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The effect of short sale constraints on analyst forecast quality: Evidence from a natural experiment in China

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ABSTRACT

We examine the effect of short selling on analyst forecast quality following the pilot program in China in 2010 that allows short selling for selected companies. We find that reduction in short sale constraints significantly improves analyst forecast quality for these pilot-firms when compared to non-pilot firms. Specifically, analyst forecast errors for pilot firms are smaller and forecast dispersions are narrower. Further, we show that the improvement of analyst forecast quality is more prominent for firms with lower prior price efficiencies and disclosure quality, and in locations with lower institutional development. Our findings suggest that short selling activities serve an important role in facilitating the speed of information incorporation and improving the information environment faced by firms.

1. Introduction

Extant literature (Miller, 1977; Diamond and Verrecchia, 1987; Seguin, 1990; Boehmer and Wu, 2012) has documented the positive effect of short selling on stock liquidity and price efficiency. Short selling is found to improve the overall price efficiency by allowing price to promptly incorporate negative information. Furthermore, reduction in short sale constraints is also found to improve overall market stability and reduce asset price fluctuation (Hong and Stein, 2003; Diether et al., 2009). The fundamental argument in support of short selling comes from the proposition that company stock price will be biased upward if short sale constraints prohibit investors from trading on the pessimistic information about the company. Interestingly, most of the studies on short sale focus on its final impact on stock price behavior rather than the direct information environment faced by firms.

We examine the impact of short selling on one important information component - the quality of analyst forecast. We focus on analysts because of their essential role as the intermediary between investors and corporations. Since analyst forecast quality often depends on the extent of information disclosure and its accuracy from both the market and the corporation, activities that reduce information uncertainty in the market may improve analyst forecast accuracy and enhance overall corporate information environment (e.g. Zhang, 2006; Jiang et al., 2005). One such activity is from short-sellers: by constantly putting downward pressure on stock prices, the existence of short-sellers may facilitate the speed of information incorporation and increase analyst information accuracies.

Prior studies show that compared to analysts, short sellers have superior information and short selling activities sometimes precede analyst forecast revisions (e.g. Desai et al., 2006; Francis et al., 2005; Boehmer et al., 2015). For example, Francis et al. (2005) show that short sellers mainly exploit information concerning the market's misperception of firms' fundamentals. Boehmer et al. (2015) also document that short selling predicts future returns after controlling for information in analyst actions, and conclude that short sellers have more information than analysts do. However, direct evidence linking how short-selling activities influence analyst forecast accuracy is scare. Probably due to the endogenous nature of the research question, it is hard to convincingly argue if analysts change their forecasts in response to short selling pressure, or short sellers strategically target particular firms based on their information environment. Several studies took advantage of an exogeneous event, the Regulation SHO in the U.S. between May 2005 and July 2007, to study the role of short-selling on different perspectives of firms' information environment. The evidence is mixed: the reduction of short-selling constrains increases timely disclosure of good news (Chen et al., 2014) and decreases analyst optimisms (Ke et al., 2015); however, bad news precisions are also found to be lower (Li and Zhang, 2015).

Evidence on the effect of short sale constraints on information environment in other countries, especially emerging markets, are even more

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limited. Healy and Palepu (2001) point out disclosure choices are closely linked to contracting and capital market considerations. Given the wide disparities in market development, short selling rules and disclosure practices between emerging and developed markets, we might not easily extend the findings in the U.S. market to a global setting. For example, Chang et al. (2000) point out that analyst forecasts are greatly influenced by country-specific variables, and it is therefore imprudent to argue the changes in analyst forecast quality due to short sale constraints' removal can be universally applied to emerging markets.

In this paper, we rely on the lifting of short selling ban for a selected number of pilot firms in China as a natural experiment, and test how analyst forecast quality might change in response to changes in short sale constraints. From March 2010 to 2014, selected Chinese stocks were chosen to be eligible for short-selling at five different dates. Since firms cannot self-select to be included in the pilot list, this event creates an exogeneous shock that allows us to overcome the endogeneity mentioned above. Further, because the short-selling ban was removed for different stocks at five different dates, our analysis is less likely to be affected by confounding events. By comparing the pilot firms to their peer companies not in the pilot program, we find that both analyst forecast errors and forecast dispersions significantly go down after removal of short selling ban for pilot companies. Our results are robust when different models, such as multi-period regression model and propensity score matching are used.

We further study the conditions under which short-selling is more effective in increasing analyst forecast accuracy. By acting as informed traders, short-sellers inject information into the markets through their trading activities (Christophe et al., 2010; Darke et al., 2011; Messa et al., 2015). This can reduce the information uncertainty faced by analysts. Ample evidence shows that analysts display heuristics and biases under uncertainty (e.g. Daniel et al., 1998; Hirshleifer, 2001). Such uncertainty inevitably reduces the precision of their forecasts. If short-selling influences analyst forecast accuracy by improving their information accuracies, we should expect our results to be stronger for firms with lower information accuracies prior to the removal of short-selling constraints.

We examine two conditions for information accuracy: information quality and information transmission efficiency. First, we directly look at information available to the analysts from the information provider-corporate management. Compared to management teams, analysts are generally believed to be outsiders of firms. Prior literature shows analyst forecast errors are smaller for firms with greater disclosure amount (e.g. Lang and Lundholm, 1996; Ashbaugh and Pincus, 2001) and analyst forecast revisions are often triggered by earnings announcements (Stickel, 1989; Barron et al., 2002). Those findings support the view that corporate disclosures are important in analysts' forecast process. Taken together, we show that analyst forecast errors and dispersions decrease for the pilot firms with less timely corporate disclosures and higher earnings management prior to the lift of the short-selling ban. This is consistent with the idea that short-selling activities improve analyst information accuracies when the information provided by alternative information sources is limited.

While the first condition pertains to information quality, the second condition relates to the speed and accuracy of information transmitted into the market. Regulators and academic literature often endorse the benefit of short selling because of its importance in facilitating the processing of information in the market (e.g. Miller, 1977; Diamond and Verrecchia, 1987). Chang et al. (2014) document significant higher price efficiencies in China after short selling restrictions were removed. More efficient stock prices enable analysts to obtain more timely and precise information about firms. We conjecture that short-selling activities should improve stock price efficiencies and play a more important role in increasing the speed and accuracy of information transmission in firms with poorer information transmission quality. We use two measures to proxy for the information transmission quality prior to the event. Our first measure is stock price synchronicity, which captures the amount of firm specific information incorporated in a firm's stock prices (e.g. Morck et al., 2000; Jin and Myers, 2006). Lower stock price synchronicity means more informative stock price: that stock prices incorporate greater amount of firm fundamentals. The second measure is an index for the marketization of different provinces in China. This index measures the degree of legal and institutional development across China and is important because different areas in China display significant regional disparity. Since La Porta et al. (1998), many studies have documented that institutional differences matter to corporate government, allocation of capital, and ultimately information efficiency (e.g. La Porta et al., 2000; Wurgler, 2000; Hasan et al., 2014). We argue that institutional support is important in facilitating information transmission. In firms with low management disclosure promptness and regions with low institutional development, we should expect firms to have lower price efficiencies and thus benefit more in analyst forecast accuracy after the lifting of the short-selling ban. Our findings are consistent with these hypotheses.

Our study contributes to the literature on short sale constraints in multiple ways. First, our study directly documents how an important group of financial market participant, short seller, influences firms' information environment. Our paper adds to Ke et al. (2015) that find short sellers mitigate analyst forecast optimisms. Also, by focusing on the Chinese stock market, our study shows that the short seller-analyst relationship also exists in one of the fastest growing stock markets in the world. Compared to a mature market such as the U.S., the Chinese setting is unique because of its lack of other alternative financial contracts to short securities in China, such as options or futures. This makes the role of short sellers more important in China than in the U.S. Our study also helps to understand the short-sellers' role in an emerging economy in general, when government regulations and legal protections for investors are weak, market forces such as short selling can play an important role in mitigating information asymmetry and improve the overall market transparency. Finally, by providing direct evidence on the effect of the short-selling regulation on information providers in China, our study lays the empirical foundation for studies on the effect of short sale on liquidity and price efficiency that are often preceded by changes in information environment.

The remainder of this paper proceeds as follows. Section 2 provides institutional background of China. Section 3 describes the data and measurement of key variables. Section 4 presents the empirical results on the impact of removing of the short-selling constraints on analyst disclosure qualities. Section 5 studies the effect of pre-event disclosure quality and price efficiencies on the relationship between short selling and analyst forecast. Section 6 concludes.

2. Institutional background

Since the establishment of the Shanghai Stock Exchange and the Shenzhen Stock Exchange in China in the 1990, the Chinese government has prohibited short selling activities fearing market volatility driven by excessive speculation. However, with the growth of the stock market and demand for new financial instruments, the authorities start to explore the possibility of allowing short-selling to improve market liquidity and price efficiencies. In 2008, the China Securities Regulatory Commission (CSRC) picked 11 top brokerages to run a trial program, which lasted for about two years. A more structured pilot program was introduced in March 2010, when 90 constituent stocks from the Shanghai Stock Exchange (SSE) 50 Index and the Shenzhen Stock Exchange (SZSE) Component Index were made eligible for margin trading and short selling. After seeing its successful operations for over a year, the CSRC decided to expand the program on December 5, 2011, and added 189 constituent stocks from the SSE 180 Index and the SZSE 100 Index to the eligibility list. Seven ETFs were also added to the list. In 2013, the CSRC substantially increased the number of eligible stocks to 700. In September 2014, CSRC increased the total number of firms to 899, representing 34.26% of issuing firms in China.

For a firm to be eligible for short selling, it must have no fewer than 200 million tradable shares and a public float of no less than RMB800 million. In addition, the firm must have more than 4000 shareholders. Furthermore, on a three-month rolling basis, the daily turnover must be more than 15% of the index turnover, and the daily trading volume must be more than RMB50 million. Meanwhile, only "qualified" investors who have a good trading record, low bankruptcy risk and minimum capital of RMB500,000 and who demonstrate basic investment knowledge are allowed to short sell. It appears that CSRC is taking steps to ensure that investors are informed and companies are liquid.

Unlike the practice of many developed markets, in which multiple short selling vehicles coexist, there is no other alternative to short selling a stock in China. Because there is no option or futures market for individual stocks in China, the short selling mechanism provides one major way for investors to trade their bearish views. This unique institutional background allows us to construct a more robust analysis compared with studies that focus on other markets. Another unique feature of the Chinese market is that only a small number of predetermined securities are available for short selling. More importantly, during our sample period, the list of stocks eligible for short selling was changed several times. This interesting feature allows us to depict a clear picture of the causality of the relationship, with less bias introduced by potential confounding events. By studying the differences between the information environment of firms that are eligible and ineligible for short selling along with the changes in analyst forecasts before and after the approval of short selling for each stock, we can empirically gain new insights into the effect of short selling on analyst forecast accuracies. It is also worth noting that the privilege of short selling is not available to every investor. As described earlier, the investors are typically more sophisticated and more likely to be informed. Short selling activities by these investors are more likely to be driven by information rather than pure speculation.

3. Sample and variables

3.1. Sample

We start our sample with all firms listed on the Shanghai and Shenzhen stock markets from 2009 to 2014. This period was chosen because the short sales program was initially introduced in early 2010. Our data are from several sources: firms' financial information and all disclosure variables are from the WIND database; data on analyst forecast are from the Chinese Stock Market and Accounting Research (CSMAR) database; and short-selling information are from the GENIUS Finance database. We apply the following filters to construct our final sample. First, we exclude firms with ST and PT[1] records during our sample period because firms with such records are facing significant different trading rules from other stocks. We also exclude firms from the finance industry because disclosure requirements and accounting rules are significantly different for the financial services industry. Firms listed on the ChiNext[2] are also excluded because their listing requirements are quite different from the major exchange. Finally, we delete firms that were chosen as pilot firms more than once during different time. A firm is also dropped out from our sample if the time between it was chosen to be included in the pilot program and the time it was removed from the program is less than a year. We use these steps to make sure that our sample of pilot firms is clean and control groups can be clearly identified.

[1] ST is short for Special Treatment and PT is short for Particular Transfer. These stocks are subject to different trading rules such as narrower daily price limit and so on.

[2] ChiNext is a Nasdaq-style board of the Shenzhen Stock Exchange that attracts fast growing and innovative enterprise.

3.2. Variable definitions

3.2.1. Analyst forecast quality

To measure analyst forecast quality, we use both analyst forecast errors and forecast dispersions following Hong and Kubik (2003). Forecast error captures the mean difference between the forecast and the actual EPS. The forecast dispersion captures the degree of disagreement among different analysts covering a particular firm. Specifically,

$$A\_Error1_{i,t} = \left|\frac{1}{N_{i,t}}\sum_{j=1}^{N_{i,t}} FEPS_{i,t,j} - AEPS_{i,t}\right| \Big/ Close\_\text{Price}_{i,t} \; A\_Error2_{i,t} = \frac{1}{N_{i,t}}\sum_{j=1}^{N_{i,t}}\left|FEPS_{i,t,j} - AEPS_{i,t}\right| \Big/ Close\_\text{Price}_{i,t}$$

and

$$Dispersion_{i,t} = \sqrt{\frac{1}{N_{i,t}}\sum_{j=1}^{N_{i,t}}\left(FEPS_{i,t,j} - \overline{FEPS_{i,t,j}}\right)^2} \Big/ Close\_\text{Price}_{i,t}$$

where A_*Error*$_{i,t}$ and Dispersion$_{i,t}$ refer to analyst forecast error and forecast dispersion, respectively, for firm *i* in year *t*. $FEPS_{i,t,j}$ represents analyst *j*'s earnings per share forecast for firm *i* in year *t*. $AEPS_{i,t}$ is the actual *EPS* for firm *i* in year *t*. Among which, we use two methods to measure analyst forecast error, i.e. $A\_Error1_{i,t}$ and $A\_Error2_{i,t}$. These two methods are slightly different, through which $A\_Error1_{i,t}$ demonstrates the absolute average forecast error, while the second method measures the average absolute forecast error of an analyst for the year.[3] We expect that if analyst forecast quality improves, both the forecast error and forecast dispersion would become smaller.

3.2.2. Other information related variables

We estimate the pre-event management disclosure using the promptness of management performance forecast (*Horizon*). Similar to prior studies (Chambers and Penman, 1984; Goodman et al., 2013; Li and Zhang, 2015) that use the horizon of the disclosure as a measure of the promptness of the disclosed information, we argue that firms provide more timely information regarding the future if the forecast horizon is longer. Specifically, disclosure horizon is the difference between the scheduled reporting date and the announcement date. In another word, if the management performance announcement date is way before the reporting date, the firm is more prompt in disseminating the information before the expected reporting date.

$$Horizon_{i,t} = \text{Ln}(ReportDate_{i,t} - AnnouncementDate_{i,t} + 1)$$

where $Announcement\_Date_{i,t}$ and $Report\_Date_{i,t}$ refer to the performance announcement date and scheduled routine reporting date for firm *i* in year *t*.

We construct discretionary accruals through the Jone's model to estimate the degree of earnings management. Following Dechow et al. (1995) and Fang et al. (2016), we first run the following regression within each fiscal year and industry: $\frac{TA_{i,t}}{ASSET_{i,t-1}} = \beta_0 + \beta_1\frac{1}{ASSET_{i,t-1}} + \beta_2\frac{\Delta REV_{i,t}}{ASSET_{i,t-1}} + \beta_3\frac{PPE_{i,t}}{ASSET_{i,t-1}} + \varepsilon_{i,t}$; where *i* indexes firm *i* and *t* indexes year *t*. $TA_{i,t}$ stands for total accruals defined as earnings before extraordinary items and discontinued operations minus operating cash flows for year *t*. $ASSET_{i,t-1}$ is total assets at the end of year $t-1$. $\Delta REV_{i,t}$ is sales revenue changes from year $t-1$ to year *t*. $PPE_{i,t}$ represents the gross property plant and equipment in year *t*. The OLS estimates of coefficients β_0, β_1, β_2, and β_3 enable us to calculate the estimated nondiscretionary accruals

[3] These two methods differ in the way the negative values of the difference between analysts' forecast and the actual EPS of each firms are handled. We keep both methods to show the consistencies of our results.

using the following regression: $NDA_{i,t} = \bar{\beta}_0 + \bar{\beta}_1 \frac{1}{ASSET_{i,t-1}} + \bar{\beta}_2 \frac{\Delta REV_{i,t}}{ASSET_{i,t-1}} + \bar{\beta}_3 \frac{PPE_{i,t}}{ASSET_{i,t-1}}$. Finally, we can calculate the firm-year specific discretionary accruals as: $DA_{i,t} = \left| \frac{TA_{i,t}}{ASSET_{i,t}} - NDA_{i,t} \right|$. $DA_{i,t}$ is positively related to corporates' earnings management, and thus negatively related to corporates' information quality.

Following Morck et al. (2000), we calculate stock price synchronicity by first running the following regression $r_{i,s} = \alpha + \beta \times r_{m,s} + \varepsilon$ for each firm-year. Specifically, $r_{i,s}$ is the daily return of stock *i* on day *s*, and $r_{m,s}$ is the daily market value-weighted return on day *s*. The R-squared from this regression captures the extent to which the stocks move together with the relative amount of market-level information to firm-level information. High R-squared from the equation thus implies that significant amount of stock return movement comes from market information. One drawback of the direct R-squared measure is that this measure is bounded between 0 and 1. Thus, we follow Morck et al. (2000) and transform the R-squared in the following form: $SYN = \log\left(\frac{R^2}{1-R^2}\right)$ Similar to R-squared, SYN is higher when there is higher return movement together with the market and hence lower firm specific information incorporated in stock prices.

Finally, we define marketization of the region where the firm is located using the marketization index constructed by Fan et al. (2017). This index is an annual comparative indicator calculated for each of the provinces in China. It measures the relative position of marketization process compared to other provinces. To calculate the index, for each province, Fan et al. (2017) obtain five indicators, such as indicators for development of legal institution and property rights protection, for different aspects of marketization. They then compare each component across 31 provinces in China in the base year[4] and transform the components into scores scaling from 0 to 10. Those component scores are then adjusted in the years following the base year to reflect the changes of marketization in each province. Finally, they construct the final index by adding the scores of each component using arithmetic mean method.

3.2.3. Other control variables

We also control for variables that might affect the information environment faced by the firm. Following Ke et al. (2015) and Hong and Kacperczyk (2010), we control for firm *Size* (the natural logarithm of a company's total asset), *ROE* (a company's return on equity), *Growth* (yearly net profit growth rate), *Retvol* (annual return volatility), *Institution* (the percentage of shares held by institutions by the end of the year), *Analyst Coverage* (the natural logarithm of number of analysts following a company by the end of the year plus 1), and *Age* (the natural logarithm of number of years that a company is public). Table 2 summarizes descriptive statistics for all our variables. In the correlation matrix,[5] all three measures for analyst forecast quality are positively and significantly correlated. Analyst forecast error is also positively related to the stock price synchronicity (SYN), negatively related to the disclosure quality, horizon and financial market development, supporting the idea that analysts utilize other information sources and better transmitted information to generate more accurate forecasts.

4. Analyst forecast quality and short-selling constraints

To empirically test whether short-selling affects analyst forecast quality, we use the removal of short-selling constraints in China as a natural experiment. After the firms were added to the pilot program, they started to experience short-selling pressure. Given that the change in analyst forecast quality could be driven purely by time-series variation around the event time, it is important for us to conduct difference-in-difference analysis and contrast the changes in forecast quality between the pilot firms and the control firms.

4.1. Main results: multi-period regression models

Because the pilot firms were chosen into the pilot program at five different times, we use the difference-in-difference model for multiple-period shocks, following Bertrand and Mullainathan (1999) and Chan et al. (2012). Specifically, our empirical models are defined as follows:

$$ForecastQuality_{i,t} = \beta_0 + \beta_1 PostTreat_{i,t} + \beta_2 Treat_{i,t} + \beta_3 X_{i,t} + Year_t + Ind_j + \varepsilon_{i,t} \quad (1)$$

where forecast quality is one of the three measures for analyst forecast quality *A_Error1, A_Error2 and Dispersion* for firm *i* in year *t*. $PostTreat_{i,t}$ is our variable of interest and it equals to one for company *i* in year *t* if it is included in the short-selling program; and equals to zero for both non-pilot firms and pilot firms prior to the inclusion of the short-selling program. The coefficient on the *PostTreat* dummy (β_1) represents the changes in analyst forecast quality for pilot firms before and after the event date compared to the changes for the control group in the same period. The coefficient on the *Treat* dummy (β_2) captures the baseline difference between the pilot-firm and non-pilot firms *before* the initialization of the event. $X_{i,t}$ is a set of control variables as discussed before. Year and Industry denote year- and industry-specific fixed effects to account for time and industry specific conditions that may influence the relationship between short selling and analyst forecast quality. Standard errors are clustered at firm level to account for within-firm covariances (Peterson, 2009).

Table 3 reports the main results of our regression model (1). Column 1 and 2 represent the regression results when we use analyst forecast errors as our dependent variables and column 3 uses analyst forecast dispersion. In all three regressions, we show that the coefficients on the *PostTreat* dummy are negative and significant, suggesting that compared to non-pilot firms, pilot firms experience a decrease in forecast errors and forecast dispersions after inclusion into the program. In fact, our regression coefficients suggest that compared to the control firms, after being included into the short-selling program, analyst forecast errors and forecast dispersion for pilot firms go down by 0.0032/0.0034 and 0.0016 respectively. These represent around 15% of the standard deviations of the variables (the mean value for *A_Error* is around 0.018 and for *Dispersion* is around 0.01). The coefficient on the *Treat* dummy is also negative and significant, indicating that our pilot firms on average has lower analyst dispersions than the non-pilot firms before the event. To sum, our main results suggest that pilot firms experience significant increase in analyst forecast quality after short selling became available.

4.2. Robustness tests

4.2.1. Multi-period model with firm fixed effect

To confirm our results are robust, we conduct two sets of robustness tests. In the first set, we include firm fixed effect in our multi-period model. This is to examine whether the inclusion into the short-selling program would increase the analyst forecast quality, compared to the same firm prior to the inclusion. Our model is as follows:

$$ForecastQuality_{i,t} = \beta_0 + \beta_1 PostTreat_{i,t} + \beta_2 X_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (2)$$

where β_1 captures the average impact of within firm changes of the inclusion of the short selling event on analyst forecast quality. $Firm_i$ refers to the firm fixed dummies. All other variables are defined the same way as they are in equation (1).

In Table 4, the results of the multi-period model with firm fixed effect are reported. *PostTreat* is negative with 1% significance in all three regressions, suggesting that the within firm analyst forecast errors and

[4] The base year of report 2016 is year 2008 (Fan et al., 2017).

[5] To save space, we do not provide the correlation matrix table in the paper. They are available upon request.

Table 1
Major Changes to the List of Stocks Eligible for Short Selling[a]. Since the launch of the short selling pilot program in March 2010, five major adjustments about how many and which stocks should be added into the pilot list have been made to achieve a better policy effect. This table presents the detail of each adjustment from 2010 to 2014.

Time	Added to the list	Removed from the list	Total number of firms on the list	Number of firms on the exchange	% of firms eligible for short selling in the market
1. Mar 31, 2010	90	–	90	1627	5.5%
2. Dec 5, 2011	189	1	278	1935	14.37%
3. Jan 31, 2013	276	56	500	2048	24.41%
4. Sep 16, 2013	206	6	700	2468	28.36%
5. Sep 22, 2014	218	13	899	2624	34.26%

[a] In addition to the five major changes to the short selling stock list, there are a few very minor changes and we do not include them in Table 1.

Table 2
Summary Statistics. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *PostTreat* is a dummy variable that equals to one if the company is included in the pilot program in this year and equals to zero otherwise. *Treat* is a dummy variable which equals to one if the firm is chosen into the pilot program. *DA* is the discretionary accruals, measured using the Jones model. *SYN* measures the extent to which stocks move together with the relative amount of market-level information to firm-level information. *Horizon* is the difference between the announcement date and the scheduled reporting date, representing the promptness of information dissemination. *Develop* is defined according to the marketization index constructed by Fan et al. (2017). *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public.

Variables	N	Mean	Std	Min	Median	Max
A_Error 1	13560	0.0173	0.0283	0	0.0083	0.5781
A_Error 2	13560	0.0185	0.0298	0	0.0094	0.6356
Dispersion	13560	0.0109	0.0188	0	0.0061	0.8023
PostTreat	13560	0.1020	0.3026	0	0	1
Treat	13560	0.3633	0.4810	0	0	1
DA	13560	0.0778	0.1946	0	0.0421	7.4633
SYN	13560	−0.6304	0.7761	−6.3182	−0.5552	2.2587
Horizon	13560	4.5463	0.6313	0.6931	4.5747	5.9026
Develop	13560	7.6244	4.2907	−0.7	7.04	16.19
Size	13560	21.7805	1.3732	18.4796	21.6494	26.7086
Roe	13560	0.1123	0.1307	−0.3891	0.0951	0.6029
Retvol	13560	0.0276	0.0071	0.0151	0.0267	0.0632
Growth	13560	−0.0453	2.6874	−17.7732	0.1226	7.865
Institution	13560	0.3947	0.2357	0.0042	0.3984	0.8803
Age	13560	2.1271	0.8241	0	2.3979	3.2958
Analyst Coverage	13560	1.2912	1.2118	0	1.0986	3.7377

dispersions of the pilot firms decrease dramatically after the lifting of the short-selling ban. The reduction averaged around 0.0067/0.0073 in forecast errors and 0.0034 in forecast dispersions.

4.2.2. Propensity score matching

In the second set of robustness tests, we adopt the propensity score matching method to identify a group of control firms, rather than using the entire sample as controls. We use propensity score matching to control for the possibility that the criteria used to select the firms into the pilot firms are not completely random. The choice of pilot firms as short selling firms is based on the firm size, volatility and other similar indicators, which may result in significant differences between the chosen firms and unchosen firms. Other unquantifiable factors such as government influence could also affect the choice of pilot firms of short selling. As such, simply using the pilot firms as treatment group and unchosen firms as control group may cause endogeneity issues. Hence, we use propensity score matching models to ensure the comparability between pilot firms and our control firms prior to the removing of the short selling constraint.

We match each of our pilot firm to a control firm that is not included in the pilot program, but is similar enough to the pilot firm prior to the initiations of the program. Following Chen et al. (2015), Rosenbaum (1989), and Parsons (2004), we conduct propensity score matching as follows. We first divide our sample into two groups: pilot group as the treatment group and non-pilot group as the counterparty. Based on the selected covariates, we then run a logit regression to get the probability of being chosen to the pilot group, i.e. the propensity score. Finally, we use the caliper matching algorithm to match the control group to the treatment group on a 2 to 1 ratio with replacement. In case of multiple matches, we randomly select a control sample to a treatment sample.

In Table 5 Panel A column 1, we report the logit model that is used to predict the probability of being included into the pilot program. We include firm size, ROE, growth, institutional ownership, firm age, and analyst coverage prior to the event as our covariates following Chen et al. (2015). Compared to the entire universe of non-pilot firms, the pilot firms are significantly bigger, older, more profitable, and with more institutional ownership and analyst coverage. After the propensity matching, following Mola et al. (2013) and Han et al. (2018), we show in Panel A column 2 that all of the covariates are no longer significant between the pilot sample and their matched pairs prior to the event year. Therefore, we are confident that the pilot firms and their propensity score matched control firms are similar enough to conduct the difference-in-difference analysis.

Table 5 Panel B reports the regression results based on the propensity score matched sample that controls for selection bias. Our regression results show that similar to what we observed before, *PostTreat* dummy is still negative and significant (with $\beta = -0.0047$/-0.0043 for forecast errors and $\beta = -0.004$ for forecast dispersions), which indicates that our results are robust when selection bias is considered. We show that our results continue to be robust when firm fixed effect is added in Table 5 Panel C.

Table 3
Multiple-period differences in differences analysis for analyst forecast quality. This table presents the multiple-period differences in differences regression results. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *PostTreat* is a dummy variable that equals to one if the company is included in the pilot program in this year and equals to zero otherwise. *Treat* is a dummy variable which equals to one if the firm is chosen into the pilot program. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public. All regressions control for year and industry fixed effects. Standard errors are all clustered at the firm level. T-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively.

	A_Error1	*A_Error2*	*Dispersion*
PostTreat	−0.0032*** (−2.97)	−0.0034*** (−3.01)	−0.0016** (−2.18)
Treat	−0.0031*** (−4.07)	−0.0031*** (−3.88)	−0.0018*** (−3.09)
Size	0.0035*** (9.08)	0.0040*** (9.55)	0.0027*** (9.07)
Roe	−0.0718*** (−10.88)	−0.0749*** (−9.75)	−0.0197*** (−6.46)
Retvol	0.1811*** (3.61)	0.1969*** (3.59)	0.0956*** (2.94)
Growth	−0.0033*** (−11.06)	−0.0039*** (−8.45)	−0.0006*** (−3.04)
Institution	−0.0050*** (−3.68)	−0.0047*** (−3.28)	−0.0048*** (−4.59)
Age	0.0021*** (5.04)	0.0023*** (5.33)	0.0014*** (5.29)
Analyst Coverage	0.0008* (1.95)	0.0008* (1.77)	0.0009*** (3.01)
Industry-level FE	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes
Observation	13560	13560	13560
Adj-Rsquare	0.2964	0.3056	0.1236

5. The role of disclosure, efficiency, and institutional development

In this section, we consider how management disclosure, price efficiency and institutional development interact with short-selling constraints to improve analyst forecast quality.

5.1. The effect of management disclosure

Previous studies document ample evidence that management disclosure is an important information source for analysts. For example, Lang and Lundholm (1996) find that more informative disclosure policies are associated with better analyst forecast accuracy. Similarly, Ashbaugh and Pincus (2001) show analyst forecast quality increases after firms adopt the International Accounting Standards which has significantly higher disclosure requirements.

Short sellers transmit information to the market in various ways. Short-selling may influence the amount of internal information provided by the management team. Chen et al. (2014) show that good news is reported more timely, while Li and Zhang (2015) show significantly lower bad news precisions after the implementation of short-selling programs. At the same time, short-sellers may act as information intermediary by directly transmitting their private and pessimistic information into the market (Boehmer and Wu, 2012; Ke et al., 2015). As such, we hypothesize that short selling activities increase analyst forecast quality in firms with poor internal information environment.

To test this hypothesis, we partition our treatment firms into two groups according to the level of management disclosure promptness and the degree of earnings management in the year prior to the inclusion of the pilot program. If *Horizon* is below the sample median, we define disclosure promptness as low. Otherwise, a firm is defined to have high pre-event disclosure promptness. Similarly, if *DA* is above the sample median, we define earnings management to be high.

Table 4
Multiple-period differences in differences analysis for analyst forecast quality, with firm fixed effect. This table presents the results of multiple-period differences in differences regressions controlling for firm fixed effect. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *PostTreat* is a dummy variable that equals to one if the company is included in the pilot program in this year, and equals to zero otherwise. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public. All regressions control for year and firm fixed effects. Standard errors are also clustered at the firm level. T-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively.

	A_Error1	*A_Error2*	*Dispersion*
PostTreat	−0.0067*** (−6.99)	−0.0073*** (−7.05)	−0.0034*** (−4.73)
Size	0.0037*** (3.24)	0.0043*** (3.52)	0.0011* (1.82)
Roe	−0.1045*** (−11.47)	−0.1089*** (−10.64)	−0.0329*** (−6.19)
Retvol	−0.1256** (−2.07)	−0.1268** (−2.08)	−0.0593 (−1.11)
Growth	−0.0031*** (−10.33)	−0.0037*** (−8.08)	−0.0007*** (−2.94)
Institution	−0.0097*** (−5.06)	−0.0086*** (−4.49)	−0.0074*** (−4.07)
Age	−0.0004 (−0.44)	−0.0006 (−0.59)	0.0016*** (2.77)
Analyst Coverage	0.0018*** (3.26)	0.0017*** (3.01)	0.0022*** (5.17)
Firm-level FE	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes
Observation	13560	13560	13560
Adj-Rsquare	0.2600	0.2775	0.0497

Because we are interested in whether the poor disclosure firms have a more significant increase in analyst forecast quality, conditioning on the inclusion in the short-selling program, we focus only on the treatment firms in this set of regression analysis. Hence, we run the following regression models based on the sub-samples of high/low promptness/earnings management:

$$ForecastQuality_{i,t} = \beta_0 + \beta_1 Post_{i,t} + \beta_2 X_{i,t} + Year_t + Ind_i + \varepsilon_{i,t} \quad (3)$$

where $Post_{i,t}$ equals to one after the inclusion into the pilot program, and this variable captures the effect of short-selling on analyst forecast conditioning on the sub-groups of high/low disclosure promptness (discretionary accruals).

We report our results in Table 6. For the subsample of firms with low pre-event disclosure promptness (Panel A), the coefficient on the *Post* dummy is negative and significant, consistent with our prior observation that analyst disclosure quality is significantly improved after the removal of the short-selling constraints. The average forecast error drops by around 0.014 after the event and forecast dispersion drops by 0.0045; all are economically significant given the mean/median of the forecast error/dispersion. However, when we consider the subsample of firms with high pre-event disclosure quality, the coefficients on the *Post* dummy are insignificant. Similarly, in Panel B of Table 6, we show that the drop in analyst forecast accuracies concentrates in the subsample of firms with high pre-event discretionary accruals.

5.2. The effect of stock price efficiency

When stock prices are more efficient, information is reflected into

Table 5
Propensity Score Matching. This table reports results of DID regression adopting the propensity score matching method. The pilot firms are matched using propensity score matching with caliper matching algorithm. Panel A shows the validity of our PSM method. Column 1 reports the logit model that is used to predict the probability of being included into the pilot program before matching, also known as the first stage of PSM. Column 2 shows the regression of the identic probit model using the matched sample. The matching variables include variants of Size *(Size)*, ROE (*Roe*), Growth (*Growth*), Institutional Ownership (*Institution*), Firm age (*Age*) and Analyst Coverage (*Analyst Coverage*) prior to the event. Panel B presents the DID regression based on the matched sample. Industry and year fixed effects are controlled. Panel C presents the DID regression based on the matched sample, controlling for the firm and year fixed effect. Standard errors are also clustered at the firm level. t-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *PostTreat* is a dummy variable that equals to one if the company is included in the pilot program in this year, and equals to zero otherwise. *Treat* is a dummy variable which equals to one if the firm is chosen into the pilot program. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return. *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public.

Panel A. Verification of PSM method

Dependent Variable: Treat	(1)	(2)
Independent Variable:	First Stage of PSM	Verification of PSM validity
Size	0.7784*** (10.14)	−0.1080 (−1.16)
Roe	4.6919*** (7.58)	0.6903 (0.84)
Growth	−0.0136 (−0.51)	0.0194 (0.52)
Institution	1.1128*** (3.78)	0.4434 (1.22)
Age	0.5167*** (5.63)	−0.1285 (−1.02)
Analyst Coverage	0.5419*** (7.89)	0.1010 (1.12)
Con.	−21.1542*** (−12.11)	1.6503 (0.77)
Industry-level FE	Yes	Yes
Year-level FE	Yes	Yes
Observation	9368	2103
Rseudo-Rsquare	0.3283	0.0240

Panel B. DID results after propensity score matching, with industry fixed effect

	A_Error1	A_Error2	Dispersion
PostTreat	−0.0047*** (−2.81)	−0.0043*** (−2.81)	−0.0040*** (−3.29)
Treat	−0.0065*** (−2.90)	−0.0061*** (−3.12)	−0.0053** (−2.53)
Size	0.0035*** (4.89)	0.0038*** (5.98)	0.0030*** (5.94)
Roe	−0.0621*** (−5.08)	−0.0613*** (−5.15)	−0.0228** (−2.04)
Retvol	0.0347 (0.25)	0.0205 (0.17)	0.0087 (0.07)
Growth	−0.0039*** (−6.69)	−0.0038*** (−7.36)	−0.0028* (−1.94)
Institution	−0.0047 (−1.37)	−0.0033 (−1.05)	−0.0052** (−2.37)
Age	0.0017** (2.00)	0.0017** (2.22)	0.0019*** (3.13)
Analyst Coverage	0.0009 (1.07)	0.0007 (0.84)	0.0013 (1.61)
Industry-level FE	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes
Observation	6097	6097	6097
Adj-Rsquare	0.2939	0.3122	0.2186

Panel C. DID results after propensity score matching, with firm fixed effect

	A_Error1	A_Error2	Dispersion
PostTreat	−0.0026** (−2.07)	−0.0027** (−2.11)	−0.0006 (−0.96)
Size	0.0044** (2.01)	0.0048** (2.15)	0.0016 (0.84)
Roe	−0.0887*** (−3.61)	−0.0928*** (−3.80)	−0.0113 (−0.63)
Retvol	0.0777 (0.54)	0.0870 (0.62)	0.0373 (0.36)
Growth	−0.0039*** (−5.52)	−0.0038*** (−6.50)	−0.0029 (−1.54)
Institution	−0.0030 (−0.44)	−0.0021 (−0.30)	−0.0073** (−2.13)
Age	0.0033 (1.39)	0.0030 (1.32)	0.0064*** (2.84)
Analyst Coverage	0.0012 (1.28)	0.0009 (0.96)	0.0021* (1.86)
Firm-level FE	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes
Observation	6097	6097	6097
Adj-Rsquare	4563	4563	4266

stock prices quicker and hence, stock prices provide a more accurate picture of the information. Analysts who learn from stock prices will benefit from more timely and precise information about firms. Previous literature documents evidence that stock price synchronicity measures firm specific information incorporated in stock prices, and directly relates to information content about future earnings, capital allocation and firm transparency (Morck et al., 2000; Wurgler, 2000; Jin and Myers, 2006; Durnev et al., 2003). The above literature takes the perspective that firms with low stock price synchronicity aggregates more firm specific information and market factors should explain smaller proportion of the stock price variations. Therefore, a firm with low stock price synchronicity should have more informed stock prices in a more timely and accurate manner, which will be beneficial to analysts who often need firm specific information in making their forecasts. Given that, in a firm with low synchronicity, short-selling activities might be less beneficial.

We define firms to have high (low) stock price efficiency when the stock price synchronicity is below (above) the median value. In Table 7, we present evidence that the benefit of short-selling on analyst forecast accuracy and dispersions indeed concentrates in firms with low pre-event price efficiency. This is consistent with the conjecture that the role of short-sellers in transmitting information is more effective in firms with poor information efficiency prior to the short-selling allowance.

5.3. *The effect of institutional development*

Finally, we consider the role of institutional development on the

Table 6

The effect of disclosure quality. This table presents the relationship between short selling constraints and analyst forecast quality, conditioning on pre-event disclosure promptness (Panel A) and discretionary accrual (Panel B). In Panel A, we report regression results of subsample of firms with (1) lower pre-event disclosure promptness and (2) high pre-event disclosure promptness by partition the treatment firms into two groups according to the level of management disclosure promptness (*Horizon*) of each firm one year before the inclusion of the pilot program. In Panel B, we report regression results of subsample of firms with low and high discretionary accruals. *Horizon* is the difference between the announcement date and the scheduled reporting date, representing the promptness of information dissemination. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *Post* is a dummy variable that equals to one after the firm is included into the pilot program. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public. T-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively.

Panel A. Disclosure Promptness

	(1) Low Pre-Event Disclosure Promptness			(2) High Pre-Event Disclosure Promptness		
	A_Error1	A_Error2	Dispersion	A_Error1	A_Error2	Dispersion
Post	−0.0142*** (−3.37)	−0.0146*** (−3.47)	−0.0045** (−2.01)	−0.0029 (−1.03)	−0.0015 (−0.48)	−0.0013 (−0.52)
Size	0.0057*** (4.58)	0.0061*** (5.01)	0.0045*** (4.63)	0.0035*** (4.30)	0.0042*** (5.27)	0.0032*** (5.88)
Roe	−0.0545*** (−3.20)	−0.0664*** (−3.30)	−0.0083 (−0.89)	−0.0243** (−2.42)	−0.0210* (−1.86)	−0.0159*** (−2.77)
Retvol	0.1072 (0.53)	0.1449 (0.71)	0.1035 (0.78)	0.1618* (1.66)	0.2068* (1.86)	0.0809 (1.16)
Growth	−0.0036*** (−5.46)	−0.0038*** (−4.85)	−0.0011*** (−3.20)	−0.0039*** (−8.16)	−0.0043*** (−6.01)	−0.0010*** (−3.66)
Institution	−0.0012 (−0.23)	0.0013 (0.23)	−0.0083** (−2.03)	−0.0100*** (−4.15)	−0.0108*** (−4.29)	−0.0057*** (−3.81)
Age	0.0003 (0.14)	0.0006 (0.31)	0.0010 (0.77)	0.0023*** (2.68)	0.0029*** (3.06)	0.0019*** (3.28)
Analyst Coverage	−0.0005 (−0.30)	−0.0007 (−0.46)	−0.0006 (−0.47)	−0.0005 (−0.45)	−0.0004 (−0.45)	0.0006 (0.82)
Industry-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1341	1341	1341	1341	1341	1341
Adj-Rsquare	0.3701	0.3942	0.1886	0.3027	0.3296	0.2249

Panel B. Discretionary Accruals

	(1) High pre-event discretionary accruals			(2) Low pre-event discretionary accruals		
	A_Error1	A_Error2	Dispersion	A_Error1	A_Error2	Dispersion
Post	−0.0062** (−2.40)	−0.0059** (−2.32)	−0.0041** (−2.52)	−0.0039 (−1.52)	−0.0033 (−1.28)	−0.0026 (−1.17)
Size	0.0033*** (3.85)	0.0039*** (4.87)	0.0032*** (4.99)	0.0038*** (5.50)	0.0042*** (5.86)	0.0025*** (6.34)
Roe	−0.0425*** (−4.30)	−0.0379*** (−3.66)	−0.0134*** (−2.59)	−0.0337*** (−2.87)	−0.0397*** (−2.86)	−0.0077 (−1.35)
Retvol	0.0051 (0.05)	0.0435 (0.38)	0.0688 (0.96)	0.2463** (2.36)	0.2670** (2.50)	0.0549 (0.68)
Growth	−0.0024*** (−4.48)	−0.0028*** (−3.74)	−0.0005** (−2.01)	−0.0046*** (−6.94)	−0.0047*** (−6.57)	−0.0013*** (−3.80)
Institution	−0.0078*** (−2.63)	−0.0077*** (−2.72)	−0.0068*** (−2.95)	−0.0066*** (−2.71)	−0.0061** (−2.31)	−0.0060*** (−3.39)
Age	−0.0005 (−0.53)	−0.0003 (−0.26)	0.0007 (1.02)	0.0026*** (3.78)	0.0029*** (4.28)	0.0014*** (3.02)
Analyst Coverage	−0.0004 (−0.46)	−0.0005 (−0.53)	−0.0005 (−0.55)	−0.0006 (−0.64)	−0.0006 (−0.65)	0.0004 (0.71)
Industry-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2385	2385	2385	2418	2418	2418
Adj-Rsquare	0.2018	0.2284	0.1084	0.3457	0.3495	0.1544

Table 7

The effect of stock price efficiency. This table presents the relationship between short selling constraints and analyst forecast quality, conditioning on pre-event price efficiency. We report regression results of subsample of firms with (1) Low pre-event price efficiency and (2) high pre-event price efficiency by partition the treatment firms into two groups according to the level of stock synchronicity (*SYN*) of each firm one year before the inclusion of the pilot program. *SYN* measures the extent to which stocks move together with the relative amount of market-level information to firm-level information. Thus, higher value of *SYN* indicates high co-movement with the market and low firm specific information incorporate in stock prices and vice versa. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *Post* is a dummy variable that equals to one after the firm is included into the pilot program. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public. T-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively.

	(1) Low pre-event price efficiency			(2) High pre-event price efficiency		
	A_Error1	*A_Error2*	*Dispersion*	*A_Error1*	*A_Error2*	*Dispersion*
Post	−0.0069*** (−2.87)	−0.0064*** (−2.67)	−0.0034** (−2.31)	−0.0022 (−0.76)	−0.0023 (−0.78)	−0.0021 (−0.87)
Size	0.0025*** (4.16)	0.0030*** (4.97)	0.0022*** (5.47)	0.0038*** (4.13)	0.0044*** (4.66)	0.0023*** (4.81)
Roe	−0.0472*** (−4.30)	−0.0467*** (−3.97)	−0.0168*** (−2.98)	−0.0353*** (−3.16)	−0.0359*** (−2.67)	−0.0063 (−1.23)
Retovl	0.1318 (1.17)	0.1510 (1.26)	0.0739 (0.92)	0.1411 (1.33)	0.1645 (1.53)	0.0701 (1.16)
Growth	−0.0037*** (−6.37)	−0.0038*** (−6.19)	−0.0011*** (−3.79)	−0.0029*** (−3.80)	−0.0033*** (−3.04)	−0.0005 (−1.55)
Institution	−0.0064** (−2.37)	−0.0060** (−2.19)	−0.0064*** (−3.28)	−0.0067*** (−2.69)	−0.0068** (−2.57)	−0.0048*** (−2.60)
Age	0.0020** (2.50)	0.0026*** (3.35)	0.0018*** (3.13)	−0.0003 (−0.26)	−0.0002 (−0.16)	−0.0000 (−0.08)
Analyst Coverage	0.0005 (0.54)	0.0006 (0.69)	0.0004 (0.56)	−0.0012 (−1.42)	−0.0015* (−1.70)	0.0002 (0.44)
Industry-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2538	2538	2538	2373	2373	2373
Adj-Rsquare	0.2915	0.3200	0.1479	0.2337	0.2319	0.1002

Table 8
The effect of institutional development. This table presents the relationship between short selling constraints and analyst forecast quality, conditioning on institutional development. We report regression results of subsample of firms with (1) Low level of institutional development and (2) high level of institutional development by partition the treatment firms into two groups according to the development level of the region where firms' headquarters are located one year before the inclusion of the pilot program *Develop* is defined according to the marketization index constructed by Fan et al. (2017). Higher value of *Develop* indicates high institutional development and vice versa. *A_Error1* and *A_Error2* are forecast error measures that capture the mean difference between the forecast and the actual EPS. *Dispersion* is the degree of disagreement among different analysts covering the firm. *Post* is a dummy variable that equals to one after the firm is included into the pilot program. *Size* is the natural logarithm of company total assets, *ROE* is the return on equity, *Retvol* is the annual volatility of stock return, *Growth* is the yearly net profit growth rate compared to the same period last year, *Institution* is the percentage of shares held by institutions by the end of the year, *Analyst Coverage* is the natural logarithm of number of analysts by the end of the year plus 1, and *Age* is the natural logarithm of number of years the company are public. T-values of each coefficient are reported in parentheses. Coefficients with ***, ** and * are statistically significant at 1%. 5%, and 10% level, respectively.

	(1) Low pre-event institutional development			(2) High pre-event institutional development		
	A_Error1	*A_Error2*	*Dispersion*	*A_Error1*	*A_Error2*	*Dispersion*
Post	−0.0074*** (−3.01)	−0.0073*** (−2.96)	−0.0029** (−1.97)	−0.0012 (−0.49)	−0.0003 (−0.13)	−0.0028 (−1.03)
Size	0.0049*** (5.94)	0.0056*** (6.83)	0.0031*** (7.51)	0.0020*** (3.63)	0.0024*** (4.76)	0.0022*** (4.99)
Roe	−0.0546*** (−4.70)	−0.0593*** (−4.45)	−0.0168*** (−3.13)	−0.0291*** (−3.26)	−0.0228** (−2.48)	−0.0073 (−1.34)
Retvol	0.1950* (1.71)	0.2023* (1.72)	0.1292 (1.64)	0.0205 (0.21)	0.0933 (0.95)	−0.0285 (−0.37)
Growth	−0.0035*** (−5.41)	−0.0037*** (−5.51)	−0.0011*** (−3.10)	−0.0032*** (−5.16)	−0.0035*** (−3.89)	−0.0007*** (−3.22)
Institution	−0.0056** (−1.98)	−0.0053* (−1.84)	−0.0050*** (−3.13)	−0.0083*** (−3.60)	−0.0080*** (−3.52)	−0.0065*** (−2.76)
Age	0.0012 (1.19)	0.0017 (1.61)	0.0009 (1.56)	0.0005 (0.63)	0.0008 (1.00)	0.0011* (1.71)
Analyst Coverage	−0.0003 (−0.31)	−0.0003 (−0.30)	0.0003 (0.44)	−0.0006 (−0.76)	−0.0008 (−0.97)	−0.0002 (−0.32)
Industry-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2685	2685	2685	2241	2241	2241
Adj-Rsquare	0.3067	0.3212	0.1853	0.2189	0.2441	0.0932

relationship between short selling and analyst forecast quality. As noted before, a well-developed institutional structure facilitates information disclosure and transmission. For example, Morck et al. (2000) show significantly higher firm specific information in economies with better protected property rights. Djankov et al. (2007) show creditor rights improvement associates with better information sharing. As such, we expect regions with better developed legal and institutions to have better pre-event information transmission and quality. If short-selling improves analyst forecast accuracy through increasing the efficiency of information incorporation, we should expect firms located in less developed areas to benefit more.

Consistent with our conjecture, when we run regression analysis separately for the group of firms located in more developed regions and less developed regions in Table 8, we show that the improvement in analyst forecast errors and dispersions is only significant in the subsample of firms in less developed regions.

To sum, we show significant increase in analyst forecast accuracies after the lifting of the short-selling bans in China. We find that analyst forecast accuracy improvement mainly concentrates in subsample of firms with poor pre-event information quality or poor information transmission, which is consistent with the idea that short-selling activities help improve the corporate information environment by facilitating information incorporation and strengthening information quality.[6]

6. Conclusion

In this paper, we take advantage of a unique exogeneous event in China, the removing of the short-selling ban, and study its impact on analyst forecast quality. In using a multi-period difference-in-difference model, we find that pilot firms that are included in the short-selling program experienced significant decrease in both the analyst forecast errors and analyst forecast dispersions after the inclusion. Our findings are robust when firm fixed effect is included and when propensity score matching technique is applied. We also show that the increase in analyst forecast accuracy concentrates in firms with lower prior management disclosure promptness, higher degree of earnings management, lower stock price efficiency and located in provinces with worse institutional development. This finding suggests that short selling may improve analyst forecast quality through making the information quality better and information transmission process more efficient.

Our study is one of the few studies that directly link the impact of short-selling to the information environment faced by firms. This paper adds to the understanding of the consequence of the short-sell constraints, in addition to the prior papers that focus on stock price behaviors. One extension of this study is to consider changes in firm disclosure behavior after removal of short sale constraints. It would also be interesting to explore if decline in analysts forecast errors is linked to greater investor attention and/or higher analyst coverage.[7] Our findings on the impact of short-selling on analyst disclosure quality in China, the fastest growing emerging market, might also be relevant to many other emerging countries that are currently considering the relax of the short-selling constraints. While regulators from those countries may fear that short-selling activities will destabilize the market, our findings suggest that those activities can be an important vehicle to improve the information environment as well.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.econmod.2019.06.001.

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[6] In untabulated results, we also show that the short selling-analyst forecast accuracy relationship concentrates in a subsample of firms that have higher improvement in management forecast quality and stock price efficiencies. These results suggest that one channel that short selling improves analyst forecast accuracy is through a direct improvement of information quality.

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