由于股价压力产生的管理层预测偏差
--来自开放式基金火速买卖的证据

Renhui Fu[1], Guochang Zhang[2]

(1. Shanghai Jiaotong University, Shanghai 200052, China; 2. Hong Kong University of Science and Technology, Hong Kong 999077, China)

Abstract: This paper establishes evidence of a causal link between stock price pressures and management forecast biases based on the exogenous events of fire sales and purchases of stocks by mutual funds. We find that managers issue optimistically biased forecasts in response to downward stock price pressures caused by fire sales of mutual funds, especially when their firms' stocks have low market liquidity, when their firms are under financial constrains, or when their earnings is difficult to forecast, but they do not issue pessimistically biased forecasts in response to upward price pressures from fire purchases of mutual funds. We further find that optimistic forecast biases have the effect of mitigating downward price pressures and thus speeding up the price recovery process. Additional analysis suggests that the board does not penalize managers for issuing optimistically biased forecasts, in terms of manager dismissal, when a firm's stock experiences fire sales. Taken together, our findings indicate that management forecast biases can serve as a tool to mitigate price pressure when stocks undergo exogenous trading shocks.

Keywords: management forecast biases, fire sales, fire purchases, mutual funds

JEL Classification: G12, G14, M41

1. Introduction

Managing market perceptions about firm value is one of the primary objectives that managers pursue when they make voluntary disclosure decisions, and management earnings forecasts are an important type of information they disclose (Bergman and Roychowdhury [2008], Beyer et al. [2010], and Li and Zhang [2014]). A large number of studies have thus far examined the motives for voluntary disclosures including, among others, capital market transactions (e.g., Ruland et al. [1990]; Marquardt and Wiedman [1998]; Lang and Lundholm [2000]) and management compensation (e.g., Aboody and Kasznik [2000]; Nagar et al. [2003]); see Beyer et al. [2010] for a comprehensive survey of this literature. However, existing studies typically focus on documenting cross-firm associations between stock price and disclosure behavior, and as such it is difficult to infer a causal relationship between them given that both are likely driven by the underlying business fundamentals. The purpose of this study is to provide evidence that management forecast behavior, as a key part of voluntary disclosure, is indeed affected by stock price pressures.

To do so, we identify exogenous market events that have significant consequences for stock prices but are unrelated to firms' business activities, and examine whether and how firms respond to such events through choices on management forecast disclosures.

Specifically, to circumvent endogeneity concerns in examining the relation between stock price and management forecasts, we identify price swings caused by fire sales and purchases of mutual funds, which are exogenous events to the firms issuing the management forecasts. Due to portfolio rebalancing needs, mutual funds from time to time execute fire sales or purchases of individual stocks. The size of such trades is large enough to cause significant downward or upward price pressures on the traded stocks, and the resulting price impact can last for a considerable period of time, about one and half years on average. This is a clear scenario of stock mispricing because the price movements induced by fire sales and purchases are unrelated to the firms' fundamentals and exogenous to the firms (Coval and Stafford [2007]; Ali, Wei and Zhou [2011], Edmans, Goldstein and Jiang [2012]). Thus, it is an ideal setting for investigating the effect of stock price pressures on disclosure choices.

We explore three specific questions in the study. First, whether managers provide optimistically (pessimistically) biased forecasts when their firms' stocks experience under- (over-) pricing arising from mutual funds' fire sales (purchases). Second, whether forecast biases are greater for firms with illiquid stocks which have prices more sensitively affected by fire sales and purchases, for firms under financial constrains which have stronger needs for external financing, and for firms with earnings difficult to be predicted whose management forecasts are difficult to be evaluated by investors regarding their truthfulness. Third, whether management forecast biases play a role in mitigating market mispricing; or, put differently, whether depressed (inflated) stock prices revert back to "normal" levels more quickly when accompanied by optimistic (pessimistic) forecast biases.

Using a sample of 49,306 firm-quarter observations for the period 1996-2010, we find that managers indeed issue optimistically biased forecasts when their firms' stocks experience downward price pressures as caused by fire sales of mutual funds. However, they do not issue pessimistically biased forecasts when stocks experience overpricing from fire purchases of mutual funds. These results suggest that a causal link does exist from stock price pressure to biased management forecast disclosure when firms' stock are fire sold by mutual funds, but not when fire purchased by mutual funds.

Then, we examine whether the effects of stock mispricing on management forecast biases (MFBs hereafter) vary across firms. First, we test whether the link between price pressure and biased management forecasts is stronger for firms whose stocks are less liquid, given that price pressures from fire sale (purchase) of mutual funds exist mainly due to liquidity shortage (Coval and Stafford [2007]). Consistent with this conjecture, we find that MFBs generally are greater in magnitude when firms' stocks have low market liquidity, but again this result holds mainly for the subsample of fire sales. Second, the price pressure might be a bigger concern for firms under financial constrains who have larger needs for external financing (Matsumoto [2002]; Cotter et al. [2006]; Hirst et al. [2008]; Beyer et al. [2010]; Li and Zhang [2014]). Consistent with this intuition, we find that managers issue more optimistic forecasts against stock underpricing but do not issue more pessimistic forecasts against stock overpricing when their firms are under larger financial constrains. Third, managers have less restrictions to use MFBs against stock mispricing when firms' earnings is difficult to predict and MFBs are difficult to be evaluated by investors (Matsumoto [2002]; Rogers and Stocken [2005]; Cotter et al. [2006]; Lee, Matsunaga and Park [2012]). In line with this conjecture, we find that managers use more biased forecasts in response to stock underpricing driven by forced sales but not to stock overpricing driven by forced purchases when investors have more difficulty in detecting such biases.

Finally, we examine whether MFBs help to speed up price corrections in the context of mutual fund flow-driven price pressures. Our analysis shows that when extreme outflow-driven trades by mutual funds are followed by disclosure of optimistically biased forecasts, subsequent return reversals are significantly smaller. This result holds after controlling for firms' insider trading and concurrent net stock issues, which could also occur in response to mispricing (Khan, Kogan, and Serafeim [2010], Ali, Wei and Zhou [2011]), and for firm characteristics such as size, book to market, and past returns. Thus, we conclude that MFBs against flow-constrained mutual fund trades help to mitigate mispricing and speed up the process of price recovery.

This paper contributes to the literature on the determinants of MFBs. Current literature mostly concentrates on the strategic forecasting biases in order to affect stock price (e.g., Aboody and Kasznik [2000], Lang and Lundholm [2000], Rogers and Stocken [2005] and Cheng and Lo [2006]). For example, Lang and Lundholm [2000] document that management earnings forecasts around equity offerings are optimistically biased. Aboody and Kasznik [2000] find that managers issue bad-news earnings forecasts around stock option award periods to temporarily depress stock prices and take advantage of a lower strike price on managers' option grants. In a similar vein, Rogers and Stocken [2005] and Cheng and Lo [2006] show that managers tend to issue more pessimistic forecasts before insider purchases in an attempt to extract more trading profit. Recently, there are a couple of studies start to examine the effect of stock price on management forecast behavior (Bergman and Roychowdhury [2008] and Li and Zhang [2014]). In Bergman and Roychowdhury [2008], managers use good news forecasts to increase investors' expectations when market sentiment is low but they do not issue bad news forecasts to walk down the expectations when market sentiment is high, whereas in Li and Zhang [2014], managers reduce the precision of bad news forecasts in response to removal of short selling constraints. Our study is among the first to examine the effect of price pressures on MFBs. In specific, different from Bergman and Roychowdhury [2008] and Li and Zhang [2014], we show that managers use optimistic forecast biases, not forecast news or forecast precision, to counteract downward price pressures. Furthermore, we find that forecast biases improve the speed of price recovery and hence contribute to market efficiency, which is not touched in these two studies.

Our study also contributes to understanding the consequences of MFBs in general. We demonstrate that MFBs actually have a distinctive benefit, that is, they can be strategically used to correct mispricing caused by fire sales. This result contrasts with prior findings that have focused on the opportunistic nature of MFBs and their adverse effects. For example, Aboody and Kasznik [2000], Rogers and Stocken [2005] and Cheng and Lo [2006] show that managers use MFBs to extract more profits from option awards and insider trading, and Hillary and Hsu [2011] and Lee, Matsunaga and Park [2012] show that management forecast errors are considered as a signal of CEOs' inability which lead to CEO turnovers. Interestingly, we find that managers do not need to bear the consequence of an increased likelihood of managerial dismissal when forecast biases are used to correct underpricing.

Lastly, our paper also contributes to the literature on stock mispricing. Coval and Stafford [2007] initially document evidence of stock mispricing resulting from rebalancing of mutual funds. Following Coval and Stafford [2007], several studies examine the consequences of such mispricing. For example, Ali, Wei and Zhou [2011] show that insiders trade against stock mispricing from fire sales (purchases) of mutual funds, and Edmans, Goldstein and Jiang [2012] find that stock mispricing caused by mutual funds rebalancing leads to more mergers and acquisitions. Our study extends this line of research by showing that stock mispricing has additional effects on corporate decisions in that it induces disclosure of biased management forecasts.

The remainder of the paper is organized as follows. Section 2 develops the hypotheses. Section 3 discusses the sample and research design. Section 4 presents the empirical results. Section 5 provides the additional analysis on the effect of outflow-driven MFBs on CEO turnover. Section 6 concludes.

2. Hypothesis Development

Management forecast is an important type of voluntary disclosures on financial information (Hirst et al. [2008]). Beyer et al. [2010] show that management forecasts account for 15.67% of the total information measured by return variance. Prior studies document that management uses their forecasts to manage earnings expectations to the degree that they can meet or beat analyst forecast consensus during earnings announcement (Matsumoto [2002]; Cotter et al. [2006]). The underlying concern is that managers do not want to disappoint the market and try to avoid the situation that the share price decreases dramatically when they announce their earnings. If share price is such an important concern for managers to design their forecast strategy, then why not directly look at the share price and see whether managers' voluntary disclosures of their forecasts are affected by price pressure. The benefits are two folds. First, it looks at the price pressure not only during earnings announcement period but also in other periods. Second, it is a more direct way to examine the effect of price pressure on management forecast strategy.

We use the fire sales (purchases) of mutual funds as exogenous shocks to the share price (Coval and Stafford [2007]; Ali, Wei and Zhou [2011], Edmans, Goldstein and Jiang [2012]). When the stocks are fire sold (purchased) by mutual funds, then their price would be under significant downward (upward) pressure. Managers do not want their share price to decrease for various reasons such as managerial evaluation, compensation and personal wealth portfolio. By contrast, managers do not have problems with the artificial increase in share price which do not harm managers. Ali, Wei and Zhou [2011] further show that insiders take advantage of stock overpricing by liquidating their shares. Hence, managers have incentives to interfere when their stocks are fire sold but do not get involved when their stocks are fire purchased by mutual funds. Given the significant role played by management forecasts in the capital market, managers likely use their forecasts to serve such purpose. Specially, when their share price is under downward pressure driven by fire sale of mutual funds, managers might issue more optimistic or less conservative forecasts to signal the health of the company's fundamentals and further help push up the share price. On the other hand, when their share price is artificially high due to fire purchase of mutual funds, then they don't have much incentive to guide down the price and hence don't change their forecast strategy.

However, optimistic forecasts contain costs to managers. Previous research has documented that forecast accuracy or forecast consistency reflects management's ability to process information or anticipate and respond to future events (Lee, Matsunaga and Park [2012] and Hilary, Hsu and Wang [2014]). When the actual earnings turn out to be lower than their forecast earnings, the share price would decrease dramatically and the board would raise concern about managers' ability and increase their litigation risk and dismissal risk (e.g., Matsumoto [2002]; Cotter et al. [2006]; Lee, Matsunaga and Park [2012]). Jointly considering the negative effects of forecast biases, it is an empirical question whether managers would issue more optimistic forecasts to mitigate the price pressure driven by fire sale of mutual funds. Hence, our first set of hypotheses is developed as below:

H1a: Ceteris paribus, managers' forecast biases are positively related to the fire sales of mutual funds.

H1b: Ceteris paribus, managers' forecast biases are insignificantly related to the fire purchases of mutual funds.

The price pressure driven by fire sale (purchase) of mutual funds is mainly due to liquidity shortage (Coval and Stafford [2007]). Following this idea, we examine whether managers issue more optimistic forecasts in response to fire sales of mutual funds when their stocks are less liquid. We do not expect any incremental effect for the response to fire purchases of mutual funds given the insignificant response we discussed above. Therefore, our second set of hypotheses is formed as below:

H2a: Ceteris paribus, the positive effects of the fire sales of mutual funds on managers' forecast biases increase with stock liquidity.

H2b: Ceteris paribus, the insignificant effects of the fire purchases of mutual funds on managers' forecast biases do not change with stock liquidity.

Previous literature has shown that maintaining or increasing stock prices is one of the most important targets in managers' disclosure decisions (Matsumoto [2002]; Cotter et al. [2006]; Hirst et al. [2008]; Beyer et al. [2010]; Li and Zhang [2014]). Such incentive is particularly strong when firms are under financial constrains and consequently in need of external financing (Hirst et al. [2008]; Beyer et al. [2010]). Mapping the argument to our setting, we expect that managers issue more biased forecasts against stock mispricing when their firms are in poor financial health and hence have more needs for external financing. Such incentive applies only to stock underpricing but not to stock overpricing. Accordingly, we form our third set of hypotheses as below:

H3a: Ceteris paribus, the positive effects of the fire sales of mutual funds on managers' forecast biases increase with the level of financial constrains.

H3b: Ceteris paribus, the insignificant effects of the fire purchases of mutual funds on managers' forecast biases do not change with the level of financial constrains.

The quality of managerial forecasts is evaluated by investors with the subsequent earnings reports and other information. When their forecasts deviate dramatically from the actual earnings, managers' reputation might be damaged and they might suffer legal censure and unemployment (e.g., Matsumoto [2002]; Cotter et al. [2006]; Lee, Matsunaga and Park [2012]). However, the usefulness of actual earnings to assess the credibility of managerial forecasts decreases with the difficulty of accurately predicting earnings (Rogers and Stocken [2005]). When firms' earnings vary dramatically across circumstances, it is more difficult for managers to predict the earnings and therefore, more difficult for investors to evaluate the truthfulness of managers' forecasts. Hence, we expect managers use more biased forecasts to counteract stock mispricing when investors have more difficulty in detecting such biases. In line with the discussion earlier, we expect such incremental effect exists only for the response to the underpricing driven by fire sales of mutual funds but not to the overpricing driven by fire purchases of mutual funds. We develop our fourth set of hypotheses as below:

H4a: Ceteris paribus, the positive effects of the fire sales of mutual funds on managers' forecast biases increase with forecasting difficulty.

H4b: Ceteris paribus, the insignificant effects of the fire purchases of mutual funds on managers' forecast biases do not change with forecasting difficulty.

If managers' forecast strategy is indeed affected by price pressure, then we expect that such strategy should work to increase share price and mitigate price pressure in the rational world. In specific, we expect the share price would increase in the short window when managers announce their forecasts. Therefore, we develop the first part of our fifth hypotheses based on the short window.

H5a: Ceteris paribus, managers' forecast biases are positively related to the short-term stock return during forecast announcement period.

Similarly, we expect the price would increase faster in the long run after the market learns the signal from management forecasts on the financial health and hence speed up the price reversal. Since forced trades by mutual funds drives stock mispricing and hence is negatively related to future abnormal return, we expect such negative effect would intensify when it is accompanied by the signal of forecast optimism. Hence, the second part of our fifth hypotheses based on the long window is developed as below:

H5b: Ceteris paribus, the interaction between managers' forecast biases and forced trades of mutual funds is negatively related to the long-term stock return after the forced trades of mutual funds.

3. Research Design

3.1 MEASUREMENT OF MUTUAL FUND TRADES

We collect fund information from two databases. First, we obtain the portfolio holdings at quarter end for domestic equity mutual funds during the period of 1996 to 2010 from

Thomson Reuters Mutual Fund Holdings Data and we infer fund purchases and sales from changes in their quarterly positions. We focus on trades made by actively managed, diversified U.S. domestic equity funds and exclude all trades by index funds, international funds, municipal bond funds, “bond and preferred” funds, and sector funds. Then we obtain fund returns and total net asset value from the CRSP Survivorship Bias Free Mutual Fund Database. These two mutual fund databases are then linked via the MFLINKS data set provided by Wharton Research Data Services (WRDS).

To identify funds experiencing extreme flows, we compute quarterly fund flows as the change in total net assets during the quarter, adjusted for investment returns (assuming flows occur at the end of each quarter). That is,

$$Flow_{jt}=TNA_{jt}-TNA_{jt-1}(1+R_{jt})/TNA_{jt-1} \qquad (1)$$

where TNA_{jt} is the total net assets of fund *j* at the end of quarter *t*, and R_{jt} is the quarterly return of fund *j* during quarter *t*. We assume there is no difference on the share classes and combine quarter-end total net assets across all share classes of each fund, and calculate fund returns as the weighted average of returns across share classes with the weight as the beginning-of-quarter total net asset value. A fund is considered to be experiencing extreme capital flows if it has realized flows above/below the 90th/10th percentile among all funds during the quarter.[1]

To examine price pressure due to mutual fund trades that are forced by extreme flows, we follow Coval and Stafford [2007] and Ali, Wei and Zhou [2011] and construct a stock level price pressure measure. First, we sum up all inflow-driven purchases and outflow-driven sales made by funds trading a stock in a given quarter. When then normalize the difference by the firm’s shares outstanding at the beginning of the quarter, obtained from the CSRP monthly stock database. The flow-driven price pressure measure of the stock is defined as

$$Forced_{it}=\frac{\sum_j\left(\max(0,\Delta holding_{jit})\middle|flow_{jt}>percentile\ (90th)\right)-\sum_j\left(\max(0,-\Delta holding_{jit})\middle|flow_{jt}<percentile\ (10th)\right)}{Shares\ Outstanding_{it-1}}$$

(2)

Where $\Delta holdings_{jit}$ is the change in fund *j*’s holding of stock *i* in quarter *t*, and $flow_{jt}$ is the capital flow for fund *j* in quarter *t*. Essentially, *Forced* measures the degree to which a stock’s trading is accounted for by mutual funds experiencing significant inflows or outflows. Lower (upper) range of *Forced* values means stocks being fire sold (purchased) by mutual fund.

For voluntary mutual fund trading, Coval and Stafford [2007] show that there is no price reversal, contrasted to mutual fund flow-forced trade. This is in line with the view that unconstrained fund trading contains information about firms’ fundamental value. Following Ali, Wei and Zhou [2011], we control for trades by unconstrained funds in our analysis. Specially, we measure these trades as

$$Unforced_{it}=\frac{\sum_j\left(\Delta holding_{jit}\middle|percentile\ (10th)\le flow_{jt}\le percentile\ (90th)\right)}{Shares\ Outstanding_{it-1}} \qquad (3)$$

This measure is similar to the dollar trade imbalance ratio used in Lakonishok, Shleifer, and Vishny [1992]. To exclude flow forced trades, we only sum up trades made by those mutual funds that are not in the top or bottom 10 percentile according to their quarterly percentile ranks of capital flows.

3.2 REGRESSION MODEL FOR THE EFFECT OF MUTUAL FUND FLOW-DRIVEN TRADES ON MANAGEMENT FORECAST BIASES

To examine whether the fire sales and purchases of mutual funds cause management forecast biases, we regress MFBs on the flow-driven price pressure measure (*Forced*). We expect significantly negative coefficients on *Forced* if managers issue optimistic (pessimistic) forecasts to counter against the downward (upward) price pressures from the fire sales (purchases) of mutual funds.[2] To account for the effects of mutual fund trading imbalance that is unrelated to extreme flows, we control for *Unforced*, as against trades forced by extreme capital flows. The regression model is as below:

$$MFB=\alpha+\beta1Forced+\beta2Litigation+\beta3InsTrd10D+\beta4Zscore+\beta5Herf+\beta6FN+\beta7Horizon+\beta8Car\_120+\beta9Size+\beta10BM+\beta11DA\_Jones+\beta12Unforced+\varepsilon \quad (4)$$

The model's variables are defined and discussed below :

Management forecast bias (*MFB*) : Following Shroff et al. [2013], management forecast bias is defined as

$$MFB=(Management\ forecast\text{-}Actual\ EPS)/|Actual\ EPS|.^{3} \quad (5)$$

Litigation (*Litigation*) : To capture the incentives created by the litigation environment, we estimate the lagged probability of litigation using a probit specification where we regress the incidence of a lawsuit onto firm-specific measures and high-litigation industry membership ; see Appendix Table 2 for further details. *Litigation* is defined as the previous quarter's probability of litigation obtained from this model.

Insider transactions (*InsTrd10D*) : Rogers and Stocken [2005] and Cheng and Lo [2006] document that insider trading lead to biased management forecasts. To control for the incentives from insider trading activities, we calculate *InsTrd10D* as the number of shares purchased minus the number of shares sold over the ten-trading-day window beginning the day of the forecast, scaled by shares outstanding. We obtain insider transactions from Thomson Financial database.

Financial health (*Zscore*) : We expect a firm's financial health to affect its manager's forecasting incentives when the firm is in relatively poor financial health. Following prior research, we use a modified version of Altman's Z-score (Altman [1968]) to proxy for a firm's financial health:

$$Zscoreit=0.3NIitAssetsit+1.0SalesitAssetsit+1.4Retained\ EarningsitAssetsit$$

$$+1.2Working\ CapitalitAssetsit+0.6Market\ ValueitTotal\ Liabilitiesit \quad (6)$$

Higher values of *Zscore* indicate a healthier financial condition.

Herfindahl index (*Herf*) : Industry concentration affects industry competition, which could affect managers' forecast behaviors. We use Herfindahl index (*Herf*) as the proxy and calculate it as the sum of the squares of the market shares of the firms' within an industry reporting on Compustat sharing the same four-digit SIC code.

Forecast news (*FN*) : McNichols [1989] argues that management incentives to bias their forecasts may cause forecast news and forecast biases to be positively correlated. We use forecast news to control for managements' implicitly revealed incentives to misrepresent their information. Forecast news, *FN*, is defined as:

$$FN = (\text{Management forecast} - \text{Consensus analyst forecast}) / |\text{Actual EPS}| \quad (7)$$

Forecast horizon (*Horizon*) : Johnson, Kasznik and Nelson [2001] find that forecast errors decline as forecasts are issued closer to the fiscal year-end. Hence, we include it in the regression and calculate it as the log value of the number of calendar days between the forecast release date and earnings announcement date.

Momentum (*Car_120*) : McNichols [1989] find that forecast errors are correlated with previous cumulative abnormal returns. We control for this effect by calculating the cumulative market-adjusted return over the period 120 days before to one day before the forecast date, denoted *CAR_120*.

Firm size (*Size*) : Baginski and Hassell [1997] and Bamber and Cheon [1998] find that forecast behavior is associated with firm size. We use the log value of total assets in previous fiscal quarter to proxy for the firm size.

Book-to-Market ratio (*BM*): Bamber and Cheon [1998] document that growth opportunities affect a firm's forecasting behavior. We use book-to market ratio (*BM*) as a measure of growth opportunities. *BM* is calculated as the ratio of the book value of equity divided by the firm's market capitalization at the end of previous fiscal quarter.

Earnings management (*DA_Jones*): McNichols [1989] and Kasznik [1999] find evidence suggesting that managers manipulate earnings to fall in line with their forecast. To control for the firm's ability to manipulate earnings, we follow Dechow et al. [1995] and calculate the discretionary accruals using the cross-sectional modified Jones model (*DA_Jones*).

Lastly, we include fixed effects for industry and year. We define an industry based on the four-digit SIC code reported on Compustat. *Forced* and *Unforced* are defined before.

3.3 REGRESSION MODEL FOR THE EFFECT OF STOCK ILLIQUIDITY

If managerial forecasts biases arise from the price pressures from fire sales and purchases of mutual funds, then the effects should be more severe for illiquid stocks that are more sensitive to trading shocks from mutual funds. To test this argument, we augment equation (4) with an interaction term between *Forced* and a measure of stock illiquidity (*Illiquidity*) plus the illiquidity measure. The regression model is as below:

$$MFB = \alpha + \beta 1 Foreced \times Illiquidity + \beta 2 Forced + \beta 3 Illiquidity + \beta 4 Litigation + \beta 5 InsTrd10D + \beta 6 Zscore + \beta 7 Herf + \beta 8 FN + \beta 9 Horizon + \beta 10 Car\_120 + \beta 11 Size + \beta 12 BM + \beta 13 DA\_Jones + \beta 14 Unforced + \varepsilon \quad (8)$$

Following Amihud [2002], we use the price impact of trading as the proxy of stock illiquidity.[4] Hasbrouck [2003] shows that this measure is the best available price-impact proxy constructed from daily data. The Amihud [2002] illiquidity ratio is calculated as the absolute daily return divided by the dollar trading volume (number of shares traded multiplied by end-of-day stock price).

$$Illiquidity_{id} = |r_{id}|/V_{id} \quad (9)$$

where $|r_{id}|$ is stock *i*'s absolute return on day *d*. V_{id} is the dollar trading volume.

To avoid the effects of extreme observations, we follow Daske, Hail, Leuz and Verdi [2008] and use the median value over the quarter as the proxy at quarterly level. In addition, to reduce the noise in the construction of this measure, we require the number of daily return observations larger than 30. Given that NYSE/AMEX and NASDAQ report trading volume differently, we employ an adjusted Amihud illiquidity measure as the raw Amihud [2002] illiquidity ratio standardized by the average value of the ratio for all stocks traded in the same exchange. Since this measure captures the absolute price impact of a given dollar volume, larger value means more illiquid stocks.

3.4 REGRESSION MODEL FOR THE EFFECT OF FINANCIAL CONSTRAINS

Firms under financial constrains have stronger incentive to maintain or increase stock price in order to obtain external financing (Matsumoto [2002]; Cotter et al. [2006]; Hirst et al. [2008]; Beyer et al. [2010]; Li and Zhang [2014]). Such incentive could pressure managers to issue more biased forecasts. To investigate this conjecture, we augment equation (4) with an interaction term between *Forced* and a measure of financial constrain (*Constrain*) plus the constrain measure (*Constrain*). The regression model is as below:

$$MFB = \alpha + \beta_1 Foreced \times Constrain + \beta_2 Forced + \beta_3 Constrain + \beta_4 Litigation + \beta_5 InsTrd10D + \beta_6 Zscore + \beta_7 Herf + \beta_8 FN + \beta_9 Horizon + \beta_{10} Car\_120 + \beta_{11} Size + \beta_{12} BM + \beta_{13} DA\_Jones + \beta_{14} Unforced + \varepsilon \quad (10)$$

We employ two proxies to measure financial constrains (*Constrain*). First, we use the financial health score of Piotroski [2000] (*Pindex*), ranging from 0 to 9 with a higher score indicating stronger financial health; one point is given for each of the following items if its value is greater than 0: ROA (= ib/at_lag), CFO (=oancf/at_lag), ΔROA, CFO-ROA, -Leverage (leverage=dltt/at_lag), ΔCurrent ratio (current ratio= act/lct), no common equity issuance (cshi=0), ΔMargin (margin=(revt-cogs)/revt), and ΔTurn (turn=revt/at_lag). The data is obtained from Compustat. Piotroski [2000] show that the financial health score measures the strength of a firm's financial position. To facilitate the interpretation of our results, we multiply the financial health score by -1 to capture the level of financial constrains. Second, we use the financial constraint index of Hadlock and Pierce [2010] (*HPindex*), equal to -0.737 × Size + 0.043 × Size2-0.040 × Age, where Size is the natural log of total assets (Compustat variable at) capped at \$4.5 billion, and Age is the total number of years that a firm has been on Compustat capped at thirty-seven years. Hadlock and Pierce [2010] show that this measure beats other proxies of financial constraints.

3.5 REGRESSION MODEL FOR THE EFFECT OF FORECASTING DIFFICULTY

Forecasting biases incur costs to managers in terms of their reputation, litigation risk and dismissal risk (e.g., Matsumoto [2002]; Cotter et al. [2006]; Lee, Matsunaga and Park [2012]). Such costs are mitigated when it is difficult for managers to issue accurate forecasts and hence difficult for investors to evaluate managers' forecasts (Rogers and Stocken [2005]). Accordingly, managers face less constrains and are free to issue more biased forecasts to counteract stock mispricing. To examine this argument, we add equation (4) with an interaction term between *Forced* and a measure of forecasting difficulty (*Difficulty*) plus the difficulty measure (*Difficulty*). The regression model is as below:

$MFB=\alpha+\beta 1Foreced\times Difficulty+\beta 2Forced+\beta 3Difficulty+\beta 4Litigation+\beta 5InsTrd10D+\beta 6Zscore+\beta 7Herf+\beta 8FN+\beta 9Horizon+\beta 10Car\_120+\beta 11Size+\beta 12BM+\beta 13DA\_Jones+\beta 14Unforced+\varepsilon$ (11)

Following Rogers and Stocken [2005], we measure forecasting difficulty (*Difficulty*) as the first principal component of the following seven variables: 1) the standard deviation of analyst forecasts outstanding when the management forecast is released, 2) the standard deviation of previous analyst forecast errors scaled by price for five years prior to the release of the management forecast, 3) the indicator variable with the value of one when a firm's quarterly earnings preceding the management forecast is negative and zero otherwise, 4) the indicator variable with the value of one when the management forecast of earnings is negative and zero otherwise, 5) the standard deviation of daily stock price for 120 days before the management forecast date, 6) the average relative bid-ask spread for a 20-trading-day period ending two days before the forecast date, and 7) the width of range forecasts with the value of zero for point estimates.

3.6 REGRESSION MODEL FOR THE EFFECT OF MANAGEMENT FORECAST BIASES ON PRICE CORRECTION

Coval and Stafford [2007] show that the price pressure on stocks due to concentrated mutual fund sales and purchases forced by extreme money flows takes as long as one and half years to correct. If managers provide biased forecasts against the trading direction of mutual funds, i.e., provide optimistic (pessimistic) forecasts when facing fire sales (purchases), then MFBs might help stock price reverse back to normal and hence speed up the price recovery process.

We use two approaches to examine such possibility. First, we focus on the short window around management forecast release and see whether the market reaction depends on the forecast biases. The model below is used to test the short-term effect of MFBs on share price:

$Car\_01=\alpha+\beta 1Forced\times MFB+\beta 2\mathrm{Forced}+\beta 3MFB+\beta 4Esurp+\beta 5Size+\beta 6BM+\beta 7Car\_120+\varepsilon$ (12)

The variables are defined as follows:

Event return (*Car_01*): The market reaction to the forecast release is the cumulative daily return less CRSP value-weighted index return over the windown that includes the day of the forecast release to one day after the release. When the forecast is released after the close of trading, we adjust the forecast date to the next trading day.

Earnings surprise (*Esurp*): Earnings surprise, *Esurp*, is defined as:

$Esurp=(Actual\ EPS-Consensus\ analyst\ forecast)/|Actual\ EPS|$ (13)

Consensus analyst forecast is based on the period right before the management forecast release, same as the one used in the calculation of forecast news (*FN*). Hence, by construction, forecast news (*FN*) euqual to the sum of management forecast bias (*MFB*) and earnings surprise (*Esurp*).

Industry and year fixed effects are included as before. Other variables are defiend before. *Size*, *BM* and *Car_120* are included to control for risk premiums related to firm size, growth potential and momentum.

We expect positive sign on management forecast bias (*MFB*) if MFBs help increase stock price and negative sign on the interaction between *Forced* and *MFB* if the market reaction to MFBs is more positive (negative) when shares are undervalued (overvalued) due to fire sales (purchases) of mutual funds.

Second, we look at the six-quarter long window (the average time required to correct the mispricing according to Coval and Stafford [2007]) and examine whether MFBs help with the price recovery. We use the following model to test the long-term effect of MFBs in the price correction process:

$$ABH6Q=\alpha+\beta1Forced\times MFB+\beta2Forced+\beta3MFB+\beta4Forced\times InsTrd1Q+\beta5InsTrd1Q+\beta6Forced\times NetIssue+\beta7NetIssue+\beta8Size+\beta9BM+\beta9PastReturn+\beta10Unforced+\varepsilon \quad (14)$$

The variables are defined as follows:

Long-term abnormal return (*ABH6Q*): The cumulative market-adjusted abnormal return during the six quarters following the fire sales (purchases) of mutual funds.

Insider trading (*InsTrd1Q*): The absolute value of the number of shares purchased minus the number of shares sold in the calendar quarter of the fire sales (purchases) of mutual funds, scaled by shares outstanding.

Net stock issue (*Netissue*): The log value of the ratio of the split-adjusted shares outstanding in quarter t divided by the split-adjsuted shares outstanding in quarter t-1.

Past return (*PastReturn*): The market-adjusted cumulative abnormal return in four quarters prior to the fire sales (purchases) of mutual funds.

As before, we control for industry and year fixed effects. Other variables are defiend before.

Netissue and its interaction with *Forced* are included to control for the confounding effect of stock issuance that can impact the firm's subsequent abnormal returns. We include *InsTrd1Q* and its interaction with *Forced* due to the finding of Ali, Wei and Zhou [2011] on the role of insider trading on the price correction. As before, we include *Size*, *BM* and *PastReturn* to control for risk premiums related to firm size, growth potential and momentum. We control for *Unforced* to compare the effect of *Forced* and to control for the effects of non-extreme-flow mutual fund trading.

4. Empirical Results

4.1 SAMPLE AND DESCRIPTIVE STATISTICS

Following Rogers and Stocken [2005], Anilowski et al. [2007] and Hillary and Shen [2013], we include all point and range quarterly management earnings forecasts in the sample.[5] We obtain both quarterly and annual management forecasts issued between 1996 and 2010 from the First Call database which generates 3,711 firms and 41,464 management forecasts. Chuk, Matsumoto, and Miller [2013] discuss the limited coverage and systematic biases related to CIG database. Specially, they find that CIG covers only about 51% forecast press releases. Those press releases more likely convey bad news and come from firms with high analyst following, high institutional ownership, or non-losses performance in the recent past. Those coverage biases unlikely systematically lend support to our findings on the effects of price pressure and management forecast optimism (pessimism). If anything, such coverage should bias against our finding given that our results are stronger for illiquid stocks, which tend to be firms with low analyst following and low institutional ownership.

The top and bottom one percentiles of the data are winsorized for all variables except those with a natural boundary including *Litigation*, *Pindex*, *Herf* and *NetIssue*. Table 1 reports descriptive statistics. The summary statistics for all variables are similar to those in prior studies.

TABLE 1
Descriptive Statistics

Variable	Mean	Q1	Median	Q3	Std. Dev.
Variables in the main model					
MFB	0.331	-0.078	0.000	0.343	1.886
Forced	-0.001	-0.003	0.000	0.002	0.031
Litigation	0.087	0.035	0.056	0.096	0.110
InsTrd10D	-1.320	-1.256	-0.278	-0.026	3.409
Zscore	4.129	1.488	2.559	4.661	4.980
Herf	0.116	0.000	0.002	0.024	0.498
FN	0.119	-0.049	0.000	0.100	1.535
Horizon	4.650	4.344	4.595	5.347	0.927
Car_120	0.033	-0.147	-0.003	0.150	0.350
Size	7.240	5.949	7.099	8.383	1.728
BM	0.498	0.257	0.416	0.657	0.353
DA_Jones	0.003	-0.028	0.000	0.028	0.068
Unforced	0.004	-0.007	0.002	0.012	0.054
Variables in the model of incremental effects					
Illiquidity	9.254	0.393	1.359	5.120	33.761
Pindex	-5.116	-6	-5	-4	1.549
HPindex	-3.482	-3.637	-3.517	-3.357	0.220
Difficulty	-0.004	-0.696	-0.296	0.238	1.339
Variables in the model of price correction					
Car_01	-0.006	-0.054	-0.001	0.049	0.128
Esurp	-0.212	-0.097	0.014	0.091	1.777
ABH6Q	1.074	0.774	0.997	1.267	0.514
InsTrd1Q	0.176	0.000	0.014	0.128	0.460
NetIssue	0.014	-0.002	0.001	0.005	0.090
PastReturn	1.120	0.830	1.028	1.274	0.613

The table provides descriptive statistics for the sample of 49,306 firm-quarter observations from 1996 to 2010. The sample size for each variable varies and depends on its availability. Variables are defined in Appendix Table 1.

4.2 MANAGEMENT FORECAST BIASES AND FIRE SALES (PURCHASES) OF MUTUAL FUNDS

In this section, we test whether managers provide more optimistic (pessimistic) forecasts in response to fire sales (purchases) of mutual funds.

TABLE 2

Management Forecast Biases and Fire Sale (Purchase) of Mutual Funds

$MFB=\alpha+\beta_1 Forced+\beta_2 Litigation+\beta_3 InsTrd10D+\beta_4 Zscore+\beta_5 Herf+\beta_6 FN+\beta_7 Horizon+\beta_8 Car\_120+\beta_9 Size+\beta_{10} BM+\beta_{11} DA\_Jones+\beta_{12} Unforced+\varepsilon$

Variable	Full sample	Forced sales + benchmark sample	Forced purchases + benchmark sample
	Model 1	Model 2	Model 3
Forced	**-4.131** (-2.25)**	**-8.527** (-2.43)**	**0.556 (0.45)**
Litigation	1.060*** (4.41)	1.071*** (3.96)	1.034*** (4.33)
InsTrd10D	0.003 (0.60)	0.003 (0.51)	0.002 (0.34)
Zscore	-0.008*** (-3.00)	-0.008*** (-2.74)	-0.008*** (-2.92)
Herf	-0.018 (-0.89)	-0.008 (-0.37)	-0.020 (-1.13)
FN	0.869*** (13.01)	0.880*** (13.16)	0.890*** (14.29)
Horizon	0.091*** (4.59)	0.101*** (4.65)	0.093*** (4.54)
Car_120	-0.236*** (-5.49)	-0.226*** (-4.29)	-0.197*** (-4.81)
Size	-0.070*** (-4.66)	-0.080*** (-5.40)	-0.059*** (-4.01)
BM	0.123** (1.99)	0.128** (1.97)	0.151** (2.37)
DA_Jones	0.000 (0.00)	0.081 (0.24)	-0.104 (-0.31)
Unforced	-0.075 (-0.18)	-1.042** (-2.09)	-0.440 (-1.06)
Intercept	0.034 (0.17)	0.027 (0.12)	-0.004 (-0.02)
Industry/time fixed effects	Yes	Yes	Yes
Adjusted R2	62.63%	65.20%	66.60%
F-statistic	22.54***	265.58***	30.60***
Sample Size	11,114	9,358	9,811

The table provides regression results on management forecast biases in response to fire sale (purchase) of mutual funds based on the sample of 11,114 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 2 presents the results of estimating equation (4) where we regress management forecast bias (*MFB*) on the forced trading imbalance of mutual funds (*Forced*) after controlling for known determinants from prior literature. We include industry and year-fixed effects and calculate t-statistics using robust standard errors that adjust for clustering by firm.

When full sample is used to run regression based on equation (4), the results are reported in Model 1. The control variables generally show expected sign. For example, the coefficient on *FN* is significantly positive while the coefficient on *Size* is significantly negative, suggesting that management forecast bias is positively correlated with forecast news and negatively correlated with firm size. For the variables of interest, we find that the coefficient on *Forced* is significantly negative while the coefficient on *Unforced* is insignificantly negative, suggesting that managers provide optimistic (pessimistic) forecasts in response to fire sales (purchases) of mutual funds but not to the informed trading of mutual funds. Next, we run regression separately for forced sales and forced purchases sample combined with benchmark sample that is not the top and bottom ten percentile of *Forced* (see model 2 and

3, respectively). We find that the coefficient of *Forced* is significantly negative only in the regression based on the forced sales plus benchmark sample but not in the regression based on the forced purchases plus benchmark sample, implying that managers provide optimistic forecasts when facing fire sales of mutual funds but do not provide pessimistic forecasts when their stocks are fire purchased by mutual funds.

4.3 THE EFFECT OF STOCK ILLIQUIDITY

The results so far suggest that managers provide biased forecasts against extreme mutual fund imbalance. Coval and Stafford [2007] and Ali, Wei and Zhou [2011] indicate that more illiquid stocks will experience larger price pressure given the same amount of extreme mutual fund flow. If mitigating the price pressure is the goal of earnings management, then we expect that the effects of extreme mutual fund flow on MFBs are stronger for illiquid stocks.

To test this argument, we use the Amihud illiquidity measure as the proxy of illiquidity and add the interaction between the illiquidity measure (*Illiquidity*) and extreme fund flow (*Forced*) to the regression model in equation (4), as described in equation (8). We rely on the interaction term, *Forced×Illiquidity*, to interpret the incremental effect of stock illiquidity beyond that of extreme fund flow (*Forced*).

TABLE 3

Stock Illiquidity and the Effect of Flow-Driven Trading Pressure on Management Forecast Biases

$$MFB=\alpha+\beta_1 Forced*Illiquidity+\beta_2 Forced+\beta_3 Illiquidity+\beta_4 Litigation+\beta_5 InsTrd10D+\beta_6 Zscore+\beta_7 Herf+\beta_8 FN+\beta_9 Horizon+\beta_{10} Car\_120+\beta_{11} Size+\beta_{12} BM+\beta_{13} DA\_Jones+\beta_{14} Unforced+\varepsilon$$

Variable	Full sample	Forced sales + benchmark sample	Forced purchases + benchmark sample
	Model 1	Model 2	Model 3
Forced*Illiquidity	**-0.220** (-2.42)**	**-0.221** (-2.41)**	**0.253 (1.10)**
Forced	**-2.681* (-1.77)**	**-6.119** (-2.06)**	**-0.177 (-0.14)**
Illiquidity	-0.000 (-0.03)	-0.000 (-0.21)	0.000 (0.46)
Litigation	1.077*** (4.49)	1.099*** (4.08)	1.033*** (4.33)
InsTrd10D	0.003 (0.55)	0.003 (0.47)	0.002 (0.34)
Zscore	-0.008*** (-2.96)	-0.008*** (-2.68)	-0.008*** (-2.89)
Herf	-0.019 (-0.93)	-0.010 (-0.47)	-0.021 (-1.16)
FN	0.870*** (13.06)	0.881*** (13.25)	0.891*** (14.33)
Horizon	0.092*** (4.65)	0.103*** (4.70)	0.094*** (4.59)
Car_120	-0.235*** (-5.53)	-0.224*** (-4.33)	-0.194*** (-4.73)
Size	-0.069*** (-4.59)	-0.080*** (-5.23)	-0.058*** (-3.90)

BM	0.123* (1.92)	0.125* (1.87)	0.147** (2.23)
DA_Jones	-0.008 (-0.03)	0.074 (0.21)	-0.102 (-0.30)
Unforced	-0.153 (-0.37)	-1.024** (-2.06)	-0.398 (-0.97)
Intercept	0.022 (0.11)	0.026 (0.11)	-0.012 (-0.07)
Industry/time fixed effects	Yes	Yes	Yes
Adjusted R2	62.75%	65.38%	66.60%
F-statistic	22.14***	262.84***	29.72***
Sample Size	11,114	9,358	9,811

The table provides regression results on stock illiquidity and the effect of fire sale (purchase) of mutual funds on management forecast biases based on the sample of 11,114 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

The results are presented in Table 3. As we can see in model 1 where full sample is used, both the coefficient of *Forced* and the coefficient of the interaction between *Forced* and *Illiquidity* are significantly negative, suggesting that extreme fund flow negatively affects MFBs, especially for illiquid stock, consistent with our conjecture. When we run regression separately for forced sales sample and forced purchased sample combined with benchmark sample (see model 2 and 3), we find that the effects exist only for forced sales sample, in line with our prior findings that MFBs are affected only by extreme fund outflow but not by extreme fund inflow, suggesting that the incremental effect of stock illiquidity applies only for the former but not for the latter.

4.4 THE EFFECT OF FINANCIAL CONSTRAIN

Besides stock illiquidity, financial constrain could increase the sensitivity of management forecast biases to stock mispricing, given that firms under financial constrains have stronger incentives to maintain and increase stock price in order to obtain external financing (Matsumoto [2002]; Cotter et al. [2006]; Hirst et al. [2008]; Beyer et al. [2010]; Li and Zhang [2014]). To investigate this argument, we add the proxy of financial constrains (*Constrain*) and its interaction with the forced fund flows (*Forced*) to the regression model in equation (4), as described in equation (10). Two proxies are used to measure financial constrains (*Constrain*), including *Pindex* (Piotroski [2000]) and *PHindex* (Hadlock and Pierce [2010]). As before, *Forced* and the interaction term *Forced×Constrain* are the variables of our interest.

TABLE 4

Financial Constrain and the Effect of Flow-Driven Trading Pressure on Management Forecast Biases

$$MFB=\alpha+\beta_1 Forced*Constrain+\beta_2 Forced+\beta_3 Constrain+\beta_4 Litigation+\beta_5 InsTrd10D+\beta_6 Zscore+\beta_7 Herf+\beta_8 FN+\beta_9 Horizon+\beta_{10} Car\_120+\beta_{11} Size+\beta_{12} BM+\beta_{13} DA\_Jones+\beta_{14} Unforced+\varepsilon$$

Variable	Constrain=*Pindex*			Constrain=*HPindex*		
	Full sample	Forced sales + benchmark sample	Forced purchases + benchmark sample	Full sample	Forced sales + benchmark sample	Forced purchases + benchmark sample
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Forced*Constrain	**-3.924*** (-2.69)**	**-7.039*** (-3.01)**	**-0.377 (-0.27)**	**-11.270* (-1.95)**	**-16.752* (-1.73)**	**-10.731 (-1.54)**
Forced	**-23.936** (-2.56)**	**-43.504*** (-2.91)**	**-1.372 (-0.15)**	**-41.785** (-2.05)**	**-64.104* (-1.88)**	**-36.265 (-1.46)**
Constrain	0.093*** (8.00)	0.077*** (5.90)	0.085*** (6.85)	-0.209** (-2.19)	-0.250** (-2.29)	-0.178 (-1.64)
Litigation	0.703*** (2.72)	0.672** (2.40)	0.375* (1.85)	0.842*** (3.09)	0.856*** (2.85)	0.473** (2.26)
InsTrd10D	0.009** (2.04)	0.011** (2.06)	0.007* (1.86)	0.010** (2.32)	0.012** (2.24)	0.009** (2.35)
Zscore	-0.007*** (-2.88)	-0.007** (-2.43)	-0.007*** (-2.70)	-0.005** (-2.02)	-0.005* (-1.79)	-0.004 (-1.63)
Herf	-0.040** (-2.29)	-0.033* (-1.80)	-0.032** (-2.16)	-0.011 (-0.70)	-0.009 (-0.50)	-0.006 (-0.41)
FN	0.928*** (18.27)	0.933*** (18.66)	0.942*** (21.63)	0.923*** (17.62)	0.929*** (17.96)	0.938*** (20.88)
Horizon	0.047*** (2.63)	0.060*** (3.02)	0.047** (2.57)	0.051*** (2.89)	0.066*** (3.30)	0.052*** (2.81)
Car_120	-0.161*** (-3.49)	-0.133*** (-2.75)	-0.163*** (-3.79)	-0.244*** (-5.01)	-0.230*** (-4.50)	-0.225*** (-4.89)
Size	-0.022 (-1.53)	-0.028* (-1.94)	-0.012 (-0.83)	-0.061*** (-3.77)	-0.069*** (-4.03)	-0.046*** (-3.21)
BM	0.129** (2.33)	0.121** (2.47)	0.141*** (2.59)	0.142** (2.54)	0.140*** (2.77)	0.155*** (2.79)
DA_Jones	-0.279 (-0.75)	-0.042 (-0.11)	-0.463 (-1.17)	-0.215 (-0.57)	0.014 (0.04)	-0.383 (-0.97)
Unforced	0.210 (0.45)	-0.236 (-0.51)	0.092 (0.19)	0.254 (0.55)	-0.371 (-0.80)	0.042 (0.09)
Intercept	0.721*** (3.06)	0.682*** (2.62)	0.512** (2.11)	-0.323 (-0.89)	-0.415 (-1.03)	-0.384 (-0.92)
Industry/time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	76.18%	79.70%	79.55%	75.64%	79.12%	79.21%
F-statistic	59.70***	542.19***	81.54***	50.35***	502.96***	70.17***
Sample Size	7,784	6,619	6,888	7,784	6,619	6,888

The table provides regression results on financial constrain and the effect of fire sale (purchase) of mutual funds on management forecast biases based on the sample of 7,784 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

The results are reported in Table 4. As shown in model 1 and model 4 where full sample is used, both the coefficients of *Forced* and the coefficients of the interaction between *Forced* and *Constrain* are significantly negative, implying that managers use their own forecasts to mitigate stock price pressure from extreme mutual fund flows, especially when firms are under financial constrains, in line with our conjecture. Then we separately examine whether our results differ across downward price pressure from forced sales versus upward price pressure from forced purchases. The results are reported in model 2 and model 4 for forced sales and in model 3 and model 6 for forced purchases. We find that the incremental effects exist only for forced sales sample, indicating that the incremental effect of financial constrain applies only for forced sales but not for forced purchases, consistent with the finding on stock illiquidity.

4.5 THE EFFECT OF FORECASTING DIFFICULTY

Managers are constrained to use biased forecasts to counteract stock mispricing, since their forecasts can be easily verified by the subsequent earnings reports (e.g., Matsumoto [2002]; Cotter et al. [2006]; Lee, Matsunaga and Park [2012]). Such constrain is mitigated when earnings is difficult to predict (Rogers and Stocken [2005]). Hence, it is possible that managers use more biased forecasts in response to price pressure when they face less constrains to do so. To examine this conjecture, we augment the model in equation (4) with a measure of forecasting difficulty (*Difficulty*) and its interaction with extreme fund flow (*Forced*), as described in equation (11). As before, we mainly rely on *Forced* and the interaction term *Forced*×*Difficulty* to test the conjecture.

TABLE 5

Forecasting Difficulty and the Effect of Flow-Driven Trading Pressure on Management Forecast Biases

$MFB=\alpha+\beta_1 Forced*Difficulty+\beta_2 Forced+\beta_3 Difficulty+\beta_4 Litigation+\beta_5 InsTrd10D+\beta_6 Zscore+\beta_7 Herf+\beta_8 FN+\beta_9 Horizon+\beta_{10} Car\_120+\beta_{11} Size+\beta_{12} BM+\beta_{13} DA\_Jones+\beta_{14} Unforced+\varepsilon$

Variable	Full sample	Forced sales + benchmark sample	Forced purchases + benchmark sample
Model 1		Model 2	Model 3
Forced*Difficulty	**-5.712** (-2.14)**	**-10.184*** (-4.26)**	**6.599* (1.86)**
Forced	**1.326 (0.52)**	**-1.003 (-0.36)**	**4.670 (1.28)**
Difficulty	-0.047 (-0.97)	-0.073 (-1.29)	-0.096* (-1.83)
Litigation	0.247 (0.78)	0.184 (0.55)	-0.052 (-0.15)
InsTrd10D	0.009 (1.61)	0.013** (2.16)	0.006 (0.82)
Zscore	-0.003 (-0.53)	-0.003 (-0.59)	-0.002 (-0.42)
Herf	-0.031 (-0.94)	-0.024 (-0.66)	-0.033 (-1.01)
FN	0.697*** (4.64)	0.701*** (4.15)	0.599*** (3.91)
Horizon	0.096*** (2.66)	0.121*** (3.00)	0.130*** (3.35)
Car_120	-0.219** (-2.40)	-0.144 (-1.54)	-0.148 (-1.50)
Size	-0.039* (-1.68)	-0.054** (-2.20)	-0.036 (-1.35)
BM	0.235** (2.56)	0.200** (2.40)	0.234*** (2.63)
DA_Jones	-0.890 (-1.23)	-0.510 (-0.83)	-0.855 (-1.13)
Unforced	0.970 (1.28)	-0.086 (-0.11)	1.331* (1.66)
Intercept	-0.395 (-1.13)	-0.390 (-0.96)	-0.580 (-1.60)
Industry/time fixed effects	Yes	Yes	Yes
Adjusted R2	33.43%	37.20%	24.58%
F-statistic	227.62***	215.70***	198.59***
Sample Size	3,699	3,117	3,308

The table provides regression results on forecasting difficulty and the effect of fire sale (purchase) of mutual funds on management forecast biases based on the sample of 3,699 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

The results are provided in Table 5. When full sample is used, the coefficient of *Forced×Difficulty* is significantly negative while the coefficient of *Forced* is insignificant, suggesting that managers more likely use MFBs to mitigate price pressure when MFBs are more difficult to be evaluated by investors, consistent with our conjecture. When forced sales sample (combined with benchmark sample) and forced purchased sample (combined with benchmark sample) are separately examined (see model 2 and 3), we find that the effects exist only for forced sales sample, implying that the incremental effect of forecasting difficulty applies only for fire sales but not for fire purchases, similar to the findings above.

4.6 MANAGEMENT FORECAST BIASES AND PRICE CORRECTION PROCESS

Our results above indicate that managers provide biased forecasts to mitigate the price pressures from extreme mutual fund flow, especially for firms with illiquid stock, for forms under financial constrain or for firms with earnings difficult to be predicted. If it is true, then more biased management forecasts should speed up the price recovery. We use two approaches to test this idea. The first approach focuses on the short window around management forecast releases. We expect forecast biases would be positively related to the market reaction. The regression model is described in equation (12) and the results are reported in Table 6.

TABLE 6

Effect of Management Forecast Biases on the Market Reaction to Management Forecast Releases

$Car\_01=\alpha+\beta_1 Forced*MFB+\beta_2\text{Forced}+\beta_3 MFB+\beta_4 Esurp+\beta_5 Size+\beta_6 BM+\beta_7 Car\_120+\varepsilon$

Variable	Full Sample			Forced sales + benchmark sample	Forced purchases + benchmark sample
	Model 1	Model 2	Model 3	Model 4	Model 5
Forced*MFB			**-0.186*** (-3.62)**	**-0.306*** (-3.94)**	**0.043 (0.34)**
Forced			**0.389*** (3.86)**	**0.621*** (4.03)**	**0.205 (1.55)**
MFB (1)	**0.009*** (5.07)**	**0.008*** (4.42)**	**0.010*** (3.70)**	**0.008*** (3.15)**	**0.010*** (3.27)**
Esurp (2)	**0.015*** (8.96)**	**0.014*** (7.83)**	**0.019*** (6.14)**	**0.023*** (9.70)**	**0.018*** (5.34)**
Size		0.002*** (4.15)	0.002*** (3.82)	0.003*** (4.33)	0.001* (1.94)
BM		0.009*** (3.44)	0.009*** (3.59)	0.010*** (3.57)	0.007*** (2.83)
Car_120		0.008** (2.01)	0.006 (1.44)	0.002 (0.43)	-0.001 (-0.13)
Intercept	-0.005 (-0.58)	-0.032*** (-2.88)	-0.031*** (-2.74)	-0.033** (-2.46)	-0.011 (-1.01)

Industry/time fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R2	5.12%	5.10%	5.44%	6.62%	4.27%
F-statistic	11.14***	10.32***	10.14***	10.03***	8.00***
Sample Size	49,306	40,095	39,980	33,942	34,752
Test: (1)-(2)	<0.000	0.000	<0.000	<0.000	<0.000

The table provides regression results on effect of management forecast biases on the market reaction to management forecast announcement based on the sample of 49,306 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

First, we regress market reaction (*Car_01*) on management forecast bias (*MFB*) and earnings surprise (*Esurp*).[6] The results are reported in model 1. We find that the coefficients on both *MFB* and *Esurp* are significantly positive, indicating that both forecast error and earnings surprise increase share price. When we compare the magnitude of these two coefficients, we find that the coefficient on *Esurp* is 0.015, much larger than the coefficient on *MFB*, i.e., 0.009. The difference is significant at 1% level. The findings suggest that although market responds positively to both earnings surprise news and forecast biases, it does see through the difference between these two and at least partially discount the reaction to forecast biases. Controlling for size, book-to-market ration and momentum does not change the results (see model 2). Next, we augment the model with the interaction between management forecast bias (*MFB*) and mutual fund trading imbalance (*Forced*) to examine whether the market differentiates the MFBs due to underpricing from mutual fund outflow from other MFBs and react accordingly. We find the coefficient on the interaction term is significantly negative (see model 3), suggesting that MFBs increase the share price more when accompanied with underpricing from fire sales of mutual fund. Economically, our results suggest that on average the stock price increases by 1.886% (=0.010*1.886) when MFBs increase by one standard deviation (i.e., 1.886); when MFBs are used to correct the underpricing of one standard deviation relative to the mean (i.e., -0.031), one standard deviation of MFBs is associated with the increase of stock price by 2.973% (=(0.010-0.186*(-0.031))*1.886), which is 57.66% higher than the magnitude of the reaction to the average MFBs, i.e., 1.886%. As before, we find such results apply only to the underpricing driven by forced sales (see model 4) but not to the overpricing driven by forced purchases (see model 5).

The second approach is based on the long window followed after fire sales (purchases) of mutual funds. Table 6 reports the regression results based on model in equation (14).

TABLE 7

Management Forecast Biases Against Flow-Driven Price Pressure and Future Abnormal Returns

$$ABH6Q=\alpha+\beta_1 Forced*MFB+\beta_2 Forced+\beta_3 MFB+\beta_4 Forced*InsTrd1Q+\beta_5 InsTrd1Q+\beta_6 Forced*NetIssue+\beta_7 NetIssue+\beta_8 Size+\beta_9 BM+\beta_9 PastReturn+\beta_{10} Unforced+\varepsilon$$

Variable	Full Sample			Forced sales + benchmark sample	Forced purchases + benchmark sample
	Model 1	Model 2	Model 3	Model 4	Model 5
Forced*MFB		**-0.485** (-2.29)**	**-0.465** (-1.97)**	**-0.612** (-2.52)**	**-0.221 (-1.17)**
Forced	**-0.929*** (-3.16)**	**-0.193 (-0.48)**	**-0.325 (-0.80)**	**-0.440 (-1.05)**	**-0.152 (-0.20)**
MFB		0.014*** (3.18)	0.014*** (3.14)	0.015** (2.51)	0.012* (1.74)
Forced*InsTrd1Q	1.018 (1.23)		0.865 (1.02)	0.176 (0.13)	0.066 (0.07)
InsTrd1Q	0.039*** (3.39)		0.039*** (3.38)	0.027** (2.19)	0.036*** (2.99)
Forced*NetIssue	1.132 (0.67)		-0.104 (-0.05)	11.105 (1.15)	-9.074*** (-3.70)
NetIssue	-0.036 (-0.54)		-0.047 (-0.73)	0.071 (0.71)	-0.004 (-0.05)
Size	-0.016*** (-3.64)	-0.017*** (-4.05)	-0.015*** (-3.57)	-0.014*** (-3.32)	-0.017*** (-4.01)
BM	0.096*** (4.65)	0.098*** (4.76)	0.099*** (4.79)	0.091*** (4.29)	0.086*** (4.16)
PastReturn	-0.058*** (-4.69)	-0.055*** (-4.55)	-0.059*** (-4.69)	-0.068*** (-4.70)	-0.063*** (-4.81)
Unforced	0.814*** (5.51)	0.865*** (6.12)	0.908*** (5.76)	1.498*** (6.90)	1.102*** (6.35)
Intercept	1.150*** (15.96)	1.160*** (16.22)	1.142*** (15.85)	1.149*** (16.51)	1.205*** (16.33)
Industry/time fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R2	7.03%	7.27%	7.37%	7.50%	7.56%
F-statistic	10.46***	11.22***	10.75***	11.72***	10.22***
Sample Size	37,708	37,384	37,333	31,835	32,796

The table provides regression results on whether management forecast biases in response to fire sale (purchase) of mutual funds speed up the price reversal based on the sample of 37,708 firm-quarter observations from 1996 to 2010. Forced sale sample include the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). Forced purchase sample include the firms who experience fire purchase by mutual funds, i.e., those stocks that are ranked in the top decile according to the *Forced* measure in quarter t (i.e., inflow-driven purchase). Benchmark sample include the firms who experience neither fire sales nor fire purchases. All variables are defined in Appendix Table 1. The table reports OLS coefficient estimates and (in parentheses) t-statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

We first follow Ali, Wei and Zhou [2011] and regress long-term abnormal return on proxies of insider trading and net stock issue and their interactions with the extreme trading imbalance of mutual funds, *Forced*, while controlling for size, book-to-market ratio and momentum. The results are shown in model 1. We find that the coefficient of *Forced* is significantly negative while the coefficient of *Unforced* is significantly positive, suggesting that extreme trading flows caused by mutual funds are associated with price reversal while non-extreme or normal trading flows of mutual funds are informative and are not accompanied by price reversal. The interaction between insider trading proxy (*InsTrd1Q*) and extreme trading flow (*Forced*) is positive while insignificant. When we exclude observations without insider trading, unreported results show that the coefficient on such interaction is significantly positive, consistent with Ali, Wei and Zhou [2011]. To examine whether the price reversal effect is accelerated by management forecast bias (*MFB*), we augment the model with *MFB* and its interaction with *Forced*, we find the interaction terms (*Forced**MFB*) have significantly negative coefficients (see model 2 and 3), similar to the coefficients on *Forced*, implying that management forecast biases speed up the price reversal. In terms of the economical magnitude, our results suggest that when one standard deviation of MFBs is coupled with stock underpricing, the price reversal effect of *Forced* on long-term abnormal return is -1.202 (=-0.325-0.465*1.886), which is 3.7 times of that effect when no MFBs is used, i.e., -0.325. Again, we find such acceleration effect exists only when stocks are underpriced due to forced sales (see model 4) but not when stocks are overpriced due to forced purchases (see model 5).

Taking together, the findings above suggest that management forecast biases counter against mispricing driven by fire sales (purchases) of mutual funds and helps stock price reverse back to the "normal" level.

5. Additional Analyses

In previous sections, we have documented that MFBs driven by mutual fund outflow benefit shareholders in terms of quicker price correcting. On the other hand, Lee et al. [2012] show that MFBs indicate poor ability of managers and hence lead to higher likelihood of CEO turnover. To reconcile these two findings, we attempt to replicate Lee et al. [2012] and examine whether the board of directors treats the flow-driven MFBs differently from other MFBs. In another word, the former type of MFBs might not lead to higher CEO dismissal risk associated with regular MFBs.

To test the differential effect of MFBs on CEO turnover, we follow Lee et al. [2012] and estimate a seemingly unrelated bivariate probit with a stacked model. Specially, we model both the management forecast and CEO turnover decisions, include the management forecast issuance dummy from the first model as an independent variable in the second model, and jointly estimate the two regressions. This procedure corrects the self selection biases of management forecast issuance decision. We use the two-stage models of Lee et al. [2012] and augment the second stage model with two more variables, i.e., the dummy of fire sales of mutual fund and the three-way interaction term between the absolute value of MFBs, management forecast issuance dummy, and the fire sales dummy. Lee et al. [2012] find that CEOs are more likely to be fired if they make large forecast errors, given the significant positive coefficients on the two-way interaction term between the absolute value of MFBs and management forecast issuance dummy. If MFBs driven by mutual fund outflow are less likely penalized by the board of directors, then we expect significantly negative coefficients on the three-way interaction term.

The regression models are as below:

$$MF=\alpha+\beta_1 Prev\_Forecast+\beta_2 Abs\_CXR+\beta_3 LvMV+\beta_4 Num\_Analysts+\beta_5 MB+\beta_6 Earn\_Vol+\beta_7 Ret\_Vol+ \beta_8 High\_Tech+\beta_9 Reg+\beta_9 Tenure+\beta_{10} Inst\_Own+\beta_{11} Chair\_Dual+\varepsilon \quad (15)$$

$$Turnover=\alpha+\beta_1 Abs(MFB)\times MF\times FS+\beta_2 Abs(MFB)\times MF+\beta_3 MF+\beta_4 FS+\beta_5 AFE+\beta_6 ROE+\beta_7 CAR+\beta_8 Earn$$

$\_Vol+\beta_9 Ret\_Vol+\beta_{10} LnSALES+\beta_{11} AGE+\beta_{12} AGE65+\beta_{13} Tenure+\beta_{14} Inst\_Own+\beta_{15} Chair\_Dual+\varepsilon$
(16)

The variables are defined as follows :

Management forecast issuance dummy (*MF*): dummy variable with the value of one if the firm issues an earnings forecast during quarter t-1 and 0 otherwise;

Number of previous management forecasts (*Pre_Forecast*): number of quarters for which the firm issued a forecast from quarter t-4 to t-2;

Earnings surprise and revisions (*Abs_CXR*): absolute value of cumulative market adjusted stock returns over the 62-day window that ends on the day following the earnings announcement for quarter t-1;

Market capitalization (*LnMV*): natural log of the market value of common equity at the beginning of quarter t-1;

Analyst following (*Num_Analysts*): number of analysts following the firm prior to the earnings announcement date for quarter t-1;

Market to book ratio (*MB*): market-to-book value of common equity at the beginning of quarter t-1;

Earnings volatility (*Earn_Vol*): variance of changes in quarterly earnings per share relative to the same quarter of prior year in the past 16 quarters, scaled by assets per share at the beginning of quarter t-1;

Return volatility (*Ret_Vol*): variance in daily raw stock returns over the 250 trading days prior to the beginning of quarter t-1;

High tech dummy (*High_Tech*): dummy variable with the value of one if the firm reports Compustat SIC codes 2833-2836 (Drugs), 8731-8734 (R&D services), 7371-7379 (Programming), 3570-3577 (Computers), or 3600-3674 (Electronics), and zero otherwise;

Regulated industry dummy (*REG*): dummy variable with the value of one if the firm reports Compustat SIC codes 4812-1813 (Telephone), 4833 (TV), 4811-4899 (Communications), 4922-4924 (Gas), 4931 (Electricity), 4941 (Water), or 6021-6023, 6035-6036, 6141, 6311, 6321, 6331 (Financial firms), and zero otherwise;

CEO tenure (*Tenure*): number of years that the CEO has held the position of chief executive officer as of the beginning of the fiscal year containing quarter t-1;

Institutional ownership (*Inst-Own*): percentage of outstanding shares owned by institutions at the beginning of quarter t-1;

CEO ownership (*CEO-Own*): ownership of the CEO as of the beginning of the fiscal year containing quarter t-1;

CEO chair duality (*Chair-Dual*): dummy variable with the value of one if the CEO has the dual positions of chairman at the beginning of the fiscal year containing quarter t-1 and zero otherwise;

CEO Turnover (*Turnover*): dummy variable with the value of one if the CEO leaves the firm during quarter t and zero otherwise;

Fire sales dummy (*FS*): dummy variable with the value of one if *Forced* is in the bottom ten percentile and zero otherwise;

Absolute value of management forecast biases (*Abs(MFB)*): absolute value of the management forecast bias (*MFB*) (see section 3.2 for the definition of *MFB*);

Analyst forecast biases (*AFE*): difference between actual earnings per share for quarter t-1 and the most recent analyst forecast of earnings per share for quarter t-1 issued prior to the earnings announcement date for quarter t-2, scaled by the share price at the beginning of quarter t-1;

Accounting performance (*ROE*): firm's ROE minus industry median ROE over the four quarters prior to quarter t;

Market performance (*CAR*): cumulative market-adjusted stock returns over 12 months prior to the CEO turnover quarter;

Sales revenue (*LnSALES*): natural log of the sum of sales from quarter t-5 to quarter t-1;

CEO age (*AGE*): age of the CEO at the beginning of the fiscal year including quarter t-1;

Age of 65 dummy (*AGE65*): dummy variable with the value of one if the age of the CEO equals to 64, 65, or 66 and zero otherwise.

TABLE 8

Differential Effects of Management Forecast Biases on CEO Turnover

Management Forecast Issuance Model		CEO Turnover Model	
Variables	Coef.	Variables	Coef.
		Abs(MFB)*MF*FS (1)	**-0.211** (0.041)**
		Abs(MFB)*MF (2)	**0.881** (0.029)**
		MF	0.061 (0.217)
Prev_Forecast	0.878*** (0.002)	FS	-0.651** (0.031)
Abs_CXR	0.511*** (0.005)	AFE	-0.107*** (0.000)
LnMV	0.082* (0.053)	ROE	-0.207** (0.047)
Num_Analysts	0.211** (0.025)	CAR	-0.128** (0.046)
MB	0.019*** (0.003)	Earn_Vol	0.766 (0.139)
Earn_Vol	0.198 (0.727)	Ret_Vol	0.633*** (0.003)
Ret_Vol	7.665 (0.281)	LnSALES	0.025* (0.067)
High_Tech	0.111** (0.026)	AGE	0.022*** (0.000)
REG	-0.127** (0.043)	AGE65	0.328*** (0.005)

Tenure	-0.001 (0.717)	Tenure	-0.008** (0.019)
Inst_Own	0.006** (0.013)	Inst_Own	-0.000 (0.851)
CEO_Own	0.022 (0.215)	CEO_Own	-0.017** (0.014)
Chair_Dual	-0.185** (0.024)	Chair_Dual	-0.089* (0.077)
Constant	-0.557 (0.320)	Constant	-3.004*** (0.000)
Sample Size	18,956		18,956
Test: (1)+(2)	0.670	P value	0.143

The table presents the results of bivariate probit regressions estimated simultaneously based on the sample of 18,956 firm-quarter observations from 1996 to 2010. The dependent variable for the first-stage regression, *MF*, is included as an independent variable in the second-stage (CEO turnover) regression. *FS* = 1 for the firms who experience fire sales by mutual funds, i.e., those stocks that are ranked in the bottom decile according to the *Forced* measure in quarter t (i.e., outflow-driven sale). All variables are defined in Appendix Table 1. The table reports coefficient estimates and (in parentheses) p-values adjusted by time-series correlation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

The results based on the two-stage models are presented in Table 8. As we can see, the results are generally consistent with those in Lee et al. [2012]. For example, the coefficient on the two-way interaction is significantly positive (0.881, P value=0.029), suggesting that MFBs increase CEO turnover likelihood. For the variable of our interest, the three-way interaction term has the significantly negative coefficient (0.211, P value =0.041), consistent with our conjecture that the board less likely punish CEOs for their MFBs if they are used to counter against the stock under pricing. The sum of the two-way and three-way interactions is insignificant, suggesting that overall the outflow-driven MFBs do not increase CEO dismissal risk. To interpret the economic magnitude of the effect, we follow Norton et al. (2004) in calculating the marginal effects of *Abs(MFB)*×*MF* and *Abs(MFB)*×*MF*×*FS*, which are 0.098, -0.053. This means that when *Abs(MFB)* increases by one standard deviation, 0.067 (unreported), the probability of a CEO turnover increases by 0.66% (=0.098×0.067), which accounts for about 25% of the unconditional CEO turnover rate (the mean CEO turnover rate in our sample is only 2.66%); however, when MFBs are used to counter against stock under pricing, such increase in the probability of a CEO turnover is mitigated by 0.36% (=0.053×0.067) and the net increase is only 0.30% (=0.66%-0.36%) and not statistically significant.

6. Conclusion

In this paper, we examine whether managers provide optimistically (pessimistically) biased earnings forecasts in response to fire sales (purchases) by mutual funds. We find that when there are fire sales of mutual funds, managers release optimistic forecasts. On the other hand, managers do not respond to fire purchases of mutual funds by increasing pessimistic biases in forecasts. The results suggest that managers are concerned about downward price pressures but not worried about upward pressures, and they use management forecast biases as a way to raise stock prices when their stock prices have been depressed. Such results become stronger for firms with illiquid stock, for firms under financial constrain or for firms with earnings difficult to be predicted. We also find that MFBs help speed up the stock price recovery.

Previous studies on management forecasts have not examined the effect of stock price pressures on management forecast biases. Our paper shows that exogenous shocks on stock prices from extreme mutual fund flows indeed can lead to biased management forecast disclosures. In this sense, the study enriches the literature on management forecast incentives and properties. Our result that management forecast biases help to mitigate mispricing and speed up the price correction process also adds a new dimension to the consequences of forecast biases. Here, optimistic forecast biases are actually beneficial to investors in that it helps to reduce underpricing. Finally, by showing that exogenous stock price shocks affect management forecast behavior, our study extends prior research documenting that price shocks have an effect on insider trading and on mergers and acquisitions.

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APPENDIX TABLE 1

Variable Definition

Variable	Definition
Variables in the main model	
MFB	Management forecast bias defined as the management forecast less actual earnings deflated by the absolute value of actual earnings.
Forced	The degree to which a stock’s trading is accounted for by mutual funds experiencing significant inflows or outflows.
Litigation	The probability of securities-related litigation lagged by one quarter estimated using a probit model; See Appendix B for variable definitions related to this model.
InsTrd10D	The net volume of insider transactions by officers and directors in the firm's shares scaled by shares outstanding over the ten-trading-day window beginning the day of the forecast.
Zscore	0.3(NIt/Assett)+1.0 (Salest/Assett)+1.4 (Retained Earningst/Assett)+1.2 (Working Capitalt/Assett)+0.6×([Stock Price×Shares Outstandingt]/Total Liabilitiest).
Herf	Industry concentration measured as the Herfindahl index calculated using revenues of all firms in the same four-digit SIC code.
FN	Forecast news defined as the management forecast minus the most recent consensus (mean) analyst forecast deflated by the absolute value of actual earnings.
Horizon	Log value of the number of calendar days between the management forecast and the corresponding earnings announcement.
Car_120	Market-adjusted cumulative abnormal return for the 120 days prior to the forecast release date;
Size	Log value of total assets.
BM	Book-to-market ratio at the end of quarter before the management forecast.
DA_Jones	Discretionary accruals computed using the modified Jones Model.
Unforced	The net trade imbalance of a firm’s shares by unconstrained mutual funds.

Variables in the model of incremental effects	
Illiquidity	The raw Amihud [2002] illiquidity ratio standardized by the average value of the ratio for all stocks traded in the same exchange.
Constrain	The level of financial constrain, measured by Pindex or HPindex, as below.
Pindex	Minus one multiplied by the financial health score of Piotroski [2000], ranging from 0 to 9 with a higher score indicating stronger financial health; one point is given for each of the following items if its value is greater than 0: ROA (= ib/at_lag), CFO (=oancf/at_lag), ΔROA, CFO-ROA, -Leverage (leverage=dltt/at_lag), ΔCurrent ratio (current ratio= act/lct), no common equity issuance (cshi=0), ΔMargin (margin=(revt-cogs)/revt), and ΔTurn (turn=revt/at_lag). Source: Compustat.
HPindex	The financial constraint index of Hadlock and Pierce [2010], equal to -0.737 × Size + 0.043 × $Size^2$ - 0.040 × Age, where Size is the natural log of total assets (Compustat variable at) capped at $4.5 billion, and Age is the total number of years that a firm has been on Compustat capped at thirty-seven years.
Difficulty	The first principal component of the following seven variables: 1) the standard deviation of analyst forecasts outstanding when the management forecast is released, 2) the standard deviation of previous analyst forecast errors scaled by price for five years prior to the release of the management forecast, 3) the indicator variable with the value of one when a firm's quarterly earnings preceding the management forecast is negative and zero otherwise, 4) the indicator variable with the value of one when the management forecast of earnings is negative and zero otherwise, 5) the standard deviation of daily stock price for 120 days before the management forecast date, 6) the average relative bid-ask spread for a 20-trading-day period ending two days before the forecast date, and 7) the width of range forecasts with the value of zero for point estimates.
Variables in the model of price correction	
Car_01	Event period return measured as the market-adjusted cumulative abnormal return from the day of to one day after the management forecast release date.
Esurp	Earnings surprise measured as actual earnings minus the consensus analyst forecast right before management forecast release date deflated by the absolute value of actual earnings.
ABH6Q	Market-adjusted cumulative abnormal return during the six quarters following fire sales (purchases) of mutual funds.
InsTrd1Q	The absolute value of the difference between total shares purchased by insiders and total shares sold by insiders as a fraction of shares outstanding in quarter t.
NetIssue	Log value of the ratio of the split-adjusted shares outstanding in quarter t divided by the split-adjusted shares outstanding in quarter t-1.
Variables in the model of CEO turnover	
PastReturn	Market-adjusted cumulative abnormal return in the 4 quarters prior to the fire sales (purchases) of mutual funds.
MF	Dummy variable with the value of one if the firm issues an earnings forecast during quarter t-1 and 0 otherwise.
Pre_Forecast	Number of quarters for which the firm issued a forecast from quarter t-4 to t-2.
Abs_CXR	Absolute value of cumulative market adjusted stock returns over the 62-day window that ends on the day following the earnings announcement for quarter t-1.
LnMV	Natural log of the market value of common equity at the beginning of quarter t-1.
Num_Analysts	Number of analysts following the firm prior to the earnings announcement date for quarter t-1;
MB	Market-to-book value of common equity at the beginning of quarter t-1.
Earn_Vol	Variance of changes in quarterly earnings per share relative to the same quarter of prior year in the past 16 quarters, scaled by assets per share at the beginning of quarter t-1.
Ret_Vol	Variance in daily raw stock returns over the 250 trading days prior to the beginning of quarter t-1.
High_Tech	Indicator variable with the value of one if the firm reports Compustat SIC codes 2833-2836 (Drugs), 8731-8734 (R&D services), 7371-7379 (Programming), 3570-3577 (Computers), or 3600-3674 (Electronics), and zero otherwise.

REG	Indicator variable with the value of one if the firm reports Compustat SIC codes 4812-1813 (Telephone), 4833 (TV), 4811-4899 (Communications), 4922-4924 (Gas), 4931 (Electricity), 4941 (Water), or 6021-6023, 6035-6036, 6141, 6311, 6321, 6331 (Financial firms), and zero otherwise;
Tenure	Number of years that the CEO has held the position of chief executive officer as of the beginning of the fiscal year containing quarter t-1.
Inst-Own	Percentage of outstanding shares owned by institutions at the beginning of quarter t-1.
CEO-Own	Ownership of the CEO as of the beginning of the fiscal year containing quarter t-1.
Chair-Dual):	Indicator variable with the value of one if the CEO has the dual positions of chairman at the beginning of the fiscal year containing quarter t-1 and zero otherwise.
Turnover	Indicator variable with the value of one if the CEO leaves the firm during quarter t and zero otherwise.
FS	Indicator variable with the value of one if Forced is in the bottom ten percentile and zero otherwise.
Abs(MFB)	Absolute value of management forecast bias (MFB).
AFE	Difference between actual earnings per share for quarter t-1 and the most recent analyst forecast of earnings per share for quarter t-1 issued prior to the earnings announcement date for quarter t-2, scaled by the share price at the beginning of quarter t-1.
ROE	Firm's ROE minus industry median ROE over the four quarters prior to quarter t.
CAR	Cumulative market-adjusted stock returns over 12 months prior to the CEO turnover quarter.
LnSALES	Natural log of the sum of sales from quarter t-5 to quarter t-1.
AGE	Age of the CEO at the beginning of the fiscal year including quarter t-1.
AGE65	Indicator variable with the value of one if the age of the CEO equals to 64, 65, or 66 and zero otherwise.

Appendix TABLE 2
Likelihood Analysis of Litigation
$Prob\ (Lawsuit=1) = G(\alpha + \beta_1 Size + \beta_2 Turn + \beta_3 Beta + \beta_4 Returns + \beta_5 Std\_Ret + \beta_6 Skewness + \beta_7 Min\_Ret + \Sigma High\ Risk\ Industries + \varepsilon_i)$

Variable	Pred. Sign	Coefficient (z-stats)
Size	+	0.123*** (0.000)
Turn	+	0.073*** (0.000)
Beta	+	0.038*** (0.000)
Returns	+	-0.119 (0.186)
Std_Ret	+	-1.820** (0.016)
Skewness	-	0.028 (0.150)
Min_Ret	-	-2.903*** (0.000)
BioT	+	0.178 (0.328)
ComH	+	0.597*** (0.000)
Elec	+	0.537*** (0.000)
ComS	+	0.037 (0.859)
Intercept	N.A.	-5.219*** (0.000)
Pseudo R2		11.65%
Sample Size		457,999

This table presents the results of the regression estimating the probability of litigation. The sample consists of 226,553 firm-quarter observations from 1996 to 2010. Following Francis, Philbrick, and Schipper (1994), Johnson, Kasznik, and Nelson (2001), and Rogers and Stoken (2005), we estimate the probability of litigation using the following probit model: Lawsuit takes the value of one if a securities class action lawsuit was recorded by the Stanford Law School's *Securities Class Action Clearinghouse* during a calendar quarter and zero otherwise. To incorporate the findings in Grundfest and Perino (1997) that lawsuits are filed on average 79 days after a triggering event, we adjust filing dates by 79 days when matching a lawsuit to a calendar quarter. *Size* is the average market value of equity. *Turn* is the average daily share volume divided by the average shares outstanding. *Beta* is estimated by regressing daily returns on the CRSP equally-weighted index returns. *Returns* is quarterly buy and hold returns. *Std_Ret* is the standard deviation of daily returns. *Skewness* is the skewness of daily returns. *Min_Ret* is the minimum daily returns during the quarter. *BioT* is an indicator variable for bio-technology industries (SIC 2833 to 2836), *ComH* is an indicator variable for computer hardware industries (SIC 3570 to 3577), *Elec* is an indicator variable for electronics industries (SIC 3600 to 3674), and *ComS* is an indicator variable for computer software industries (SIC 7371 to 7379), all of which represent high risk industries. We define firms having high legal risk if the ex-ante litigation risk estimated using the above approach is higher than the sample median. All explanatory variables are measured over the calendar quarter. *z*-statistics are reported in parentheses and standard errors are corrected for firm-level clustering.***, ** and * stand for statistical significances based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

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作者简介：Renhui Fu, Antai College of Economics & Management, Shanghai Jiaotong University, Email: renhuifu@sjtu.edu.cn; Guochang Zhang, Business School, Hong Kong University of Science and Technology, Email: acgzhang@hkust.edu.

[1] Our results are quantitatively similar when top and bottom 5% instead of 10% are used to define extreme capital flows.

[2] Our results are quantitatively similar when regress management optimistic forecast frequency (the number of optimistic management forecasts in a quarter) on Forced and the control variables borrowed from Bergman and Roychowdhury [2008]. The results on the interaction between Forced and Illiquidity are weaker, which might be due to the lower statistical power of the sum of binary variables in a quarter relative to the management forecast biases.

[3] Our results are quantitatively similar when the stock price at the quarter beginning is used as the denominator.

[4] Our results are quantitatively similar when firm size is used as the inverse proxy of stock illiquidity. We don't report the results since size can be correlated with many other firm characteristics such as distress risk and B/M ratio.

[5] Following Anilowski et al. [2007], we classify management forecasts with a "CIC Code" of A, F, or Z as point forecasts, and those with a code of B, G, or H as range forecasts. Nearly 90% of the management forecasts in our sample period are either point or range forecasts.

[6] We also find that forecast news (FN, the sum of forecast error (FE) and earnings surprise (Esurp)) is positively related to the market reaction, suggesting that management forecasted good (bad) news increase (decrease) share price, in line with prior literature such as Rogers and Stocken [2005].