prevent further market decline, while permitting large IPOs during overheated markets to temper prices (Shi et al., 2018). For instance, the CSRC implemented its longest IPO suspension (13 months) starting November 3, 2012, following a three-year bear market. Conversely, the 2007 bull market was cooled through sizable IPOs of major state-owned enterprises like PetroChina and China Construction Bank.

Complementing the CSRC's efforts, the Ministry of Finance also plays a crucial role in market stabilization through its authority in adjusting transaction taxes, which influence trading behavior by altering the cost of speculation. During the 2007 bull market, it increased the stamp tax rate threefold, from 0.1% to 0.3%, shortly before the stock index peaked. When the market subsequently plunged 65% in 2008, making China's stock market the worst performer globally, the rate was reduced back to 0.1%. Deng et al. (2018) provide evidence that these tax changes helped reduce price volatility in the Chinese market.

The 2015 market rescue effort marked a new milestone in the government's formal interventions in Chinese financial markets. After the Chinese stock market soared in the first half of 2015, a dramatic decline erased about 40% of market value in just three months. The government responded with unprecedented measures to curb market panic, most notably the coordinated stock purchases by the government's wholly-owned financial institutions, dubbed the "National Team," including, for example, the State Administration of Foreign Exchange (SAFE) and China Securities Finance (Dang et al., 2023). In this instance of formal intervention, the government, through its own financial arms, acted directly in the market to purchase stocks. These direct purchases targeted over 1,000 stocks of varying sizes and performance, accounting for 5% of total market value (e.g., Allen et al., 2024; Huang et al., 2019; Dang et al., 2023). Studies show that these direct formal interventions successfully increased the stock prices of the rescued firms and reduced market volatility (e.g., Cheng et al., 2022; Dang et al., 2023).

Chinese regulators also deploy an array of other formal tools, including monetary policy adjustments, daily price movement limits, refinancing supply controls, and restrictions on short-selling. The widespread use of these various intervention mechanisms demonstrates how actively and extensively Chinese authorities work to maintain market stability. These formal tools, however, represent only part of the government's broader approach to managing financial market outcomes.

Beyond these formal mechanisms, Chinese regulators also frequently influence market outcomes through an informal mechanism known as window guidance. A phenomenon that originated in Japan in the 1950s, window guidance refers to regulatory agencies communicating their agendas to financial institution directors through private channels, such as phone calls or meetings. Unlike formal mechanisms, window guidance is non-mandatory and less rigid but carries an implicit threat: potential retribution for non-compliance via the regulator's formal powers. Despite its widespread use, the effectiveness and market impact of window guidance have received limited academic attention.

Window guidance appears particularly important in Chinese regulators' interactions with brokerage firms during periods of market turbulence. For example, during the 2007 bull market, the CSRC convened a meeting with top brokerage firm executives on September 10th to discuss market risks. Similarly, during the 2015 market crash, the CSRC met with 21 brokerage firms on July 4th to coordinate market support. Through this meeting, the government persuaded brokerage firms to commit to market stabilization. Immediately following this meeting, the participating firms jointly announced commitments to invest no less than 120 billion RMB in blue-chip ETFs and to maintain their stock holdings while the Shanghai Composite Index remained below 4,500 points. However, in the subsequent months, several companies were suspected of breaching these commitments, and some faced CSRC investigations for other violations.

2.2 Hypothesis Development

Brokerage analysts in China can play a significant role in stabilizing markets. Their reports exert a substantial influence on market participants, including both institutional investors, particular those with whom analysts share business or social ties (Gu et al., 2019b), and retail investors, especially if they trade actively or profitably (Shenzhen Stock Exchange (SSE), 2017). Prior research finds that financial analysts in China improve the information environment by identifying and disseminating firm-specific news (e.g., Wong et al., 2018; Xu et al., 2013), and their analyses can have a pronounced impact on market prices, particularly during volatile periods (e.g., Gu et al., 2019a; Andrade et al., 2013).

It is also feasible for Chinese regulators to compel brokerage firms and their analysts to adjust their information production to help stabilize the market when turbulence arises. The CSRC wields significant authority over brokerage firms. For example, brokerage firms must be licensed by the CSRC to engage in securities trading or underwriting. Until 2019, every prospective initial public offering required the CSRC's approval—a critical gatekeeping function because underwriting fees represent a major source of revenue for these firms.[1] Further, the CSRC can grant or deny permission for new business lines, such as margin trading or the issuance of asset-backed securities. Finally, its formal powers of investigating misconduct and enforcing sanctions enable the CSRC to shape brokerage firms' behavior.

While the entire Chinese brokerage industry may be subject to the CSRC's influence, government-owned brokerage firms are likely more sensitive to state objectives. First, they are ultimately

[1] A registration-based system was introduced to the STAR market in 2019, and was enforced in the whole market from February 2023.

controlled by central or local governments, which can directly shape firms' behaviors in accordance to state objectives. Second, their senior managers are effectively appointed—and can be dismissed—by the government, fostering a close alignment with state policy. For instance, as the largest shareholder in government-owned brokerages, the government has considerable sway over the board that selects or recommends top executives. Lastly, senior managers at government-owned brokerages and regulators often share professional or social networks, further enhancing policy influence. Consequently, we expect analysts in government-owned brokerages to be more responsive to the government's market-stabilization incentives across different market conditions.

Hypothesis 1 *(H1) Compared with non-government-brokerage analysts, government-brokerage analysts issue more optimistic forecasts during market rescue and issue less optimistic forecasts during market exuberance.*

The theoretical framework of Brunnermeier et al. (2022) highlights how varying intensities of government intervention produce different informational outcomes in capital markets. When intervention is heavy, investors may shift their attention from firm fundamentals to predicting state actions, thereby reducing information efficiency. By contrast, when intervention is moderate, the government can limit price volatility without undermining informational quality.

Applying this framework to China, we observe that market rescue interventions—those enacted during significant price declines—are typically more forceful than those implemented during periods of market exuberance. The government's motivation to intervene is stronger during sharp market decline to avoid liquidity crisis and risk contagion. Because sharp stock market declines usually align with an economic downturn, the government's stabilization objective is relatively straightforward: restore market confidence by supporting prices. However, during market exuberance, the stabilization goal becomes more complex, requiring a delicate balance between taming potential bubbles, maintaining sufficient market activity, and preserving investor confidence. This multifaceted challenge necessitates a more calibrated and less forceful intervention approach during hot markets.

Consistent with these differential intervention incentives, we observe that the Chinese government has historically deployed a wider array of formal policy tools during market rescue periods, such as halting IPOs, adjusting transaction taxes, and injecting funds, to counter downward price pressures. Conversely, during periods of market exuberance, interventions are usually less explicit and rely on fewer measures, mainly in restricting excessive speculative trading. For instance, many of the instruments outlined earlier are designed to support prices rather than suppress them.

Building on *Hypothesis 1*—that government-brokerage analysts are more responsive to state incentives—and drawing on the theoretical predictions of Brunnermeier et al. (2022), we expect the informational efficiency of government-brokerage analysts' forecasts to deteriorate in terms of accuracy and timeliness during intensive market rescue episodes. On the other hand, we expect government-brokerage analysts' forecast quality to remain comparable to that of non-government analysts during more moderate interventions in hot markets.

Hypothesis 2 *(H2) Compared with non-government brokerage analysts, government-brokerage analysts' forecast quality worsens during periods of market rescue but not during periods of market exuberance.*

3 Sample Selection and Research Design

Our sample consists of annual earnings forecasts from 2005 through 2019. We obtained the initial sample of earnings-forecast from the China Stock Market & Accounting Research (CSMAR) database. We focus on annual earnings forecasts rather than quarterly forecasts or target prices because Chinese analysts typically do not provide quarterly earnings forecasts, and target price forecasts are less common in our sample period (only about 100,000 observations in the CSMAR database, representing approximately 30% of our annual earnings forecast sample). We merged in information about the brokerage, the analyst, and the covered firm and eliminated observations for which we lacked necessary information on brokerage ownership (i.e., government-owned or private) or analyst characteristics.

Our overall sample consists of 327,658 earnings forecasts for 2,517 unique listed firms between 2005 and 2019. These forecasts were issued by 6,909 analysts at 90 distinct brokerage firms; approximately 84% of forecasts were issue by government-owned brokerage (*GovBro*) analysts and 16% were issued by non-government-owned brokerage (*non-GovBro*) analysts. Government-owned brokerage firms employed about 26 analysts each year; in non-government-owned brokerage firms, the number was about 25 each year. In untabulated results, we find that *GovBro* analysts and *non-GovBro* analysts cover similar firms. We do not find that the firms covered by these analysts exhibit significantly different firm characteristics, including firm size, price-to-book ratio, leverage, ROA, market beta, and sales growth.

Our main outcomes focus on analysts' earnings forecasts and their attributes. As mentioned by (Pacelli, 2019, p.125), earnings forecasts have several properties that make them particularly suitable for empirical studies: they "are continuous, have the common benchmark of actual earnings, and facilitate comparisons across analysts at different financial institutions."

Specifically, our primary dependent variable in testing *H1* 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:

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

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 sample minimum and maximum of $Raw\ Optimism_{ij\tau T}$ for all forecasts issued for firm j in year T. To limit the influence of outliers, prior to the normalization we first winsorize the variable at the top and bottom 2% of the cross-sectional distribution.[2]

In testing *H2*, our main dependent variable is forecast accuracy of an analyst's forecast of a firm's annual earnings. We again scale the raw value of forecast accuracy to the range between 0 to 1:

$$Accuracy_{ij\tau T} = \frac{\max_{jT}\left(\textit{Raw Forecast Error}_{ij\tau T}\right) - \textit{Raw Forecast Error}_{ij\tau T}}{\max_{jT}\left(\textit{Raw Forecast Error}_{ij\tau T}\right) - \min_{jT}\left(\textit{Raw Forecast Error}_{ij\tau T}\right)}, \tag{2}$$

where $Accuracy_{ij\tau T}$ is the normalized optimism of analyst i's forecast accuracy of firm j's annual earnings issued at date τ in year T; $\min_{jT}\left(\textit{Raw Forecast Error}_{ij\tau T}\right)$ and $\max_{jT}\left(\textit{Raw Forecast Error}_{ij\tau T}\right)$ are the sample minimum and maximum of $\textit{Raw Forecast Error}_{ij\tau T}$ for all the forecasts issued for firm j in year T.

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. For example, the variation in the 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. As Clement and Law (2014) explain, "this [scaled optimism] metric is conditional on the same firm-year ... [and thus] this adjustment is identical to controlling for firm-year fixed effects." Thus, our effects are mainly identified by within-firm and across-analyst variation in $Optimism_{ij\tau T}$.

To examine how government ownership in brokerage firms affects analyst research quality, we examine how *GovBro* analysts' forecasts differ from *non-GovBro* analysts during periods when the central government had strong incentives to stabilize the stock market. We identify five market-rescue periods between 2005 and 2019 during which the Chinese government had significant incentives to prop up the market and limit potential economic instability, and three "Hot" markets (or

[2] We confirm that our main results remain qualitatively the same if we instead winsorize at the top and bottom 1% of the distribution.

high-sentiment periods) during which the government had incentives to mitigate excessive enthusiasm and market bubbles.

During market rescue events, the central government took deliberate and explicit actions to prop up stock prices, allowing us to clearly identify these periods based on publicly documented interventions (see Appendix Table A1 for details). Since government actions to moderate market exuberance are more tacit and implicit, we identify "Hot" markets based on aggregate share turnover (following, e.g., Lee and Swaminathan, 2000; Baker and Wurgler, 2006). Specifically, we consider a month to be in a "Hot" market if it falls within a three consecutive month period where each month's turnover ranks in the top 20% of the sample period. (We required at least a three-month period to define "Hot" since the government is more likely to take actions when the stock market boom lasts for a period of time.) In our sample, we identified three "Hot" market periods (see Appendix Table A1 for details), all of which experienced sharp market increases. The average monthly return in "Hot" markets was around 10% compared to only 0.46% in normal periods, and the average share turnover ratio exceeded 30% during "Hot" markets compared to around 13% in normal periods.

To account for the possibility of baseline differences between the forecasts of *GovBro* and non-*GovBro* analysts, we benchmark and compare their intervention-period differences against non-intervention-period differences. For example, in testing *H1*, our empirical tests estimate variations of the following difference-in-differences (DID) specification:

$$\begin{aligned} Optimism_{ij\tau T} \text{ } or \text{ } Accuracy_{ij\tau T} \quad = \quad & \beta_0 + \beta_1 GovBro_{i\tau T} \times Rescue_{\tau T} + \beta_2 Rescue_{\tau T} \\ & + \beta_3 GovBro_{i\tau T} \times Hot_{\tau T} + \beta_4 Hot_{\tau T} + \beta_5 GovBro_{i\tau T} \\ & + \gamma' X_{i\tau T} + f_I + f_T + \xi_{ij\tau T}, \end{aligned} \tag{3}$$

where $Rescue_{\tau T}$ is an indicator variable that takes a value of 1 if the earnings forecast is issued on a date that falls within a rescue 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 government-owned brokerage firm and 0 otherwise; $Hot_{\tau T}$ is an indicator variable that takes a value of 1 if the earnings forecast is issued on a date that falls within a "Hot" market period and 0 otherwise; $X_{i\tau T}$ is a set of analyst characteristics observed as of the date of the earnings forecast; and f_I and f_T are industry- and year-fixed effects, respectively.[3]

A brokerage firm is classified as government-owned ($GovBro_{i\tau T} = 1$) when we determine its ultimate controller to be a government entity. Following prior literature (La Porta et al., 1999; Fan and Wong, 2002; Claessens et al., 2002), we define the ultimate controller as the shareholder that possesses sufficient voting rights to effectively control the company's major decisions and is not itself 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 government-owned is then determined by the identity of its largest ultimate owner.[4] In our sample, all of the largest ultimate owners possessed more than 20% of their respective brokerage firm's shares.

To account for analyst characteristics ($X_{i\tau T}$) that could explain variation in earnings forecast properties (e.g., *Optimism*), we control for the effect of the analyst's firm-specific experience (*Firm-exp*), defined as the number of days that an analyst has issued forecasts at the firm; the analyst's general experience (*Genexp*), defined as the number of days 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 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 regres-

[3]We classify industries by using the first digit of CSRC industry code, and our main results remain qualitatively the same if we use the first two-digit industry code to classify manufacturing industry.

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

sion controls appear in Appendix Table A2; their distributional summary statistics are reported in Table 1, Panel A.

For our main tests of *H1* and *H2*, the coefficients of interest are β_1 and β_3 (i.e., the "DID coefficients") in Eq., (3), which compare the average differences in earnings-forecast properties (i.e., *Optimism* or *Accuracy*) between *GovBro* and *non-GovBro* analysts during intervention-event periods (i.e., market rescue periods or "Hot" periods) to the average differences in earnings-forecast properties between the two types of analysts during non-event periods.

In keeping with *H1*—that *GovBro* analysts are more likely to respond to the government's incentives to stabilize the stock market during government intervention periods—we expect a positive and significant β_1 and a negative and significant β_3. And consistent with *H2*—that the information quality of the *GovBro* analysts is comparatively lower during market rescue and higher during "Hot" periods—we expect a negative and significant β_1 and a non-negative β_3. Moreover, if *GovBro* analysts' forecast accuracy during regular times is at least as good as *non-GovBro* analysts', we expect a β_5 that is zero or positive.

4 Empirical Results

This section presents evidence on our two central hypotheses regarding *GovBro* analysts and market stabilization. First, we test *H1* by examining whether *GovBro* analysts produce more optimistic forecasts during market rescue periods and less optimistic forecasts during hot market periods compared to *non-GovBro* analysts. We then test *H2* by analyzing whether these government-influenced forecasts exhibit differential information quality—specifically, lower accuracy and timeliness during intensive interventions (rescue periods) but not so during moderate interventions (hot markets). We conclude by examining market consequences, testing whether these differential forecasting behaviors impact stock liquidity and post-earnings announcement price adjustments.

4.1 Earnings-Forecast Optimism during Government Intervention Periods (*H1*)

Table 1, Panel A, provides descriptive statistics on the variables in our primary sample. The mean of *GovBro* is 0.84, indicating that 84% of the forecasts included in our sample were issued by analysts at government-owned brokerage firms. Approximately 19% of forecasts were issued during market rescue periods and 6% during hot periods. On average, analysts in our sample have about 1.6 years (594 days) of firm-specific forecasting experience and 4.3 years (1,563 days) of general forecasting experience, covering 19 firms across eight industries, and issuing forecasts about 228 days before the fiscal-end. The typical brokerage firm in our sample employs approximately 50 analysts.

Table 1, Panel B, presents a univariate comparison of forecast *Optimism* between *GovBro* and *non-GovBro* analysts across different market conditions. During market rescue periods, we observe an overall decline in forecast optimism by approximately 9% (from 0.4554 to 0.4157), consistent with deteriorating economic fundamentals during these periods of market stress. In contrast, during hot market periods, forecast optimism increases by about 13% (from 0.4554 to 0.5135), reflecting more positive expectations during market booms.

Notably, the patterns differ systematically between *GovBro* and *non-GovBro* analysts. *GovBro* analysts exhibit relatively more optimistic forecasts during market rescue periods, with their *Optimism* declining less severely than that of non-government analysts. Conversely, they issue relatively less optimistic forecasts during hot market periods.

Quantitatively, during rescue periods, *non-GovBro* analysts' forecast optimism declines by 11% (0.4604 to 0.4092) while *GovBro* analysts' optimism declines by only 8% (0.4544 to 0.4170). This 27% smaller decline during market rescues is consistent with *GovBro* analysts providing relatively more optimistic forecasts during downturns, in line with market support objectives. Similarly, during hot periods, *non-GovBro* analysts' forecast optimism increases by 19% (0.4604 to 0.5456) while *GovBro* analysts' optimism increases by only 12% (0.4544 to 0.5082). This 37% smaller increase during hot markets is consistent with *GovBro* analysts providing relatively less optimistic forecasts during times of market exuberance, consistent with market stabilization.

In Table 2, we examine whether these univariate patterns persist after controlling for analyst and brokerage characteristics. This table reports DID regression estimates, following Eq., (3), that isolate the effect of government ownership on analyst forecast optimism during intervention periods. Column 1 examines market-rescue events (*Rescue*), column 2 examines hot periods (*Hot*), and column 3 pools all events together.

The multiple regression results confirm our univariate findings. In column (1), the positive and statistically significant (at the 5% level) coefficient on *GovBro* $\times$ *Rescue* indicates that *GovBro* analysts issue relatively more optimistic forecasts during market rescue periods. In column (2), the negative and significant (at 1% level) coefficient on *GovBro* $\times$ *Hot* demonstrates that these same analysts issue relatively less optimistic forecasts during hot markets. These countercyclical patterns persist when pooling all events in column (3).

The economic magnitude of these effects appears substantial. Based on column (1) estimates, the coefficient on *Rescue* (-0.0627) indicates that *non-GovBro* analysts reduce their forecast optimism significantly during market rescue periods, reflecting expectations of deteriorating fundamentals. (This is a 14% decline in forecast optimism relative to the *non-GovBro* baseline average.) The positive coefficient on *GovBro* $\times$ *Rescue* (0.0094) indicates that *GovBro* analysts experience a 15% smaller decline in forecast optimism than *nonGovBro* analysts. Similarly, in column (2), the coefficient on *Hot* (0.0474) shows that *non-GovBro* analysts increase their forecast optimism during hot markets (although the increase is not statistically significant), while the negative coefficient on *GovBro* $\times$ *Hot* (-0.0195) indicates that *GovBro* analysts experience a 41% smaller optimism increase than than *nonGovBro* analysts. Column (3), which pools both types of events together, confirms these patterns with comparable coefficient magnitudes and statistical significance. These complementary patterns across different market conditions are consistent with our univariate analysis in Table 1, Panel B, and provide empirical support for *H1*, that *GovBro* analysts are more likely to align their forecasting behavior with the government's market stabilization objectives.

Interestingly, the consistently negative and statistically significant (at the 10% level) coefficients on the *GovBro* main effect suggest that, during normal market conditions, *GovBro* analysts actually issue less optimistic forecasts than their *non-GovBro* counterparts. A plausible explanation is that, absent intervention incentives, *GovBro* analysts may be less influenced by business generation pressures, potentially allowing them to produce more independent research during normal times.

4.1.1 Robustness Tests

In Table 3, we provide several additional tests to examine whether our main findings in Table 2 are indeed consistent with *GovBro* analysts' compliance with government incentives, or whether they could be confounded by omitted variables or measurement issues. We employ multiple strategies to address these concerns, including formal tests for omitted variable bias, alternative measures of market intervention periods, different forecast horizons, and sample matching techniques.

We begin by implementing the δ statistic proposed by Oster (2019) to assess the robustness of our main effect estimates to omitted variables bias. This method, widely adopted in applied economics research (Bhagwat et al., 2016; Call et al., 2018; Cohen et al., 2020; Gallemore, 2023; Green et al., 2019; Heimer et al., 2019; Jha et al., 2021; Scherf, 2024), leverages the insight that the impact of adding observable controls is informative about the potential impact of unobservable confounders (Altonji et al., 2005). The δ statistic represents the ratio of influence on the main variable of interest that unobservables would need to have relative to observables to completely nullify our main effects. For each of our main regression results in Table 2, we compute the δ that would drive the main coefficients—*GovBro* $\times$ *Rescue* or *GovBro* $\times$ *Hot*—to zero.[5] We make the conservative assumption that a fully specified model including both observed and unobserved variables would achieve a maximum R^2 of 1.

As reported in Table 3, Panel A, we find consistently negative δ values for our main coefficients. In the applied economics literature, negative δ values suggest that the addition of more control

[5] A Stata package (psacalc) written by Emily Oster performs these diagnostics. An R package (robomit) written by Sergei Schaub is also available.

variables drives the main coefficient *away* from zero, which would strengthen rather than weaken our main findings (Graham et al., 2017; Glewwe et al., 2018; Scherf, 2024). This increases our confidence that omitted variables are unlikely to explain away our results.

To be sure, in Panels B and C of Table 3, we further test the robustness of our findings to alternative specifications, dependent-variable measurements, and sample constructions. For parsimony, we focus on the specification in Table 2, column 3, where the main coefficients of interest are $GovBro \times Rescue$ and $GovBro \times Hot$.

In Panel B, column (1), we exploit ownership transitions to provide more direct causal evidence. We examine 15 brokerage firms that switched from government to non-government ownership during our sample period. We estimate a regression similar to that of Table 2, column 3, but instead of *GovBro* our main "treatment" indicator is *GovBroSwitch*, which evaluates to one when a *GovBro* brokerage firm has switched to private ownership. We find that after transitioning to private ownership, analysts issue *less* optimistic forecasts during market rescue periods and more optimistic forecasts during hot markets. This within-brokerage analysis strengthens the causal interpretation of our main findings.

In columns 2-5, we examine alternative definitions of intervention periods. Column 2 replaces *Rescue* with *Meeting*, capturing the six months preceding National Congress Meetings—periods when the government has strong incentives to project economic strength through the stock market (Piotroski et al., 2015). Similar to market rescue periods, the Chinese government has strong incentives to prop up the country's stock market prior to and during National Congress Meetings. Columns 3 and 4 redefine *Hot* using IPO proceeds and investor sentiment (Baker and Wurgler, 2006), respectively, instead of share turnover. Column 5 identifies hot markets using explicit market-cooling actions taken by the government, focusing on the June 2007 to December 2007 period when the government increased the stamp tax from 0.1% to 0.3%. Our main results remain robust across these alternative definitions.

In column (6), we address potential selection concerns—that our documented relative optimism effect is induced by factors correlated with observable differences between government-owned and non-government-owned brokerage firms—using entropy balancing. Unlike propensity score matching, which effectively assigns a weight of either 0 or 1 to each control sample observation, entropy balancing estimates and assigns continuous weight to every observation in the control group to achieve covariate balance (McMullin et al., 2019). After balancing on brokerage characteristics and covered firm attributes, we find even larger coefficient magnitudes than in our main specifications, consistent with the negative Oster (2019) δ statistic reported in Table 3, Panel A: adjusting for omitted variables strengthens our main results.

Next, we proceed to examine the robustness of results to alternative measurements of earnings-forecast optimism. Column (7) uses two-year-ahead forecasts (*Optimism2*), finding that *GovBro* analysts issue relatively less optimistic longer-horizon forecasts during hot markets, though the effect during rescue periods becomes insignificant. Column (8) restricts the sample to the last forecast per analyst-firm-quarter, following common practice in the earnings forecast literature (Clement and Tse, 2005).[6] We obtain consistent results.

In our untabulated results, we assess whether our findings are robust to using *Raw Optimism* (i.e., without the normalization described above). Under various generalized fixed effects structures, such as target-firm-year fixed effects, firm-broker fixed effects, and firm-analyst fixed effects, we find generally consistent but weaker results.

We further examine the robustness of *GovBro* analysts' differential optimism during intervention periods by examining other attributes of analysts' research output. Specifically, we examine how *GovBro* analysts' stock recommendations and earnings-forecast revisions respond to the government's time-varying market-stabilization incentives.

Stock recommendations are important, and frequently studied, summary statistics produced

[6] Our main regression results (e.g., Table 2) are based on a sample that incorporates all one-year ahead earnings forecasts issued between the prior and current fiscal-year earnings announcements. Prior literature examining the properties of earnings forecasts commonly use the last earnings forecast before the fiscal-year end (e.g., Clement and Tse, 2005). We do not keep the last forecast for each firm in each year since our analysis requires an analyst's forecasts for a given firm within and outside of the intervention periods. Keeping one analyst-firm forecast each year removes significant variation from the data.

by analysts (Jegadeesh et al., 2004; Barber et al., 2005). Therefore, *GovBro* analysts' response to government's market stabilization incentives may also manifest in their stock recommendations. In Table 4, Panel A, we report results from estimating 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 5, 4, 3, 2, and 1. The results show that *GovBro* analysts are on average less optimistic during normal periods, but issue relatively more favorable stock recommendations during market rescue periods and less favorable recommendations during hot market periods, corroborating our main results on earnings-forecast optimism.

We also examine forecast revisions (*Revision*), which are particularly valuable for studying analyst behavior because they reflect analysts' responses to new information and changing market conditions. To capture how *GovBro* analysts updated market expectations through forecast revisions, we measure *Revision* as the deviation from the consensus forecast calculated by the average of the last forecast issued by each analyst following the same firm in the past 180 days.

Table 4, Panel B, 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-*GovBro* analysts who revised tended to revise downward, consistent with deteriorating economic fundamentals. By contrast, the revisions of *GovBro* analysts tended to be on average less severe: we obtain a positive and statistically significant DID coefficient (at the 5% level). Moreover, the economic magnitudes are significant: government-brokerage analysts' downward revisions at these times are less severe, on average, by about 10% (column 1). In addition, during hot market periods (column 2), while non-*GovBro* analysts revised upward, the revisions of *GovBro* analysts are 40% smaller. We do not find significant differences between the revisions of GovBro and non-GovBro analysts during normal times.

Collectively, the robustness tests further support our hypothesis that *GovBro* analysts changed their forecasting behavior during market interventions, rather than these patterns being artifacts of measurement choices or omitted variables. The findings across alternative samples, variable definitions, and research outputs (Table 3 and Table 4) confirm our main results in Table 2: *GovBro* analysts produce relatively optimistic information about firms during market rescue periods and less optimistic information about firms during hot market periods compared to their *non-GovBro* counterparts.

4.1.2 Heterogeneity by Brokerage and Covered Firm Type

Next, we provide evidence supporting the conjecture that our main results reflect *GovBro* analysts' responsiveness to the government's market stabilization incentives. We do so by examining the heterogeneity in these effects by brokerage firm and covered firm type. We expect the relative optimism of *GovBro* analysts during intervention periods to be more pronounced in brokerage firms where analysts face stronger incentives to comply with government directives and in those covered firms whose stock prices the government may have the strongest incentives to stabilize.

First, we explore the variation in sensitivity to government incentives across brokerage firm types. Table 5, Panel A presents results from decomposing the *GovBro* indicator into *GovBro&Type* and *GovBro&Non-Type*, where *Type* indicates brokerage firms with characteristics likely associated with stronger government influence.[7]

In column (1), Panel A, *Type* identifies analysts working in brokerages where government ownership exceeds 30%. We expect the government to have a greater ability to exert pressure on such brokerage firms. The coefficient on *GovBro&Type* × *Rescue* (0.0147) is significantly larger than that on *GovBro&Non-Type* × *Rescue* (0.0025), with the difference statistically significant at the 10% level. This suggests that forecast optimism during market rescue periods is more pronounced when government ownership is higher, consistent with greater pressure to support stabilization efforts. Although we do find the coefficient on *GovBro&Type* × *Hot* to be more negative than *GovBro&Non-Type* × *Hot*, the difference is not statistically significant at the 10% level.

[7] Thus, $Type + Non\text{-}Type = 1$ and $GovBro\&Type + GovBro\&Non\text{-}Type = GovBro$.

Column (2), Panel A, considers brokerages with CSRC-connected senior managers. These CSRC connections likely serve as channels for communicating government priorities and exerting influence on analysts' forecasting behavior. Our results show the coefficient on *GovBro&Type* × *Rescue* (0.0224) substantially exceeds that on *GovBro&Non-Type* × *Rescue* (0.0070), with the difference significant at the 10% level. Although the coefficient on *GovBro&Type* × *Hot* (-0.0301) is more negative than *GovBro&Non-Type* × *Hot* (-0.0151), this difference is not statistically significant at conventional levels.

Column (3), Panel A, considers large versus small brokerages based on total assets. Larger government-owned brokerages play a more significant role in moderating market exuberance during hot periods and are thus more likely to be pressured by the government. The results show a coefficient on *GovBro&Type* × *Rescue* (0.0074) smaller than that on *GovBro&Non-Type* × *Rescue* (0.0193), though this difference is not statistically significant. However, large brokerages show a significantly stronger tempering effect during hot markets, with *GovBro&Type*× *Hot* (-0.0169) being substantially more negative than *GovBro&Non-Type* × *Hot* (0.0173), with the difference significant at the 5% level.

Next, we examine how analysts' sensitivity to government incentives varies across different types of covered firms. The underlying premise is that the government has stronger stock price stabilization incentives for certain firms than others. If the differential forecast properties of *GovBro* analysts stem from their compliance with government objectives, these patterns should be more pronounced for firms that are more critical to market stability. Table 5, Panel B, presents results from decomposing the *GovBro* indicator into *GovBro&Type* and *GovBro&Non-Type*, where *Type* indicates covered firms that are more integral to market stability.

Column (1), Panel B, considers state-owned enterprises (SOEs).[8] SOEs are more important for market stabilization because they are systemically significant to the economy, have stronger political ties to the government, and are more likely to receive state support during financial downturns.

[8]We use the ultimate controller collected by the China Center for Economic Research (CCER) database to identify SOEs and non-SOEs. Specifically, a firm is classified as an SOE if its ultimate controller is a government entity.

Their financial health is closely linked to government credibility, and their stock prices disproportionately influence major market indices, making them a key target for stabilization efforts. The results show that the coefficient on *GovBro&Type* $\times$ *Rescue* is significantly more positive than that on *GovBro&Non-Type* $\times$ *Rescue*, with the difference statistically significant at the 5% level. Additionally, the coefficient on *GovBro&Type* $\times$ *Hot* is significantly more negative than that on *GovBro&Non-Type* $\times$ *Hot*, with the difference statistically significant at the 5% level. These results suggest that *GovBro* analysts are more likely to align their forecasts with government stabilization objectives when covering SOEs, exhibiting stronger optimism during market rescue periods and greater pessimism during hot market periods.

Column (2), Panel B, considers large firms, defined as those with market capitalizations in the top 50 of all listed companies. Large firms are critical to market stabilization because they have a disproportionate influence on stock indices, attract significant institutional investment, and are closely watched as indicators of overall market and economic health. A sharp decline in the stock prices of large firms can amplify market-wide downturns, prompting stronger government intervention to maintain stability. Conversely, excessive optimism in these firms can contribute to market overheating, leading the government to take precautionary measures.

The results show that the coefficient on *GovBro&Type* $\times$ *Rescue* is significantly more positive than that on *GovBro&Non-Type* $\times$ *Rescue*, with the difference statistically significant at the 1% level. Additionally, the coefficient on *GovBro&Type* $\times$ *Hot* is significantly more negative than that on *GovBro&Non-Type* $\times$ *Hot*, at the 10% level. These findings align with the hypothesis that the government places greater emphasis on stabilizing large firms due to their systemic importance, and that *GovBro* analysts adjust their forecasts accordingly to reflect government stabilization priorities.

Column (3), Panel B, considers industry leaders, defined as the top two firms by market capitalization within each industry-year. Industry leaders are often viewed as bellwethers for their respective sectors. Their performance could have outsized effects on investor sentiment and sectorwide stability, making them a potential focus of government stabilization efforts.

The results show that the coefficient on *GovBro&Type* $\times$ *Rescue* is slightly more positive than that on *GovBro&Non-Type* $\times$ *Rescue*, and the difference is statistically significant at the 5% level. In contrast, while the coefficient on *GovBro&Type* $\times$ *Hot* is more negative than that on *GovBro&Non-Type* $\times$ *Hot*, the difference is not statistically significant at conventional levels.

Together, the results of Table 5 support the hypothesis that *GovBro* analysts' differential forecast properties during intervention periods reflect their compliance with the government's market stabilization incentives. Panel A shows that these effects are stronger in brokerage firms with deeper government ties, while Panel B indicates that they are most pronounced in forecasts of firms more critical to market stability during intervention periods. These findings reinforce the role of *GovBro* analysts as intermediaries that align market expectations with state objectives where intervention incentives are strongest.

4.2 Information Quality Under Varying Government Intervention (***H2***)

Our *Hypothesis 2* predicts that the information quality of forecasts issued by *GovBro* analysts differs systematically with the intensity of government intervention: deteriorating under intensive intervention (during market rescue periods) but not under moderate intervention (during hot market periods). We examine this hypothesis using multiple metrics of forecast quality.

4.2.1 Forecast Accuracy

First, we employ the model specified in Eq., (3)—using *Accuracy* as the dependent variable of interest—to examine how *GovBro* analysts' earnings forecast accuracy varies by government intervention periods. Table 6 reports our findings, following the same format as our main results in Table 2. Across all three specifications, we observe a positive and significant coefficient on *GovBro*, indicating that government-brokerage analysts' forecasts are generally more accurate than those of *non-GovBro* analysts during normal market periods.

However, the informational quality of *GovBro* analysts' forecasts exhibits a stark contrast between market rescue periods and hot market periods. During market rescue periods, the relative accuracy of *GovBro* analysts declines significantly: in columns 1 and 3, the coefficients on *GovBro* $\times$ *Rescue* are negative and statistically significant (at the 1% level). In contrast, during hot market periods, *GovBro* analysts demonstrate greater relative accuracy: in columns 2 and 3, the coefficients on *GovBro* $\times$ *Hot* are positive and statistically significant (at the 10% level).

In terms of magnitudes, during market rescue periods (column 1), forecast accuracy increases for all analysts, but *GovBro* analysts' accuracy improvement is 20% lower than that of *non-GovBro* analysts. This significant reduction in accuracy during market rescues is consistent with *GovBro* analysts sacrificing some informational precision to support market stabilization objectives. During hot market periods, forecast accuracy declines for all analysts, but *GovBro* analysts' accuracy decline is 29% lower than that of *non-GovBro* analysts.

A plausible explanation for the differential quality of *GovBro* analysts' forecast accuracy is their potential access to superior information. For example, these analysts might better anticipate which companies will receive preferential treatment or regulatory support during market stabilization periods. However, our results—showing relatively improved accuracy during hot markets but relatively diminished accuracy during rescue periods—suggest that any informational advantage *GovBro* analysts possess becomes subordinated to market stabilization objectives during intensive interventions (market rescues). In periods of moderate intervention (hot markets), by contrast, these analysts may have a greater ability to leverage their informational edge to produce more accurate forecasts.

These overall patterns align with Brunnermeier et al. (2022): intensive government interventions may sacrifice informational efficiency to achieve market stabilization, while more moderate interventions can maintain or even enhance informational quality. The Chinese government intervenes more intensively in market rescue periods than in hot market periods. Consequently, our findings suggest that *GovBro* analysts' forecasts are associated with reduced information quality during intense interventions but improved information quality during moderate interventions, consistent with their role in government market stabilization efforts.

4.2.2 Forecast Timeliness

Forecast timeliness represents another important dimension of analyst forecast quality. While accuracy reflects the precision of forecasts, timeliness captures how promptly analysts incorporate new information into their forecasts. More timely forecasts are generally considered higher quality as they provide market participants with updated information more quickly, allowing for more efficient price discovery. Prior research has shown that more promptly issued forecasts have a larger price impact (Cooper et al., 2001), highlighting the market value of timely information.

Table 7 reports results using *Forecast Gap* as the dependent variable in our model specification from Eq., (3). The results show that *GovBro* analysts on average update their forecasts more frequently during normal periods: the coefficient on *GovBro* is negative and significant coefficient at the 1% level in all three columns. However, during market rescue periods, this advantage diminishes significantly, as indicated by the positive coefficient on *GovBro* × *Rescue* in column 1, though this effect is only marginally significant at the 10% level. Conversely, during hot market periods, *GovBro* analysts' relative responsiveness increases, as shown by the negative and highly significant coefficient on *GovBro* × *Hot* in column 2. In column 3, where both interaction terms are included simultaneously, the results remain largely similar, although the positive coefficient on *GovBro* × *Rescue* loses its statistical significance at conventional levels while the negative effect for hot market periods remains strong and significant.

In terms of magnitudes, during market rescue periods (column 1), forecast timeliness increases for all analysts, but *GovBro* analysts' timeliness improvement is 21% smaller than that of *non-GovBro* analysts. This significant reduction in timeliness during market rescue periods is consistent with *GovBro* analysts sacrificing some informational precision to support market stabilization objectives. During hot market periods, forecast timeliness declines for all analysts, but *GovBro* analysts' timeliness reduction is 59% smaller than that of *non-GovBro* analysts. This relative improvement in timeliness during market booms suggests that *GovBro* analysts provide higher-quality information when the government's goal is to temper excessive market enthusiasm.

These findings on forecast timeliness reinforce our results on forecast accuracy. When the government intervenes intensively during market rescue periods, *GovBro* analysts not only produce less accurate forecasts but also update them less frequently, consistent with a relative deterioration in their forecast quality. In contrast, during hot market periods with more moderate intervention, *GovBro* analysts not only produce more accurate forecasts but also issue them more promptly, consistent with a relative improvement in forecast quality. This pattern further supports *H2* and the theoretical predictions of Brunnermeier et al. (2022) about the different effects of intervention intensity on information efficiency.

The results also help rule out an alternative explanation that the differential optimism we documented in Table 2 merely reflects *GovBro* analysts' general sluggishness in responding to new information. In fact, *GovBro* analysts are generally more responsive than *non-GovBro* analysts during normal periods, and especially so during hot market periods. Their relatively less frequent updates during market rescue periods are consistent with compliance with intensive market stabilization efforts rather than an inherent characteristic of their forecasting behavior.

4.3 Assessing Market Impact

Having established that *GovBro* analysts adjust their forecasting behavior in response to market conditions, we now examine whether these patterns translate into measurable market outcomes. If *GovBro* analysts' differential forecasting truly influences investor behavior, we should observe systematic differences in market characteristics corresponding to the extent of their coverage during different intervention periods. We focus on two key dimensions: market liquidity and price discovery following earnings announcements.

4.3.1 Market Liquidity

We first examine whether the differential forecasting behavior of *GovBro* analysts influences market liquidity. If these analysts effectively shape market expectations in line with stabilization objectives, we would expect to see variations in liquidity corresponding to the extent of their coverage during intervention periods.

We construct a variable *GovBro%*, representing the percentage of analysts covering a firm who are employed by government-owned brokerages, and estimate the following firm-month regression:

$$\begin{aligned} Liquidity_{jtT} &= \beta_0 + \beta_1 GovBro\%_{jtT} \times Rescue_{jtT} + \beta_2 GovBro\%_{jtT} \times Hot_{jtT} \\ &+ \beta_3 Rescue_{jtT} + \beta_4 Hot_T + \beta_5 GovBro\%_{jtT} + \gamma X_{jtT} + f_T + \epsilon_{ij\tau T}, \end{aligned} \tag{4}$$

where $Liquidity_{jtT}$ represents various market liquidity measures for firm j in month t of year T. We also control firm characteristics including firm size (*Size*), profitability (*ROA*), financial leverage (*Leverage*), cash flow from operation (*Cash*), price-to-book ratio (*PB*), and price volatility (*Stkvol*). All the regressors are defined in Appendix Table A2.

Table 8 presents results using five different liquidity measures: *Amihud Illiquidity*,*Pastor-Stambaugh Liquidity*,*Roll Liquidity*,*Proportion of Zero-Return Days*, and *Bid-Ask*, with *Amihud Illiquidity* and *Proportion of Zero-Return Days* increasing in illiquidity and others increasing in liquidity. Consistently across specifications, the coefficient on $GovBro\% \times Rescue$ is negative for illiquidity measures and positive for liquidity measures. This pattern indicates that during market rescue periods, firms with greater *GovBro* analyst coverage experience relatively better liquidity than those with less coverage, consistent with these analysts successfully supporting market stabilization efforts.

Conversely, during hot market periods, the coefficient on $GovBro\% \times Hot$ shows the opposite pattern, with positive coefficients for illiquidity measures and negative for liquidity measures. This suggests that *GovBro* analysts' tempering influence during market booms effectively reduces trading activity.

The economic impact of these forecasting patterns is substantial. Interpreting the results from column 1, during market rescue periods, stocks with a 10 percentage point higher proportion of *GovBro* analysts experience 4.4% smaller liquidity deterioration compared to other stocks (based on the Amihud illiquidity measure). Conversely, during hot market periods, stocks with a 10 percentage point higher proportion of *GovBro* analysts experience 7.3% smaller liquidity improvement. These complementary effects on market liquiditymitigating liquidity declines during downturns and tempering liquidity increases during boomsprovide direct evidence that *GovBro* analysts' forecasting behavior influences market conditions in ways consistent with the government's stabilization objectives.

4.3.2 PEAD

We next investigate how *GovBro* analysts' information production affects market price efficiency by analyzing the post-earnings announcement drift (PEAD). If markets overweight the relative optimism of these analysts during rescue periods, we would expect slower price adjustment to earnings news, particularly bad news. Conversely, during hot periods, their relatively more accurate and timely information production might lead to more efficient price discovery.

We examine how PEAD varies with the extent of *GovBro* analyst coverage by estimating:

$$\begin{aligned} CAR(\tau_1,\tau_2)_{jtT} &= \beta_0 + \beta_1 GovBro\%_{jtT} \times Surp_{jtT} \times Eventy_T + \beta_2 GovBro\%_{jtT} \times Surp_{jtT} \\ &+ \beta_3 Surp_{jtT} \times Eventy_T + \beta_4 GovBro\%_{jtT} \times Eventy_T \times + \beta_5 GovBro_{jtT} \\ &+ \beta_6 Surp_{itT} + \gamma X_{jtT} + f_T + \epsilon_{ij\tau T}, \end{aligned} \tag{5}$$

where $CAR(\tau_1,\tau_2)_{jtT}$ represents cumulative abnormal returns from τ_1 to τ_2 days relative to firm j's earnings announcement on date t in year T; $Surp_{jtT}$ is the earnings surprise, deflated by beginning-year stock price; and *Eventy* indicates either rescue years (*Rescuey*) or hot market years (*Hoty*).

The main effect for $Eventy$ does not belong to the specification because it is absorbed by year-fixed effects (f_T). All the regressors are defined in Appendix Table A2.

Table 9 presents these results, with Panel A focusing on rescue years and Panel B on hot market years. For short-window returns [-2,+2], we find no significant differential reaction based on the extent of government-brokerage coverage. However, examining longer windows reveals striking patterns. In Panel A, the positive and significant coefficient on $GovBro\% \times Surp \times Rescuey$ for the [3,360] window indicates that firms with greater government-brokerage coverage experience significantly stronger upward drift following earnings announcements during rescue years. This effect is even more pronounced in the bad news subsample (columns 4-6), suggesting markets underreact to negative earnings surprises when consensus forecasts include more *GovBro* analysts during rescue periods.

Like our findings in rescue periods, in Panel B, we find no significant differential short-window returns [-2,+2] during hot market years, based on the extent of government-brokerage coverage. In contrast to our findings in Panel A, Panel B shows significant negative coefficients on $GovBro\% \times Surp \times Hoty$ for both [3,180] and [3,360] windows, indicating that firms with greater government-brokerage coverage experience less post-announcement drift during hot market years. This suggests their relatively pessimistic yet relatively more accurate and timely earnings forecasts during market booms facilitates more efficient incorporation of earnings news. These patterns are particularly salient for negative earnings surprises.

Collectively, these results demonstrate that *GovBro* analysts not only adjust their forecasting behavior in response to market conditions but also meaningfully influence market outcomes. Their optimism during downturns helps maintain liquidity but delays price discovery, while their relative accuracy and timeliness during booms moderates liquidity but improves informational efficiency. These results are consistent with *GovBro* analysts successfully moderating market sentiment during government intervention periods. They are also consistent with the theoretical predictions of Brunnermeier et al. (2022) regarding the trade-offs between market stabilization and information efficiency under different intervention intensities.

5 Conclusion

This paper investigates how government ownership in brokerage firms shapes analyst behavior and information production to achieve market stabilization objectives in China's coordinated economy. Our findings demonstrate that the Chinese government effectively uses its influence over brokerage analysts as a flexible tool for managing market expectations and stability.

During market rescue periods, government-brokerage analysts issue forecasts that are comparatively more optimistic—yet less accurate and timely—supporting the government's efforts to bolster market confidence. During market booms, these same analysts provide relatively pessimistic forecasts that are more accurate and timely, helping temper excessive market enthusiasm. These effects are strongest in brokerage firms with deeper government ties and for systemically important firms like SOEs and large-capitalization companies. These results provide novel empirical support for theoretical predictions that government interventions aimed at financial stability can generate different levels of informational efficiency depending on intervention intensity.

Our findings also suggest that government-brokerage analysts serve two distinct functions: as information intermediaries who analyze and disseminate company information to investors, and as policy instruments who adjust their forecasts to help implement the government's market stabilization objectives. These roles are reflected in market outcomes, where firms with greater government-brokerage coverage experience relatively better liquidity during downturns but more subdued trading during booms, with corresponding effects on post-earnings price discovery.

These findings contribute to a broader understanding of how political influence affects information production in emerging markets where government ownership in financial institutions is prevalent. For example, prior work has investigated the effects of government ownership in banks (Sapienza, 2004; Chen et al., 2010). Our study extends this literature by examining how government influence operates through a different channel—brokerage analysts—and how this influence varies systematically with market conditions. Although our analysis focuses on China, these dynamics may be relevant to other coordinated economies with significant state ownership in financial intermediaries, including Japan, South Korea, Singapore, Malaysia, Vietnam, Thailand, and Indonesia. Future research could explore how the mechanisms we document manifest in different institutional contexts and examine the long-term implications of government influence on market efficiency, capital allocation, and investor behavior.

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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 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 hot market periods based on share turnover ratios.

<table>
<tr><th>Event</th><th>Intervention Period</th><th>Notes</th></tr>
<tr><td colspan="3"><u>Market Rescue</u></td></tr>
<tr><td>1st</td><td>1/23/2005–
6/5/2005</td><td>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.</td></tr>
<tr><td>2nd</td><td>4/24/2008–
10/30/2008</td><td>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 government-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.</td></tr>
<tr><td>3rd</td><td>4/1/2012–
12/4/2012</td><td>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 government-owned banks.
• On November 2, 2012, the CSRC announced that IPOs would be frozen.</td></tr>
<tr><td>4th</td><td>7/1/2015–
2/28/2016</td><td>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%). On the same day, CSRC implemented rules to restrict short selling.
• 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.
• In January 2016, according to sources cited by Bloomberg and The Wall Street Journal, state-owned funds intervened through informal methods on January 5th, 8th, and 14th.
• In February 2016, the People's Bank of China announced a 0.5 percentage point reduction in the reserve requirement ratio (RRR) for financial institutions, effective from March 1. During the first quarter of 2016, the China Securities Finance Corporation significantly increased its holdings in several bank stocks, including Agricultural Bank of China, Industrial and Commercial Bank of China, and Bank of China.</td></tr>
<tr><td>5th</td><td>7/1/2018–
10/31/2018</td><td>Notable market-rescue steps:
• On June 19, 2018, the day of a sharp market decline, Xinhua News Agency published an article titled "Multiple Positive Signals Will Support the Long-Term Stability of the A-shares Market." The next day, the "national team" announced measures to stabilize the market.
• On July 8-9, 2018, the China Securities Regulatory Commission (CSRC) held a meeting with executives of listed companies to gather suggestions on maintaining market stability.
• On September 26, 2018, the China Banking and Insurance Regulatory Commission (CBIRC) issued "Regulations on the Supervision and Administration of Wealth Management Business of Commercial Banks", further lifting the restriction that public wealth management products could not invest in stock-related public funds.
• On October 19, 2018, the China Banking and Insurance Regulatory Commission (CBIRC) issued another rule to allow wealth management subsidiaries of banks issue public wealth management products that could direct invest in stocks.
• On October 22, 2018, the standing committee of the State Council decided to launch a bond financing support program for private enterprises. After that, local governments started to establish government bailout funds.</td></tr>
</table>

Table A1. [Continued]

Event	Intervention Period	Notes
Hot Markets		
1st	Jan/2006–Jan/2008	• The Shanghai Composite Index rose by 277%, from 1161 points to 4383 points. The monthly index return is around 11%.
2nd	Feb/2009–July/2009	• The Shanghai Composite Index rose by 71%, from 1990 points to 3412 points. The monthly index return is around 11%.
3rd	Feb/2015–June/2015	• The Shanghai Composite Index rose by 33%, from 3210 points to 4277 points. The monthly index return is around 6.7%.

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.
Hot	Equals 1 if the forecast date falls in a three-month period in which the share turnover rate for each month is in the top 20% and the period has not overlap with any market-rescue periods, and 0 otherwise.
GovBro	Equals 1 if a brokerage is ultimately controlled by a government-owned enterprise or by the State-owned Assets Supervision and Administration Commission of the State Council, 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.
Optimism (raw)	Forecast optimism (analyst EPS forecast minus actual EPS) for analyst i following firm j in year t divided by stock price of firm j at the beginning of year t.
Optimism2	*Optimism* based on two-year ahead earnings forecasts.
Firm ROA	The average return on asset of firms covered by the brokerage firm at year t.
Firm Assets	The average logarithm of total assets of firms covered by the brokerage firm at year t.
Firm Leverage	The average debt to asset ratio of firms covered by the brokerage firm at year t.
Firm Sales Growth	The average sales growth of firms covered by the brokerage firm at year t.
Firm Cash Flow	The average cash flow to assets of firms covered by the brokerage firm at year t.

Table A2. Continued

REC	Equals 5 for strong buy, 4 for buy, 3 for neutral, 2 for sell, and 1 for strong sell.
Revision	The difference between the current EPS forecast (current forecast) and the consensus forecast calculated as the mean of the last forecast that each analyst issues within 180 days prior to the current forecast about the same firm for the same year, deflated by the prior forecast.
FGAP	The difference between the number of days elapsed since the last forecast about the same firm by the same 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.
Accuracy	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.
GovBro%	The proportion of government-brokerage analysts in the total cohort of analysts who follow a given firm.
Amihud Illiquidity	The monthly Illiquidity measure based on Amihud (2002).
Pastor-Stambaugh Liquidity	The monthly liquidity measure based on Pastor and Veronesi (2003).
Roll Liquidity	The monthly liquidity measure based on Roll (1984).
Proportion of Zero-Return Days	The monthly illiquidity measure calculated by proportion of days with zero returns in a month (Bekaert et al., 2007).
Bid-ask	The monthly illiquidity measure calculated by average daily bid-ask spread (Copeland and Galai, 1983).
Size	Logarithm of total assets at the beginning of the year.
ROA	Return on assets at the beginning of the year.
Leverage	Debt-to-asset ratio measured at the beginning of the year.
Cash	Cash flow from operation deflated by total assets at the beginning of the year.
PB	Price-to-Book ratio at the beginning of the year.
Stkvol	Monthly Stock price volatility in the year.
Rescuem	Equals one if the month falls in the *Rescue* period, and zero .
Hotm	Equals one if the month falls in the *Hot* period, and zero .
BHAR	Buy-and-hold market adjusted return.
Rescuey	Equals 1 for a year when at least four of the six months before an earnings-announcement date fall into a rescue period, and 0 otherwise.
Hoty	Equals 1 for a year when at least four of the six months before an earnings-announcement date fall into a hot market period, and 0 otherwise.
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 about the same firm for the same year prior to the actual earnings announcement.

Table 1.

Descriptive Statistics

Table 1 reports key summary statistics on our analysis sample. Panel A provides descriptive statistics on the variables in our main sample, which consists of 327,658 one-year-ahead analysts' forecasts issued from 2005 to 2019. 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 presents initial evidence on our main hypothesis by reporting the means of our main dependent variable of interest, *Optimism*, between the earnings forecasts issued by government-owned (*GovBro*=1) and non-government-owned (*GovBro*=0) brokerage firms, as well as their mean differences, and between the event (*Rescue*=1 or *Hot*=1) and non-event (*Rescue*=0 & *Hot*=0) periods, and their mean differences. The bottom row of the rightmost column reports the pooled difference-in-difference estimate. *T*-statistics based on robust standard errors are reported in parentheses, and significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables definitions are reported in Appendix Table A2; variables denoted *(Raw)* are the un-scaled versions of their counterparts.

Panel A: Distributional Summary Statistics

	Min	**P25**	**Mean**	**Median**	**P75**	**Max**	**SD**
GovBro	0.00	1.00	0.84	1.00	1.00	1.00	0.37
Rescue	0.00	0.00	0.19	0.00	0.00	1.00	0.39
Hot	0.00	0.00	0.06	0.00	0.00	1.00	0.23
Optimism	0.00	0.17	0.45	0.43	0.71	1.00	0.31
Accuracy	0.00	0.40	0.64	0.74	0.93	1.00	0.32
Firmexp	0.00	0.03	0.35	0.24	0.61	1.00	0.33
Genexp	0.00	0.19	0.45	0.42	0.69	1.00	0.30
Frequency	0.00	0.00	0.42	0.33	0.75	1.00	0.38
Companies	0.00	0.11	0.34	0.25	0.49	1.00	0.29
Industries	0.00	0.12	0.35	0.27	0.50	1.00	0.29
Horizon	0.00	0.36	0.58	0.58	0.90	1.00	0.31
Brokersize	0.00	0.24	0.47	0.44	0.67	1.00	0.30
Raw Optimism	-7.28	-0.01	0.12	0.05	0.17	21.92	0.38
Raw Accuracy	0.00	0.03	0.19	0.08	0.21	21.92	0.35
Raw Firmexp	0.00	40.00	593.59	309.00	879.00	5,667.00	736.37
Raw Genexp	0.00	728.00	1,563.44	1,406.00	2,219.00	5,694.00	1,065.05
Raw Frequency	1.00	1.00	3.23	2.00	4.00	37.00	2.65
Raw Companies	1.00	8.00	19.32	14.00	23.00	212.00	19.30
Raw Industries	1.00	4.00	7.59	6.00	10.00	43.00	5.39
Raw Horizon	1.00	154.00	228.30	228.00	329.00	463.00	103.89
Raw Brokersize	1.00	32.00	50.08	48.00	67.00	157.00	25.43

Panel B: Forecast Optimism

Group	**N**	**Total Sample**	**Govbro = 0**	**Govbro = 1**	**Diff (*G1-G0*)**
Total Sample	327,658	0.4513	0.4548	0.4506	-0.0042***
					(-2.864)
T1: *Rescue = 1*	61,424	0.4157	0.4092	0.4170	0.0078**
					(2.452)
T2: *Hot = 1*	18,931	0.5135	0.5456	0.5082	-0.0374***
					(-5.491)
T3: *Rescue = 0 & Hot = 0*	247,303	0.4554	0.4604	0.4544	-0.0060***
					(-3.584)
Diff (*T1-T3*)		-0.0397***	-0.0512***	-0.0374***	0.0139***
		(-28.529)	(-14.794)	(-24.600)	(3.736)
Diff (*T2-T3*)		0.0582***	0.0852***	0.0538***	-0.0313***
		(24.680)	(13.406)	(21.232)	(-4.669)

Table 2.
Government Intervention Periods and Earnings-Forecast Optimism

Table 2 table reports the results of OLS regressions testing *Hypothesis 1*. We regress *Optimism* on an event indicator (*Rescue*, or *Hot*), an indicator for a government-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables described in our methodology section. Column 1 examines differential forecast optimism during the market-rescue events (*Rescue*); column 2 examines differential forecast optimism during hot markets (*Hot*); and column 3 examines differential forecast optimism during both types of events. All specifications include year- and industry-fixed effects. *T*-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	Optimism		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0094**		0.0085**
	(2.783)		(2.453)
Rescue	-0.0627***		-0.0620***
	(-6.662)		(-5.673)
GovBro × *Hot*		-0.0195***	-0.0145***
		(-5.425)	(-4.379)
Hot		0.0474	0.0114
		(0.914)	(0.271)
GovBro	-0.0085**	-0.0059*	-0.0076**
	(-2.580)	(-1.913)	(-2.212)
Firmexp	0.0044	0.0043	0.0044
	(1.368)	(1.348)	(1.368)
Genexp	-0.0100**	-0.0095**	-0.0100**
	(-2.841)	(-2.641)	(-2.835)
Frequency	0.0257***	0.0248***	0.0257***
	(9.863)	(9.535)	(9.893)
Companies	-0.0057	-0.0065*	-0.0057
	(-1.568)	(-1.806)	(-1.581)
Industries	0.0112**	0.0109**	0.0112**
	(2.506)	(2.416)	(2.483)
Horizon	0.2951***	0.2976***	0.2952***
	(11.246)	(11.854)	(11.397)
Brokersize	0.0135***	0.0141***	0.0136***
	(3.264)	(3.496)	(3.256)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	327,658	327,658	327,658
Adj R^2	0.0966	0.0944	0.0966

Table 3.

Robustness

Table 3 reports robustness tests of the main results in Table 2. Panel A provides estimates of the relative degree of selection in unobservables that would make the coefficients on *GovBro* $\times$ *Rescue* and *GovBro* $\times$ *Hot* in Table 2 zero, respectively. We report the δ statistic, following Oster (2019), assuming that the inclusion of unobserved variables would produce a maximum R^2 of 1. Panel B considers alternative samples or measurement of *Optimism*. Column 1 reports regression estimates using difference-in-difference design, where (*GovBroSwitch*) equals one for years after brokerage firms switched from being government- to non-government-owned, and equals zero otherwise. This regression is estimated on the sample of 15 brokerage firms that switched from being government- to non-government-owned during the sample period. Column 2 to Column 5 report regression estimates based on alternative measures of *Rescue* and (*Hot*): *Rescue* is defined by National Congress Meetings in column 2, and (*Hot*) is defined by IPO proceeds in Column 3, by investor sentiment in Column 4, and by explicit government actions in Column 5. Column 6 reports our baseline specification based on an entropy balanced sample. Columns 7 and 8 consider alternative measures of forecast optimism, using two-year-ahead earnings forecasts and using only the sample of each analyst's last forecast in a quarter, respectively. T-statistics for Panel B, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

Panel A: Bounding the Effect of Omitted Variables using Oster (2019)

DV=	*Optimism*	
Primary Var=	*GovBro* $\times$ *Rescue*	*GovBro* $\times$ *Hot*
	(1)	(2)
δ	-0.00432	-0.00553
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	327,658	327,658
Adj R^2	0.0957	0.0942

Panel B: Using Alternative Samples or Measurement of *Optimism*

Sample =	*GovBro* to Non-*GovBro*	Alternative Definition of *Rescue*: Congress Meeting	Alternative Definition of *Hot*: Rank by IPO Proceeds	Alternative Definition of *Hot*: Rank by Investor Sentiment	Alternative Definition of *Hot*: Explicit Government Actions	Entropy Balanced Sample	Using Two-Year Ahead Forecast	Last Forecast Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GovBroSwitch $\times$ *Rescue*	-0.0155**							
	(-2.295)							
GovBroSwitch $\times$ *Hot*	0.0541**							
	(2.281)							
GovBro $\times$ *Meeting*		0.0153*						
		(1.844)						
GovBro $\times$ *Rescue*			0.0085**	0.0094**	0.0093**	0.0190**	0.0020	0.0124*
			(2.664)	(2.678)	(2.714)	(2.697)	(0.527)	(2.086)
GovBro $\times$ *Hot*		-0.0192***	-0.0071	-0.0107***	-0.0197***	-0.0404*	-0.0246***	-0.0210***
		(-4.887)	(-1.406)	(-4.054)	(-5.653)	(-1.796)	(-6.079)	(-4.207)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,750	327,658	327,658	327,658	327,658	264,554	290,738	125,918
Adj R^2	0.0956	0.0945	0.0976	0.0970	0.0966	0.0785	0.0668	0.0846

Table 4.
Other Research Output Attributes

Table 4 reports results examining whether government-brokerage analysts' response to market stabilization incentives manifests in other dimensions of their research output. We report OLS regressions of analysts' other research output attributes—recommendation optimism (*REC*) in Panel A and earnings-forecast revisions (*Revision*) in Panel B—on an event indicator (*Rescue* in column 1, *Hot* in column 2, or both *Rescue* and *Hot* in column 3), an indicator for a government-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables that appear in the main regressions of Table 2. All specifications include industry- and year-fixed effects. T-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	(1)	(2)	(3)
	Panel A: Recommendation Optimism (*REC*)		
GovBro × *Rescue*	0.0457**		0.0667***
	(2.929)		(4.304)
Rescue	-0.0744*		-0.0879***
	(-1.993)		(-3.610)
GovBro × *Hot*		-0.0696**	-0.0958***
		(-2.456)	(-3.651)
Hot		0.0175	0.0533
		(0.354)	(1.067)
GovBro	-0.1162***	-0.0997***	-0.1108***
	(-5.534)	(-4.947)	(-5.507)
Controls, Year FE, Ind FE	Yes	Yes	Yes
Observations	282,472	282,472	282,472
Adj R^2	0.1098	0.1098	0.1102
	Panel B: Forecast Revision (*Revision*)		
GovBro × *Rescue*	0.0045**		0.0037*
	(2.251)		(1.856)
Rescue	-0.0433***		-0.0410***
	(-4.228)		(-3.986)
GovBro × *Hot*		-0.0187***	-0.0154***
		(-7.769)	(-3.924)
Hot		0.0462*	0.0206
		(2.003)	(1.289)
GovBro	-0.0009	0.0007	-0.0001
	(-0.539)	(0.535)	(-0.058)
Controls, Year FE, Ind FE	Yes	Yes	Yes
Observations	292,829	292,829	292,829
Adj R^2	0.0245	0.0213	0.0246

Table 5.

Heterogeneous Effects on Earnings-Forecast Optimism by Market Stabilization Incentives

Table 5 reports results examining how the differential optimism of government-brokerage analysts varies by brokerage characteristics and covered firm type. We estimate a variant of Eq., (3) in which we decompose the *GovBro* indicator into *GovBro&Type* and *GovBro&Non-Type*, where *Type* (*Non-Type*) is an indicator that takes a value of 1 (0) if the analyst's brokerage firm satisfies (does not satisfy) a particular attribute. For brevity, only the coefficients on the interaction terms are reported. In Panel A, *Type* denotes forecasts by analysts employed in brokerage firms in which the central or local government owns more than 30% of the shares in column 1; brokerage firms with CSRC-connected senior managers in column 2; and brokerage firms with above-median total assets among all brokerage firms in the same year in column 3. In Panel B, *Type* denotes SOEs in column 1; forecasts issued for firms with large capitalization (i.e. the top 50 firms based on market capitalization) in column 2; and firms ranked as top 2 by market capitalization in each industry-year in column 3. All specifications include *Type* and *Non-Type* indicators as controls as well as analyst controls and industry- and year-fixed effects as in Table 2. T-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	Panel A: By Market Stabilization Incentives (Brokerage Firm Type)		
	(1)	(2)	(3)
Type =	High Gov Ownership	CSRC Manager	Large Brokerage
GovBro&Type×Rescue	0.0147**	0.0224**	0.0074**
	(2.253)	(2.784)	(2.297)
GovBro&Non-Type×Rescue	0.0025	0.0070*	0.0193*
	(0.447)	(1.946)	(1.857)
GovBro&Type×Hot	-0.0136**	-0.0301**	-0.0169***
	(-2.318)	(-2.420)	(-5.123)
GovBro&Non-Type×Hot	-0.0075	-0.0151***	0.0173
	(-0.475)	(-4.201)	(1.358)
Controls, Year FE, Ind FE	Yes	Yes	Yes
Observations	327,658	327,658	327,658
Adj R^2	0.0966	0.0967	0.0966
p-Value of F-Test (*Rescue*)	0.0787	0.0544	0.2221
p-Value of F-Test (*Hot*)	0.5818	0.2687	0.0178
	Panel B: By Market Stabilization Incentives (Covered Firm Type)		
	(1)	(2)	(3)
Type =	SOE Firms	Large Firms	Industry Leader
GovBro&Type×Rescue	0.0164***	0.0290***	0.0027
	(3.754)	(3.974)	(0.313)
GovBro&Non-Type×Rescue	0.0031	0.0061*	-0.0121
	(0.845)	(1.844)	(-1.214)
GovBro&Type×Hot	-0.0431***	-0.0539**	-0.0137
	(-4.647)	(-2.352)	(-0.731)
GovBro&Non-Type×Hot	0.0009	-0.0079	0.0096
	(0.114)	(-1.612)	(0.835)
Controls, Year FE, Ind FE	Yes	Yes	Yes
Observations	327,658	327,658	327,658
Adj R^2	0.0979	0.0968	0.0966
p-Value of F-Test (*Rescue*)	0.0484	0.0033	0.0430
p-Value of F-Test (*Hot*)	0.0146	0.0850	0.4006

Table 6.

Earnings-Forecast Accuracy

Table 6 reports the results of OLS regressions testing *Hypothesis 2*. We regress forecast accuracy (*Accuracy*) on event indicators (*Rescue* and *Hot*), an indicator for a government-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables that appear in the main regressions of Table 2. Column 1 examines differential accuracy during the market-rescue events (*Rescue*); column 2 examines differential accuracy during the hot period (*Hot*); and column 3 examines differential accuracy of forecasts issued during both types of events. All specifications include industry- and year-fixed effects. *T*-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	Accuracy		
	(1)	(2)	(3)
GovBro × *Rescue*	-0.0080***		-0.0075***
	(-4.054)		(-3.587)
Rescue	0.0395***		0.0363***
	(6.200)		(5.568)
GovBro × *Hot*		0.0119**	0.0086*
		(2.201)	(1.775)
Hot		-0.0414**	-0.0213*
		(-2.528)	(-1.798)
GovBro	0.0157***	0.0137***	0.0152***
	(6.709)	(5.359)	(6.162)
Firmexp	0.0014	0.0015	0.0015
	(0.569)	(0.618)	(0.600)
Genexp	0.0112***	0.0109***	0.0111***
	(3.285)	(3.143)	(3.286)
Frequency	-0.0177***	-0.0172***	-0.0177***
	(-6.284)	(-6.058)	(-6.252)
Companies	-0.0114	-0.0110	-0.0115
	(-1.744)	(-1.674)	(-1.752)
Industries	-0.0149**	-0.0147**	-0.0149**
	(-2.637)	(-2.614)	(-2.633)
Horizon	-0.4531***	-0.4534***	-0.4521***
	(-30.209)	(-30.808)	(-30.295)
Brokersize	-0.0092*	-0.0095**	-0.0092*
	(-2.116)	(-2.189)	(-2.090)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	327,658	327,658	327,658
Adj R^2	0.2085	0.2079	0.2085

Table 7.

Forecast Gap

Table 7 reports the results of OLS regressions of analysts' forecast gap (*FGAP*)—the number of days elapsed since the prior forecast—on an event indicator (*Rescue* in column 1, *Hot* in column 2, or both *Rescue* and *Hot* in column 3), an indicator for a government-owned brokerage firm (*GovBro*), an interaction of the two indicators, and analyst-level control variables that appear in the main regressions of Table 2. This analysis provides additional evidence for *Hypothesis 2* by examining forecast timeliness. All specifications include industry- and year-fixed effects. *T*-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	FGAP		
	(1)	(2)	(3)
GovBro × *Rescue*	0.0083*		0.0061
	(1.831)		(1.137)
Rescue	-0.0399***		-0.0334**
	(-3.576)		(-2.300)
GovBro × *Hot*		-0.0455***	-0.0425***
		(-6.084)	(-6.024)
Hot		0.0770***	0.0579*
		(3.788)	(1.964)
GovBro	-0.0187***	-0.0149***	-0.0163***
	(-4.471)	(-3.847)	(-3.899)
Firmexp	-0.0262***	-0.0265***	-0.0263***
	(-9.172)	(-9.494)	(-9.264)
Genexp	-0.0050	-0.0045	-0.0049
	(-1.600)	(-1.508)	(-1.585)
Frequency	-0.0176***	-0.0180***	-0.0176***
	(-4.993)	(-5.103)	(-5.005)
Companies	-0.0764***	-0.0769***	-0.0764***
	(-13.991)	(-14.060)	(-13.793)
Industries	-0.0943***	-0.0946***	-0.0944***
	(-20.169)	(-20.855)	(-20.416)
Horizon	-0.0534***	-0.0559***	-0.0549***
	(-14.850)	(-14.366)	(-13.030)
Brokersize	-0.0634***	-0.0632***	-0.0635***
	(-9.352)	(-9.015)	(-9.226)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	226,032	226,032	226,032
Adj R^2	0.0440	0.0434	0.0443

Table 8.
Market Liquidity

Table 8 reports the results of OLS regressions examining market consequences of government-brokerage analysts' forecasting behavior. We regress monthly market liquidity on event indicators (*Rescue* and *Hot*), proportion of analysts covering the firm employed by government brokerage firms (*GovBro%*), an interaction of the two indicators, and the following controls: firm size (*Size*), ROA (*ROA*), Cash (*Cash*), Leverage (*Leverage*), Price-to-Book Ratio (*PB*), and stock volatility (*StkVol*). The dependent variable is Amihud illiquidity in column 1, Pastor-Stambaugh liquidity measure in column 2, Roll liquidity measure in column 3, proportion of days with zero return in column 4, and bid-ask spread in column 5. All specifications include industry- and year-month fixed effects. T-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year-month levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

DV =	*Amihud Illiquidity*	*Pastor-Stambaugh Liquidity*	*Roll Liquidity*	*Proportion of Zero-Return Days*	*Bid-Ask*
	(1)	(2)	(3)	(4)	(5)
GovBro% × *Rescue*	-0.0182**	0.0178*	0.0043*	-0.0005	-0.0129*
	(-2.755)	(1.939)	(1.995)	(-0.209)	(-1.949)
GovBro% × *Hot*	0.0198**	-0.0163	-0.0124***	0.0079***	0.0165*
	(3.074)	(-1.513)	(-4.381)	(3.187)	(1.884)
Rescue	0.0414***	-0.0235**	0.0066*	0.0010	0.0396***
	(5.926)	(-2.288)	(1.854)	(0.412)	(6.042)
Hot	-0.0272***	0.0288**	0.0320***	-0.0182***	-0.0199*
	(-3.480)	(2.471)	(6.899)	(-6.959)	(-1.923)
GovBro%	0.0003	0.0032	0.0015	-0.0032**	0.0054
	(0.149)	(1.045)	(1.615)	(-2.583)	(1.777)
Controls, Year FE, Ind FE	Yes	Yes	Yes	Yes	Yes
Observations	123,751	123,751	123,751	123,751	123,751
Adj R^2	0.2860	0.0121	0.2326	0.0805	0.1604

Table 9.
Post Earnings Announcement Drift

Table 9 reports OLS results examining how post-earnings announcement drift is affected by government-brokerage analyst coverage. We regress cumulative abnormal returns around or 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 (*Rescuey* or *Hoty*), and all interactions of these three variables. Main effects for *Rescuey* and *Hoty* are not reported because they are absorbed by year fixed effects. We also include in each specification the following controls: firm size (*Size*), ROA (*ROA*), Cash (*Cash*), Leverage (*Leverage*), Price-to-Book Ratio (*PB*), and stock volatility (*StkVol*). Column 1 examines cumulative abnormal returns from 2 days before to 2 days after the earnings announcement [*BHAR (-2,2)*], and columns 2 and 3 examine 3 days to 180 days [*BHAR (3,180)*] and 3 days to 360 days [*BHAR (3,360)*] after the earnings announcement. Columns 4-6 are estimated on the subsample of "bad news" earnings announcements (negative earnings surprises), using *BHAR (-2,2)*,*BHAR (3,180)* and *BHAR (3,360)* respectively. Panels A and B separately report results of the PEAD for market rescue years (*Rescuey*) and hot market years (*Hoty*). All specifications include industry- and year- fixed effects. T-statistics, reported in parentheses, are based on two-way-cluster robust standard errors, clustering at the analyst and year levels. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively. Variables are defined in Appendix Table A2.

	Panel A: Market Rescue Years					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample =	*Full Sample*			*Bad News Sample*		
Return =	$BHAR$ $(-2,2)$	$BHAR$ $(3,180)$	$BHAR$ $(3,360)$	$BHAR$ $(-2,2)$	$BHAR$ $(3,180)$	$BHAR$ $(3,360)$
GovBro% ×*Surp* × *Rescuey*	-0.0432	2.1427	7.8246**	1.0303	4.6401	12.4744***
	(-0.080)	(0.685)	(2.219)	(1.733)	(1.613)	(6.888)
GovBro% ×*Surp*	0.2679	2.5133	1.4819	0.0333	2.8385	0.5082
	(0.636)	(1.720)	(1.392)	(0.061)	(1.517)	(0.652)
Surp ×*Rescuey*	0.0967	-3.1190	-9.4728***	-0.8261*	-4.5527*	-12.7405***
	(0.229)	(-1.128)	(-4.923)	(-1.891)	(-2.090)	(-6.763)
GovBro% ×*Rescuey*	-0.0031	-0.0144	-0.0184	0.0131**	0.0154	0.0371
	(-0.437)	(-0.589)	(-0.302)	(2.974)	(0.433)	(0.465)
GovBro%	0.0031	0.0231*	-0.0087	-0.0012	0.0272	-0.0193
	(0.862)	(1.881)	(-0.511)	(-0.277)	(1.518)	(-0.850)
Surp	0.2295	-0.6701	0.6516	0.3712	-1.1904	1.0548
	(0.718)	(-0.487)	(0.690)	(0.929)	(-0.674)	(0.902)
Controls, Year FE, Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,859	13,859	13,859	10,055	10,055	10,055
Adj R^2	0.0265	0.1199	0.1255	0.0218	0.1255	0.1296

Table 9. [Continued]

	Panel B: Hot Market Years					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample =	*Full Sample*			*Bad News Sample*		
Return =	$BHAR$ $(-2,2)$	$BHAR$ $(3,180)$	$BHAR$ $(3,360)$	$BHAR$ $(-2,2)$	$BHAR$ $(3,180)$	$BHAR$ $(3,360)$
GovBro% $\times$*Surp* $\times$ *Hoty*	0.5298	-11.5194***	-6.0199**	-2.3061***	-19.2928***	-13.4548*
	(0.367)	(-4.356)	(-2.250)	(-4.797)	(-5.613)	(-1.954)
GovBro% $\times$*Surp*	0.2606	3.0037**	2.9158**	0.2805	3.8457**	2.6956*
	(0.678)	(2.155)	(2.161)	(0.590)	(2.221)	(1.848)
Surp $\times$*Hoty*	-0.4011	13.1915***	6.5770**	2.0982***	17.9003***	12.5857**
	(-0.346)	(4.661)	(2.421)	(5.930)	(5.385)	(2.309)
GovBro% $\times$*Hoty*	-0.0148***	0.0435	0.0441	-0.0385***	-0.0168	-0.0135
	(-4.087)	(1.683)	(1.556)	(-7.261)	(-0.358)	(-0.557)
GovBro%	0.0033	0.0180*	-0.0145	0.0031	0.0288*	-0.0138
	(1.005)	(1.766)	(-0.979)	(0.870)	(1.796)	(-0.591)
Surp	0.2412	-1.3625	-1.0216	0.1630	-2.1545	-1.1525
	(0.834)	(-1.007)	(-0.713)	(0.473)	(-1.308)	(-0.657)
Controls, Year FE, Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,859	13,859	13,859	10,055	10,055	10,055
Adj R^2	0.0266	0.1201	0.1248	0.0222	0.1258	0.1288