Should I Stay or Should I Grow? Feedback Effects of Voluntary Disclosure

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Abstract

We explore the use of voluntary disclosure by managers to solicit market-based feedback on intended investment expenditures. We find that managers adjust their end-of-year investment expenditures upward (downward) in response to positive (negative) stock market reactions to their investment forecasts. These adjustments correlate with higher future performance and the feedback-effects are stronger in firms with more informed trading (greater scope for learning), long-term oriented CEOs (stronger incentives to learn), and lower financing constraints (more freedom to respond to price signals). Finally, we show that managers are more inclined to issue investment forecasts when pre-disclosure stock prices are likely less informative.

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"…disclosures may provoke the capital market's information machinery to go into operation, and the information implicit in the price reactions to such disclosures may allow managers to improve their strategic decision making"

– Dye and Sridhar (2002)

1. Introduction

The idea that stock prices not only *reflect* the manager's actions but also *provide* valuable information back to the manager to guide her decisions is well known. For example, Hayek (1945) notes that in an economic system where the knowledge of the relevant facts is dispersed, prices can coordinate the actions of different participants and relay this information back to the manager allowing her to make better resource allocation decisions. This role of stock prices is referred to as the "feedback effect" of stock prices (see survey by Bond, Edmans and Goldstein (2012)).

While evidence confirming the presence of this channel is rapidly growing (e.g., Bai, Philippon, and Savov (2016); Bakke and Whited (2010); Chen, Goldstein, and Jiang (2006); Edmans, Jayaraman, and Schneemeier (2017); Foucault and Fresard (2014)), relatively less is known about the underlying mechanisms that facilitate or impede feedback. Gleaning a better understanding of such mechanisms is important as feedback effects re-frame the question about how informational efficiency affects real efficiency (see Morck et al. (1990) for early evidence). As Bond et al., (2012) note, what matters for real efficiency is not merely how much total information is in stock prices, but rather how much of this information *was previously unknown* to the decision-marker – a construct they term revelatory price efficiency. Consistent with this view, Bai, Philippon, and Savov (2016) incorporate the role of market-based feedback into the *q*-theory of investment, and show that the connection between investment and stock prices has been increasing over time – which they attribute to greater revelatory price efficiency.

In this study, we focus on voluntary disclosure as one such mechanism that is posited to affect price-based feedback effects. Our focus is motivated by not only the conflicting theoretical predictions about how disclosure affects feedback, but also by the relatively sparse empirical evidence on the topic. Analytical studies (e.g., Bai, Philippon, and Savov (2016)) begin with the premise that managers are unaware of *all* dimensions of firm value, and that outsiders have greater expertise about some aspects of firm performance. Since informed traders impound this information into prices, informed trading is valuable to the firm as the unknown information can only be inferred from prices. The effect of firm disclosure within this context boils down to how it influences informed trading. If public disclosure by the manager and private information acquisition by informed traders are substitutes (e.g., Diamond (1985); Verrecchia (1982)) where both the manager and informed traders obtain information about the firm's fundamentals, more public disclosure may crowd-out private information acquisition (about the unknown aspect) rendering prices less informative to the manager (e.g., Dierker and Subrahmanyam (2017); Gao and Liang (2013)). In this case, voluntary disclosure could reduce price-based feedback.

On the other hand, if informed traders' information advantage lies in better interpreting the value-implications of the firm's disclosure (first modeled by Fishman and Hagerty (1989)), then disclosure can stimulate rather than dissuade informed trading. Bai, Philippon, and Savov (2016) discuss how outsiders can combine information disclosed by the manager with their own private information and communicate this information back to the manager via their trades, in turn allowing the manager to set investment optimally. Similarly, Dye and Sridhar (2002) focus on the particular case of disclosure about an impending strategic action and show that the market reaction to the announcement can provide valuable feedback to guide the manager's subsequent action. The manager looks to the capital market to gauge the desirability of implementing the proposed project, since information about the value of the project is widely dispersed, and can only be inferred from the price reaction to the announcement.[1] Dye and Sridhar (2002) note that disclosure can trigger

[1] This follows from the information-aggregation role of prices in Hayek (1945) and Grossman and Stiglitz (1980).

the capital market's information machinery into action, and the market reaction to the disclosure can provide valuable feedback to the manager. A similar mechanism exists in Langberg and Sivaramakrishnan (2010) where the manager is uncertain about the appropriate action to take given the state of the economy, technological innovations, trends in the industry; and firm disclosure provides the avenue for the manager to elicit the market's assessment of the appropriate action. Firm disclosure in these models facilitates price-based feedback by encouraging informed trading on the value-implication of the disclosure. Since the role of voluntary disclosure in price-based feedback is theoretically ambiguous across the feedback models, it makes for an interesting empirical examination.

Testing how voluntary disclosure affects price-based feedback requires careful consideration of the experimental setting and the type of disclosure. It is important to consider whether the disclosure is about an impending strategic action or one that has already been taken. Theories about the beneficial role of disclosure (such as Dye and Sridhar (2002) and Langberg and Sivaramakrishnan (2010)) point to the ability of the manager to subsequently adjust her proposed action based on the market reaction, as the source of the benefits to price-based feedback. Relatedly, Dow, Goldstein, and Guembel (2017) show that the likelihood of the manager acting on price-based signals renders firm cash flows endogenous to informed trading, thereby making private information acquisition more attractive. Disclosure about historical actions such as quarterly/annual financial statements, on the other hand, seem less relevant to the framework of these "subsequent-action" models. For example, Fishman and Hagerty (1989) model the complementarity between disclosure and informed trading but endow the manager with all relevant information and note that "the information contained in the stock price is itself, of no use to the management".

We select capital expenditure ("capex") forecasts made by managers during the year as the experimental setting. Since capex forecast announcements not only engender a stock price reaction but are also followed by a subsequent investment decision, they seem most amenable to the disclosure setting conceived in the theory. Moreover, capex forecasts are purely voluntary as modeled in the theory. This focus on voluntary disclosure invalidates earnings announcements (i.e., 10-K/Q) or material event announcements (i.e., 8-K). The requirement that the disclosure be about an intended strategic action that can be revised based on market feedback also rules out generic disclosure settings such as management forecasts and conference calls. Further, since theory requires the disclosure to be initiated by the manager, it precludes studying analyst recommendations and forecasts. Finally, in addition to comporting well with the features of feedback-effect theories, the focus on capex forecasts and real effects also provides a natural connection between stock prices and resource allocation efficiency as originally envisioned by Hayek (1945) (see Goldstein and Yang (2017); and Leuz and Wysocki (2016) for recent reviews).

We hypothesize that, if disclosure does indeed facilitate market-based feedback, then managers are likely to adjust their end-of-year investment decisions based on the market reaction to the investment forecasts they make during the year (see Luo (2005) and Zuo (2016) for similar designs in different contexts). In other words, we predict that positive (negative) market reactions to managerial capex forecasts will be correlated with upward (downward) adjustments to actual capital expenditures.[2, 3]

[2] In the hypothesis section, we discuss in greater detail other potential interpretations such as a positive market reaction indicating that the forecasted level is optimal and that the manager should not deviate from it; or a negative market reaction indicating that the manager is taking on too little of the project and that she should scale up further. These alternatives motivate our null – i.e., no association between market reactions and ex-post deviations from the forecast.

[3] Appendix 1 presents an anecdote to illustrate our main result. On April 26, 2010, Newfield Exploration (a Texas-based oil company) announced planned capital expenditures of $1.6 billion, which was met with a positive market reaction of 7.5% (market-adjusted) returns. The company's end-of-year capital expenditures were revised upwards by 23.2% to $1.971 billion. In contrast, the company's November 2014 announcement of planned capital expenditures

We test our prediction using a sample of 17,577 capex forecasts made by 1,790 firms over the period 2003 to 2015, and find that short-window stock market reactions to capex forecasts are indeed positively associated with future adjustments to end-of-year capex expenditures. In other words, managers adjust their investment expenditures upwards (downwards) in cases where the market reacts favorably (adversely) to their forecasts. In economic terms, a one standard deviation increase in the positive market reaction to capex forecasts is associated with an 8.3% upward adjustment of end-of-year capital expenditures relative to forecasted expenditures.

To shed further light on the mechanism driving these associations, we partition capex forecasts based on changes in information asymmetry around these announcements. We expect the association between capex adjustments and market reactions to capex forecasts to be stronger for forecasts with *increases* in information asymmetry around the forecast, as these likely represent greater information processing by informed traders (e.g., Fishman and Hagerty (1989), Kim and Verrecchia (1994, 1997)). Consistent with our prediction, the association between capex adjustments and market reactions is indeed positive and significant only for forecasts with increases in event-period information asymmetry. A one standard deviation increase in market reaction is associated with an 11.9% upward capex adjustment for forecasts that trigger greater information asymmetry, as compared to a 3.2% downward and statistically insignificant adjustment for forecasts that lower information asymmetry.

These results are robust not only to controlling for the self-selection of capex forecasts (more on that below) but also to including firm and time fixed effects. We interpret this evidence as supportive of the feedback channel where managers condition their investment behavior on the market's assessment of their proposed investment plans. To assuage concerns about unobservable

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of $1.6 billion for fiscal year 2016 generated a negative market reaction of -2.4%. The company's actual capital expenditures for 2016 were $1.371 billion – a downward adjustment of 14.3%.

factors, we run a falsification test where we include a pseudo market reaction around a non-forecast date from the pre-announcement period as an additional determinant. We fail to find an association between end-of-year capex adjustments and these pseudo market reactions, while that between capex adjustments and event-period market reactions remains intact. In addition, there is no difference (either economically or statistically) in the coefficient on the pseudo market reaction between forecasts that increase information asymmetry and those that decrease it.

We verify that the possible self-selection of firms into forecasting/non-forecasting groups does not alter our inferences. We follow Heckman's (1979) two-step correction for self-selection by first modeling the likelihood of an investment forecast based on firm-characteristics used by prior studies such as leverage, growth opportunities, firm size, asset tangibility, performance and volatility (e.g., Ali et al., (2017); Li (2010)). Next, we include the inverse-mills ratio from this estimation as an additional explanatory variable in the market reaction tests. While the association between capex adjustments and market reactions remains intact, the coefficient on the inverse-mills ratio is negative (when firm fixed effects are excluded) indicating that unobservable factors correlated with the decision to make an investment forecast are negatively associated with capex adjustments. However, once firm fixed effects are included, the inverse-mills ratio becomes insignificant (while the market reaction variable is unaffected), indicating that most of the unobservable bias is cross-sectional, and that including firm fixed effects purges these effects. Overall, we take assurance that any potential selection-bias does not confound our inferences.

To examine whether these price-based feedback effects correlate with higher firm performance, we correlate capex adjustments made in response to the market reaction to capex forecasts with future performance. We decompose end-of-year capital expenditures into three components – (i) forecasted expenditures, (ii) capex adjustments that correlate with the market reaction to the forecast (i.e., market adjustments); and (iii) other adjustments (i.e., non-market adjustments). We find a positive and significant correlation between market adjustments and future performance – measured using both cash flows and earnings. In contrast, there is no detectable association between non-market adjustments and future performance. We interpret these results as evidence that investment adjustments made by managers in response to market-based learning are performance-enhancing.

Two other channels could explain the positive association between capex adjustments and market reactions to capex forecasts – (i) omitted variables such as the arrival or erosion of growth opportunities could explain both capex adjustments and market reactions, and (ii) reverse causality – where markets preempt the manager's future capex adjustments. While these alternative channels are unlikely to explain why the association between capex adjustments and market reactions to capex forecasts only exists for forecast announcements that increase information asymmetry (as predicted by the feedback channel), the challenge we face is the absence of a proxy for managerial learning (see Edmans et al., (2017)). Thus, our strategy to establish causality follows Rajan and Zingales (1998) who advocate focusing on the details of the theoretical mechanisms (through which feedback is posited to affect investment behavior), and document their workings. We do so via three cross-sectional tests.

First, we split the sample based on the pre-announcement level of informed trading and predict that the association between capex adjustments and market reactions should be pronounced for firms with more informed trading – as managers are more likely to learn from prices in these cases (e.g., Dye and Sridhar (2002); Chen, Goldstein, and Jiang (2006))). Second, we split based on the CEO's long-term orientation following Langberg and Sivaramakrishnan (2010) who predict that price-based feedback should be pronounced for managers who care more about long-term value. Similarly, Dye and Sridhar (2002) note that the feedback-effect should be weaker for entrenched managers, who can afford to disregard the capital market's assessment of their actions. Third, we condition on the level of financing constraints (e.g., Chen et al., (2006), Bakke and Whited (2010) and Edmans et al., (2017)) who contend that price-based feedback should be stronger for *less* financially-constrained firms that can more easily adjust their investment decisions based on market signals. This final split, in particular, highlights the contrast between the feedback channel and the conventional role of disclosure (of reducing information asymmetry) which should be stronger for *more* constrained firms.

We find evidence consistent with the feedback channel in each case – the association between capex adjustments and market reactions is stronger for firms with more informed trading, those whose CEOs are more long-term oriented and those that are less financially constrained. Another benefit of these cross-sectional splits is that it helps rule out alternative explanations. In particular, it is not clear why either omitted variables or reverse causality should be pronounced for firms with more informed trading, long-term oriented CEOs, or lower financial constraints. If anything, reverse causality should be more applicable for firms with *less* informed trading as stock market reactions to disclosures should be stronger when there is less informed trading (see for example, Bhattacharya et al. (2000) who show that Mexican corporate news announcements generate no market reaction, since informed trading causes prices to fully incorporate the information before its public release).

Finally, we examine one possible implication of this feedback channel viz., that the likelihood of issuing of capex forecasts could endogenously be driven by managers' desire to receive investor feedback. This incentive is likely particularly strong when the regular price-formation process is interrupted by non-fundamental shocks such as large mutual-fund outflows (e.g., Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012)). Thus, we predict that managers are more likely to make capex forecasts following periods of large mutual-fund-outflows-based price pressures. Although such non-fundamental shocks could also decrease the informativeness of disclosure-period prices, we expect a countervailing effect stemming from informed traders being drawn into the market by the public announcements to exercise their superior judgment over noise traders (Fishman and Hagerty (1989; Kim and Verrecchia (1994)).[4] In addition, the "informational leverage effect", where the potential to influence the firm's future cash flows encourages informed traders to endogenously acquire more information, is likely to be pronounced around major corporate decisions (see discussion in Dow, Goldstein, and Guembel (2017)).

Using mutual funds' *hypothetical* (rather than actual) trades mechanically induced by flows by their own investors (e.g., Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012)), we find evidence consistent with our predictions. First, not only is information asymmetry in general *higher* around capex forecast announcements (consistent with greater information processing by informed traders), but is also stronger following periods of large mutual-fund-outflows. Consistent with the "informational leverage effect" (Dow, Goldstein, and Guembel (2017)), the larger increase in disclosure-period information asymmetry during outflow periods is more pronounced for capex forecasts (that involve strategic actions with future cash flow implications) than plain-vanilla earnings forecasts. Second, the likelihood of making a capex forecast increases from 6.6% during non-outflow periods to 8.2% during outflow periods – a relative increase of 24%. These

[4] Using earnings announcements as representation of general corporate disclosures, Kim and Verrecchia (1994) observe that "(i)n the absence of announcements there are no opportunities for traders capable of informed judgments to exploit their ability to process public information. This lessens the possibility of information asymmetries arising. Alternatively, earnings announcements stimulate informed judgments. These informed judgments, in turn, create or exacerbate information asymmetries between traders and market makers."

results indicate that managers make voluntary (investment-related) disclosures to substitute for the loss in learning from the stock price that results from non-fundamental-value shocks.

To further bolster this interpretation, we turn to the investment-q literature that shows that investments are more strongly correlated with q when managers learn more from the stock price (e.g., Chen et al., (2006); Bakke and Whited (2010); Edmans et al., (2017)). Consistent with our interpretation, the correlation between investment and q (but not investment and cash flows) is weaker during periods of mutual-fund outflows, and that this weaker sensitivity is concentrated in non-investment forecast periods. In other words, the sensitivity of investment to q is not any different between price-pressure periods and regular periods for firms that make an investment forecast. We interpret these results as evidence that managers issue investment forecasts as a substitute mechanism for gleaning decision-relevant information from market participants.

Our study offers several contributions. First, it contributes to the feedback-effects literature by being one of the first to empirically document the role of voluntary disclosures as one potential mechanism that affects market-based feedback. In contrast to the well-developed theoretical literature on the feedback effect of stock prices on managerial decisions (see Bond, Edmans, and Goldstein (2012) for a review), and the role of disclosure in this context (e.g., Bai et al., (2016); Dye and Sridhar (2002), Langberg and Sivaramakrishnan (2010); Gao and Liang (2013); Goldstein and Yang (2016); Dow, Goldstein, and Guembel (2017)), there is scant empirical evidence on how voluntary disclosure affects price-based feedback. A related study is Luo (2005), which shows that insiders learn from outsiders about whether to proceed with a merger via the price reaction to the announcement. This setting is different because the disclosure of a proposed merger involving a publicly traded target company falls under SEC regulations and various state laws and is not voluntary.[5] Therefore, it cannot speak to how market-based feedback interacts with voluntary disclosure. Similarly, Zuo (2016) shows that managers revise management forecasts based on market reactions to initial forecasts – consistent with feedback. However, in addition to examining earnings rather than capex forecasts, Zuo (2016) does not examine real effects – which is the primary focus of feedback theories including Hayek (1945).

Second, our study contributes to the economic consequences of disclosure. While many studies examine informational consequences (e.g., Greenstone, Oyer, and Vissing-Jorgensen (2006)), there is relatively less evidence on its real effects. Our study points to a novel channel through which voluntary disclosure influences investment decisions within the firm. In doing so, our inferences reinforce the contrast between mandatory and voluntary disclosure in the context of feedback-effects. While mandatory disclosure can potentially weaken managerial learning (e.g., Gao and Liang (2013); Goldstein and Yang (2016)), voluntary disclosure (about an intended strategic action), can reinforce learning by providing feedback for managerial investment decisions, especially when used during periods of non-fundamental shocks to the stock price.

Third, our study provides a hitherto unexplored rationale for voluntary disclosure, viz., to provide a channel through which market participants can provide valuable feedback to the manager to guide her investment decisions. We show that this channel is especially valuable when noise shocks mitigate the ability of regular prices to provide such feedback (consistent with Dow, Goldstein, and Guembel (2017)). Fourth, our results contribute to the interplay between disclosure and information asymmetry. While disclosure is argued to reduce information asymmetry (Diamond (1985)), prior work shows an increase in information asymmetry around the event-

[5] For example, "(t)he filings required by Section 14(d) of the Exchange Act and Regulation 14D provide information to the public about persons other than the company who make a tender offer. The company that is the subject of the takeover must file with the SEC its response to the tender offer on Schedule 14D-9" (source: www.sec.gov).

window (Fishman and Hagerty (1989); Kim and Verrecchia (1994, 1997); Lee, Mucklow, and Ready (1993)). Our study indicates that this increase provides economic benefits to the firm by facilitating superior information processing by informed traders thereby providing decision-relevant feedback to the manager.

We hasten to add that while our empirical evidence supports soliciting-investor-feedback as a potential motive for voluntary disclosure, it is but one of many considerations that can factor into managers' disclosure decisions. We also caution that this motive is more likely to apply to announcements of planned strategic actions such as capex forecasts, where stock prices can offer sharp actionable signals, than to more generic forms of disclosures such as earnings forecasts.

2. Motivation and Hypothesis Development

The idea that information flows can occur from outsiders to the firm is not new and goes back to Hayek (1945) who notes that even if a single person (say the manager) were in possession of all the data for some small, self-contained economic system (say the firm), she would need to solicit inputs from others every time some small adjustment in the allocation of resources needs to be made. By incorporating decision-relevant information possessed by investors dispersed throughout the economy, stock prices are posited to provide such a role by facilitating feedback to the manager and in turn guiding her investment decisions. This role of stock prices in aggregating the information of dispersed investors is referred to as the "feedback effect" of stock prices on managerial decisions (see survey by Bond, Edmans and Goldstein (2012)). While the role of stock prices in aggregating the private information of dispersed investors is also studied in the information economics literature (e.g., Grossman and Stiglitz (1980)), the feedback-effects literature takes this one-step further by examining the ensuing effect of the information aggregation on managerial decision making (i.e., the real-effects perspective).

While empirical evidence documenting the presence of feedback-effects is growing (e.g., (Bakke and Whited 2010; Chen et al., (2006); Edmans et al., (2017); Foucault and Fresard (2014); Luo (2005)), there is relatively less evidence on mechanisms that either strengthen or weaken market-based feedback effects. This paucity exists despite the rich theoretical guidance on such mechanisms. Take for example, the role of voluntary disclosure in market-based feedback. Analytical studies point to both a detrimental as well as a beneficial role for voluntary disclosure, depending on the specifics of the setting and assumptions about informed traders' information acquisition. These assumptions drive whether information disclosed by the manager discourages informed trading (as in Diamond (1985); Dierker and Subrahmanyam (2017) and Gao and Liang (2013)) thus reducing the ability of the manager to glean decision-relevant information from the stock price; or whether disclosure stimulates informed trading (as in Dye and Sridhar (2002); Fishman and Hagerty (1989); Kim and Verrecchia (1994); Langberg and Sivaramakrishnan (2010)) by allowing informed traders to impound their superior interpretation of the firm's disclosure – which in turn guides the manager's subsequent action. Since the substitutive effect of voluntary disclosure on informed trading is generally well-understood, we focus on models that study complementarity between voluntary disclosure and informed trading.

Dye and Sridhar (2002) study market-based feedback in the context of voluntary disclosure about an impending strategic action, and ask "whether capital market prices can perform simultaneously their conventional role of assessing the future cash flow implications of managers' *anticipated* actions, while at the same time serving to *direct* the firm's manager's actions toward the highest cash flow-generating activities". Their analytical model shows that market prices can, generally, perform both roles. The manager, in their model, looks to the capital market to obtain guidance about the desirability of implementing a new project, because information about the value of the proposed action is widely dispersed with no individual possessing this information. Thus, the only way for the manager to obtain the market's collective assessment about the project's value is to infer it from the price reaction to the manager's announcement about the project. Similarly, Langberg and Sivaramakrishnan (2010) examine the resource allocation role of voluntary disclosures when market-based feedback is useful to managers in taking value maximizing actions. Feedback arises in their model because the manager is uncertain about the state-appropriate action, that is, the action that would help realize the firm's full value potential for a given state of the world (e.g., state of the economy, technological innovations, trends in the industry). The manager receives a noisy signal about the underlying state and provides a public signal (say, earnings) based on this information. Informed investors (analysts in the model) use this signal in conjunction with their expertise to generate and publicly disclose information about the state of the world. This latter signal is in turn used by the manager to improve his decision-making.[6] Langberg and Sivaramakrishnan (2010) note that such a modeling structure captures the notion that knowledge of firm-specific information is not enough for decision making, and that the manager must also understand the implications of the external environment.

Thus, the common theoretical insight from these models is that managers look to the stock price to guide their real decisions when information about the value implication of the decision (or an aspect of the decision) is better known to market participants collectively as compared to the manager. Disclosure about the impending action enables these informed traders to impound the

[6] The model assumes that analysts cannot interpret and communicate the underlying state of the world to the manager in the absence of the manager's disclosure.

value implications of the proposed action into stock prices, thereby creating a feedback effect from prices to managerial actions.

To empirically test the prediction, we utilize the setting of managerial investment forecasts. One advantage of this setting, as opposed to other voluntary disclosures (e.g., earnings forecasts or press releases), is that it pertains to a well-defined real action, i.e., capital investments. Therefore, the market reaction to a forecast is likely sharply focused on the specific action, which can potentially provide a strong feedback signal to management.

On one hand, if managers voluntarily disclose investment plans with the intention of eliciting market feedback on the merits of such plans, one would expect the market reactions to investment forecasts to influence managers' subsequent decisions by triggering adjustments of the actual investments away from the initial forecasts. In other words, when investors react favorably (unfavorably) to the planned investment, managers are likely to ex pose expand (curtail) such investments in response.[7] On the other hand, the manager's disclosure about her intended plans may, in the spirit of Dierker and Subrahmanyam (2017) and Gao and Liang (2013), substitute for informed traders' private information acquisition about these plans and their value-implications, thus reducing the ability of managers to glean valuable information from the price – thus reducing market-based feedback. Given these theoretically opposing predictions, we state our first hypothesis in the null as follows:

> *Hypothesis I: There is no association between market reaction to an investment forecast and the deviation of the subsequent investment from that forecast.*

[7] While this prediction follows from the theoretical models we rely on, we acknowledge other possible interpretations to the market reaction. For example, a positive market reaction could signal that the manager's forecast is optimal, and that she should not deviate from it. This interpretation predicts no association between price reaction to forecast and the subsequent adjustment in investment. Alternatively, it could be that a negative market reaction indicates that the manager is taking on too little of the project, and that she should scale up. This works against finding evidence supporting our prediction. These alternative interpretations motivate the null hypothesis – i.e., *no* detectable association between a positive market reaction and the deviation of the subsequent investment from that forecast.

The feedback-channel, if present, implies that the disclosure of an investment forecast is likely to be an endogenous choice influenced by the manager's desire to receive investor feedback about the merits of the contemplated investment. One situation where the manager might need to "*provoke the capital market's information machinery to go into operation*" (see epigraph from Dye and Sridhar 2002)) is when the firm experiences non-fundamental price shocks that impede the manager's ability to learn from the (non-disclosure period) stock price. This follows from Dye and Sridhar (2002) who show that the feedback role of disclosures is stronger when (pre-disclosure) price is less likely to have already impounded this information. We use large mutual fund outflows to capture noise in the stock price (e.g., Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012)).

One concern is that noise trading not only reduces the information content of the pre-disclosure price, but also that of the disclosure period price reaction. We expect this crowding out effect to be counteracted by heightened activities of informed traders during the announcement period to take advantage of their superior judgment over noise traders (Kim and Verrecchia (1994)). Informed trading during announcements can be further enhanced by the "informational leverage effect" of Dow, Goldstein, and Guembel (2017), who relax the common assumption in information economics models (e.g., Grossman and Stiglitz (1980)) that firm cash flows are exogenous to informed trading and show that in a scenario where the manager relies on the market to assess the viability of an investment project, the feedback effect from informed trading to the firm's cash flows (which occurs due to managerial learning) creates an additional incentive effect for information acquisition. Informed traders' expected trading profits increase because the value of the firm is more exposed to the information about the profitability of the risky project, which in equilibrium, incentivizes more informed traders to acquire information, thereby resulting in more informative prices. Furthermore, such incentives and the associated information leverage effect are likely more pronounced around major corporate decisions.

We apply the above insights and make the following prediction:

Hypothesis II: A firm is more likely to issue an investment forecast after it experiences large mutual fund outflows.

A recent working paper by Bae et al. (2017) uses the same capex forecast setting as ours, although their focus is on how managers learn from analysts. It is unclear whether analysts' forecasts and their deviations from management forecasts can serve as an effective conduit for market-feedback because analysts forecast actual rather than optimal capex. In addition, analysts' incentives to cater to management likely interferes with their feedback role. Relatedly, Langberg and Sivaramakrishnan (2010) note that the feedback-effect of analysts would be diminished in the presence of bias and/or catering. Informed traders, in contrast, do not suffer from such conflicting incentives. This is reminiscent of Holmström and Tirole (1993) who point to "the most significant virtue of stock prices – their integrity", and their role as "objective, third-party assessments"

3. Data and Descriptive Statistics

Our data come from several sources: investment forecasts from the IBES Guidance database, accounting data from Compustat, stock price data from CRSP, and probability of informed trading (*PIN*) data from Brown, Hillegeist, and Lo (2004).

To construct the sample, we begin with firms making annual investment forecasts (as covered by IBES Guidance) and match these firms to Compustat using the IBES link file. This gives us an initial sample of 40,785 forecasts between the years 2002 and 2016 (where the year denotes the year when the forecasts are being made). Matching these forecasts with CRSP to obtain short-window market reaction (on the issuance date) reduces the sample to 36,900 forecasts. We delete 17,473 forecasts that are made concurrently with an earnings forecast and another 1,850 that are made in 2016 because we need one-year-ahead (actual) capital expenditures data.[8] The final sample comprises 17,577 investment forecasts made by 1,790 unique firms over the period 2003 to 2015. Our unit of observation in most tables is a firm-quarter.

Panel A of Table 1 present descriptive statistics for this sample. The mean investment forecast is $586.539 million dollars, and the mean (actual) capital expenditures are $654.077 million. Our focal variable, capex deviation (*CAPEX_ADJ*), is defined as the percentage difference between capital expenditures made at the end of the year and the forecasted amount (scaled by the latter). This variable takes a mean value of 10.447, which indicates a 10.447% increase in actual expenditures as compared to the forecast. The market-reaction to the investment forecast is denoted by *CAR*, defined as the cumulative abnormal return (i.e., firm return minus S&P 500 index return) over the 5 days surrounding the investment forecast date (i.e., day -2 to day 2 relative to the forecast date). This variable is denoted in percentage terms and takes a mean value of -0.148, indicating an average negative market reaction of 14.8 basis points.[9] The most favorable market reaction to the investment forecast is 25.35% return while the most negative reaction is -31.359%.

Panel B presents descriptive statistics of firm-characteristics of the forecast sample. Following prior studies such as Ali, Fan and Li (2017) and Li (2010), we select leverage (*LEV*), market-to-book (*MTB*), firm size defined as the log of market-value of equity (*SIZE*), asset tangibility (*TANG*), return on assets (*ROA*), a negative earnings indicator (*NEG_ROA*) and volatility (*ROA_VOL*). Additionally, we include the probability of informed trading (*PIN*) as this is a key partitioning variable in our empirical strategy. We define an indicator *TREAT* to denote

[8] We retain capex forecasts that are made concurrently with quarterly earnings announcements, as the latter might be a potential source that informed traders utilize to better interpret the capex forecast. However, our results are robust to excluding these forecasts (and in fact become stronger).

[9] While the average market reaction is economically small (albeit statistically significant at the 5% level), our empirical strategy exploits the *variation* in this market reaction (with the standard deviation at 8.974%).

the sample of firm-quarters with investment forecasts (i.e., *TREAT*=1). All other firm-quarters are denoted as *TREAT*=0. This sample includes not only firms that have never made an investment forecast during our entire sample period, but also observations of forecasting firms during non-forecasting quarters. As might be expected, there are several differences (all being statistically significant) between these two samples. Forecasting firm-quarters are associated with more leverage (0.286 versus 0.190), lower market-to-book (1.686 versus 1.923) and larger market-values (7.378 versus 5.899), to name a few. Our empirical strategy (described in greater detail below) corrects for these differences in two ways. First, in addition to controlling for the observable differences across these samples, we explicitly model the selection likelihood of an investment forecast in the first-stage, and control for the possible influence of unobservable factors from this stage in the second stage. Second, we include firm-fixed effects in the second-stage that absorb all time-invariant, (un)observable differences across firms and ensure that the identification of focal variables comes from within-firm variation.

Table 2 presents the frequency of investment forecasts by year. There is a generally increasing trend in the number of investment forecasts over time. This likely reflects sample coverage by IBES as well as the increasing likelihood of firms issuing investment forecasts.

4. Real effects of learning from investment forecasts

4.1 Regression model and main results

Hypothesis I predicts that managers would adjust their investment decisions in light of information gleaned from the market reaction to capex forecasts. To test this prediction, we follow prior studies (e.g., Luo (2005), Zuo (2016)) and regress the percentage deviation between the ex-post investment expenditure and the forecasted amount (i.e., *CAPEX_ADJ*) on the market reaction to the investment forecast (i.e., *CAR*). We therefore estimate the following regression:

$$CAPEX\_ADJ_{i,f} = \alpha_i + \gamma_t + \beta_1 CAR_{i,a} + \beta_2 SIZE_{i,a} + \varepsilon_{i,f} \quad (1)$$

where, $CAPEX\_ADJ_{i,f}$ refers to the (percentage) difference between actual capital expenditures made by firm *i* as of year *f* and forecasted capital expenditures announced during quarter *a* (scaled by the latter); $CAR_{i,a}$ refers to (percentage) cumulative abnormal returns in the five-days surrounding the forecast date (made by firm *i* during quarter *a*); $SIZE_{i,a}$ denotes firm size (defined as the log of market value of equity) as of quarter *a*. We augment equation (1) with firm fixed effects (α_i) to control for time-invariant differences across firms, and year-qtr fixed effects (γ_t) to control for the effect of time-trends during our sample period. We cluster the robust standard errors at the firm level but also tabulate results based on clustering at the industry level. Hypothesis I predicts that $\beta_1 > 0$, i.e., the manager adjusts her actual investments upwards (downwards) in response to a positive (negative) stock price reaction to investment forecasts.

Table 3 presents results of equation (1), with the primary variable *CAR* being standardized to have zero mean and unit standard deviation. Model (1) presents univariate evidence where *CAPEX_ADJ* is regressed on *CAR* without controlling for *SIZE* or the fixed effects. Consistent with Hypothesis I, the coefficient on *CAR* is positive (1.141) and significant (p<0.01) indicating that positive (negative) market reactions are associated with increases (decreases) in future capital expenditures as compared to planned expenditures. In terms of economic significance, the coefficient of 1.141 on *CAR* (which represents one-standard deviation) indicates a 1.141% change in capital expenditures relative to forecasts. This represents a 10.9% change relative to the mean capex adjustment (10.447).[10]

[10] Since market reactions to the capex forecast depend on the market's ex-ante expectations of the forecast (which we do not observe), we estimate an alternative model where we regress *CAR* on the difference between the capex forecast and the most recent year's actual capex expenditure. We uncover a positive and significant coefficient on the deviation of the capex forecast from the most recent year's annual capex expenditure (akin to an "ERC").

The above result is robust to controlling for firm size (model (2)), including year-qtr fixed effects (model (3)), firm and year-qtr fixed effects (model (4)), and to clustering by industry rather than by firm (model (5)). The economic significance of *CAR* falls slightly to an 8.3% change in capex adjustment (relative to the mean) in the presence of firm and time effects. Model (6) runs a falsification test by including a pseudo market reaction variable (*CAR_PRE*) defined as the five-day cumulative abnormal returns surrounding a non-forecast day (selected as two weeks prior to the forecast date). While the coefficient on *CAR* remains intact, that on *CAR_PRE* is not only statistically insignificant (p=0.396) but also economically negligible – a one-standard deviation increase in *CAR_PRE* increases *CAPEX_ADJ* by 0.271% which corresponds to a 2.66% change relative to the mean.

To further reinforce the role of *Learning*, we partition capex forecasts based on changes in information asymmetry around the forecast announcement. If our results are indeed due to managerial learning, we expect the association between future capex adjustments and market reactions to capex forecasts to be stronger in forecasts with increases in information asymmetry around the announcement, since these represent greater information processing by informed traders (e.g., Kim and Verrecchia (1994, 1997); Lee, Mucklow, and Ready (1993)). We measure information asymmetry using bid-ask spreads and partition the sample into instances where event-period (i.e., day [-2, 2]) spreads are higher versus lower than those in the pre-event period (i.e., day [-10, -3]). Models (7) and (8) present results for these sub-samples respectively.

Consistent with our prediction, the coefficient on *CAR* is positive and significant only in the "Higher spreads" sub-sample of model (7), while it is negative but insignificant in the "Lower spreads" sub-sample of model (8). These coefficients are not only statistically different from each other at the 5% level, but also economically so. A one standard deviation increase in market reaction is associated with a 11.9% upward capex adjustment for forecasts with higher information asymmetry as compared to a 3.2% (statistically insignificant) downward adjustment for those with lower information asymmetry.

Overall, these results are suggestive of the *Learning* channel at play – managers appear to condition their investment behavior on the market's assessment of their investment forecasts, especially in cases where these markets trigger information processing by informed investors.

4.2 Controlling for self-selection

Clearly, not all firms make investment forecasts, nor do they do so all the time. Thus, it could be that unobservable firm (or industry) factors correlated with firms' decision to make an investment forecast could be driving the observed association between ex-post investment adjustments and the market reaction to investment forecasts. It should be noted that we need to worry only about factors omitted from equation (1). In other words, it is unlikely that macroeconomic factors would be a culprit because equation (1) controls for year-qtr fixed effects.

We follow the classic two-step correction for self-selection proposed by Heckman (1979). First, we model the likelihood of firms issuing an investment forecast as a function of variables used in prior studies – leverage (*LEV*), market-to-book (*MTB*), firm size defined as the log of market-value of equity (*SIZE*), asset tangibility (*TANG*), return on assets (*ROA*), a negative earnings indicator (*NEG_ROA*) and volatility (*ROA_VOL*). Prior studies find that the likelihood of making an investment forecast is positively associated with leverage, asset tangibility, ROA, size and volatility, and negatively with the loss indicator. In addition to the above, we include industry, year and quarter fixed effects. We then include the inverse-Mills ratio (*INV_MILLS*) from this estimation as an additional explanatory variable in equation (1).

Table 4 presents results of this two-stage estimation. Model (1) presents results of the first-stage probit model. Consistent with prior studies, the likelihood of firms making an investment forecast is positively correlated with leverage (*LEV*), firm size (*SIZE*), asset tangibility (*TANG*), *ROA*. We also find a negative association with market-to-book (*MTB*), negative earnings (*NEG_ROA*) and volatility (*ROA_VOL*). The model generates a pseudo r-square of 0.285.

Models (2) and (3) present results of the second stage – with the former specification including year-qtr but excluding firm fixed effects, and the latter specification including both firm and year-qtr fixed effects. We do so to highlight the role of firm fixed effects in this setting. Model (2) shows that the effect of *CAR* on *CAPEX_ADJ* remains positive and statistically significant, indicating that the possibility of self-selection does not alter our inferences. The coefficient on the inverse-Mills ratio (*INV_MILLS*) is negative and significant (p<0.01) indicating that unobservable factors correlated with firms' decision to make an investment forecast are negatively correlated with capex adjustments. However, once firm fixed effects are included (in model (3)), the coefficient on the inverse-Mills ratio becomes insignificant, indicating that most of the unobservables that cause a selection-bias are cross-sectional, and that including firm fixed effects controls for this bias. The coefficient on *CAR* continues to remain positive and significant in this model. Overall, we interpret these results as indicating that any potential selection-bias (even if present) does not confound our inferences. Further, it appears that most of the unobservable factors correlated with firms' decision to make an investment forecast are cross-sectional in nature, and that including firm fixed effects in equation (1) appears to purge these effects.

4.3 Efficiency of capex adjustments

Next, we examine whether capex adjustments made in response to market reactions to the forecasts are value-increasing (as predicted by theory). To do so, we follow prior studies in the managerial learning literature (e.g., Bai, Philippon, and Savov (2016), Chen, Goldstein, and Jiang (2006), Edmans, Jayaraman, and Schneemeier (2017)) and examine the association between capex adjustments and future (accounting) performance. To isolate the component of capex adjustments that corresponds with the market reaction to capex forecasts, we estimate the predicted value from the *CAR* variable in model (3) of Table 4 (we define this *CAPEX_ADJ_MKT*). The remaining component of capex adjustment (*CAPEX_ADJ_OTH*) is defined as total capex adjustments (*CAPEX_ADJ*) minus the market-reaction component (*CAPEX_ADJ_MKT*). Hence, the firm's actual capital expenditures at the end of the year have been broken up into three components – forecasted capital expenditures (*CAPEX_FORE*), capex adjustments that correspond to the market reaction to capex forecasts (*CAPEX_ADJ_MKT*) and other adjustments (*CAPEX_ADJ_OTH*). We scale each of these components by total assets and standardize them so as to have zero mean and unit standard deviation. We correlate the subsequent year's performance with each of these components and predict a positive coefficient on *CAPEX_ADJ_MKT* – i.e., capex adjustments made in response to the market reaction to capex forecasts should be positively correlated with future performance. We continue to include firm and time fixed effects and also the inverse-mills ratio (*INV_MILLS*) in all the specifications.

Table 5 presents the results. We present results based on three measures of accounting performance – cash flows (*CFO*), income before extraordinary items (*IBEI*) and net income (*NI*). Documenting that the results hold for cash flows repudiates any concerns about earnings management of reported performance. Model (1) presents results of the regression of future cash flows on end of year capital expenditures (*CAPEX*), and indicates a positive but insignificant coefficient on *CAPEX*. Model (2) breaks *CAPEX* into its three components as described above. Consistent with our predictions, the coefficient on *CAPEX_ADJ_MKT* is positive and significant

(p. value<0.01), indicating that capex adjustments made in response to market reactions to capex forecasts correspond with higher future performance. A one standard deviation increase in *CAPEX_ADJ_MKT* increases cash flows by 0.002 which corresponds to a 1.9% increase relative to mean cash flows (0.105). In contrast, the coefficient on *CAPEX_ADJ_OTH* is insignificantly correlated with future cash flows. These inferences extend to accrual-based measures of future performance. The coefficient on *CAPEX_ADJ_MKT* is positively and significantly associated with both *IBEI* and *NI*, while *CAPEX_ADJ_OTH* is insignificant in both cases.

Overall, we interpret these results as evidence that market-based feedback effects of voluntary disclosure on the firm's capital investment decisions are value-increasing.

4.4 Cross-sectional tests

While the observed association between capex adjustments and market reactions to capex announcements is suggestive of the *Learning* channel, it could also be driven by correlated (unobservable) factors or by reverse causality. For example, it could be that the arrival of positive NPV projects is explaining both the positive market reactions to capex announcements and also the higher (ex-post) likelihood that these projects will be exercised. Or, it could be that markets are impounding the likelihood that managers will be making future adjustments to their investments – where the causality runs from investment decisions to market reactions and not vice-versa (see Luo (2005) for a discussion of these issues in the context of merger completions). We seek to address these alternative concerns/explanations by conducting cross-sectional tests.

4.4.1 High versus low informed trading

Our first cross-sectional test exploits variation in the amount of informed trading in the pre-announcement period. If the positive association between capex adjustments and market reactions is indeed due to managerial learning, then this should be more pronounced for firms with more informed trading in the pre-announcement period (e.g., Chen, Goldstein, and Jiang (2006), Goldstein and Yang (2016), Gao and Liang (2013)). This is because these are the firms where informed (i.e., sophisticated) traders are more likely to impound the value implications of capex forecasts into market prices and thereby provide guidance to managers. In addition to providing evidence consistent with the *Learning* channel, such a finding would also help rule out alternative explanations. For example, it is not clear why correlated omitted variables should explain the association between capex adjustment and market reactions more in the high informed trading subsample. Similarly, it is hard to envision why the forward looking role of stock prices with respect to future capex adjustments should be stronger for high informed trading firms. If anything, it should be stronger for low informed trading firms, which is where disclosure should have a higher marginal impact in moving stock prices (e.g., Bhattacharya et al. (2000)).

To test the above predictions, we use Easley and O'hara's (1992) probability of informed trading (*PIN*), as estimated by Brown et al., (2002) and split the sample into "Low" and "High" *PIN* (based on the median) as of the quarter prior to the capex announcement. We then estimate our main regression (equation (1)) with both the firm and year-qtr fixed effects within each subsample. Results are presented in Panel A of Table 6. Consistent with our predictions, the association between capex adjustments and market reactions is stronger in the high *PIN* subsample (coefficient on *CAR* is 1.265) as compared to the low *PIN* subsample (*CAR* coefficient is 0.049). A one standard deviation increase in *CAR* increases capex adjustments by 0.5% in the low *PIN* sample, as compared to 12% in the high *PIN* sample. Further, the coefficient on *CAR* is statistically significant only in the high *PIN* sample.[11] Thus, the *Learning* channel seems to be operating only in firms with more informed traders – consistent with theory.

[11] Tests of the differences in the coefficients on *CAR* across the two sub-samples are not significant at conventional levels in the various panels of Table 6.

4.4.2 CEO's long-term orientation

Our second cross-sectional test splits the sample based on how long-term oriented the CEO is. This is motivated by the theoretical model of Langberg and Sivaramakrishnan (2010), who argue that the likelihood that managers adjust their strategic decisions based on market-feedback from sophisticated investors depends on how much the CEO cares about long-term firm value as opposed to short-term price reactions. Hence, the prediction (from their model) that we take to the data is – the association between capex adjustments and stock market reactions to forecast announcements should be stronger for CEO's that are more long-term oriented. We measure CEO's long-term orientation using the value of total restricted stock held by the CEO (obtained from Execucomp). We define "Less" ("More") long-term oriented as firms whose CEOs hold zero (non-zero) restricted stock as of the year prior to the year of capex announcement.

Panel B of Table 6 presents the results. Consistent with our prediction and the theoretical model of Langberg and Sivaramakrishnan (2010), the coefficient on *CAR* is positive and significant in the more long-term oriented sample (coefficient = 0.832), but negative and insignificant (coefficient = -0.264) in the less long-term oriented sample. A one standard deviation increase in *CAR* is associated with upward capex adjustments of 8% in the more long-term oriented sample, as compared to a statistically insignificant *downward* adjustment of 2.5% in the less long-term oriented sample. Similar to the earlier split, the coefficient on *CAR* is statistically significant only in the more long-term oriented sample. We interpret these results as consistent with the *Learning* channel, that should work more forcefully if the CEO cares about long-term firm value and not just the short-run.

4.4.3 Less versus more financially constrained

Our final split conditions on the level of financing constraints, and follows prior studies in this literature such as Chen, Goldstein and Jiang (2007), Bakke and Whited (2010) and Edmans, Jayaraman and Schneemeier (2017). One of the unique features of the *Learning* channel is that it should be stronger for *less* financially-constrained firms because these are the firms that can better adjust their investment decisions based on market signals. This contrasts from the conventional role of disclosure in reducing information asymmetry that should in fact be stronger for *more* financially constrained firms (e.g., Stiglitz and Weiss (1981)). This evidence, if supported by the data, would further reinforce the role of the *Learning* channel in our setting. To capture financing constraints, we exploit recent developments in textual analysis that extract annual measures of financial constraints based on 10-K data. Hoberg and Maksimovic (2014) analyze the Management's Discussion and Analysis (MD&A) section of the 10-K and derive a measure of financing constraints based on instances when managers indicate the potential need to curtail or delay investment – which is suggestive of the firm investing less than what might be optimal due to the existence of challenges to its liquidity. They find that this measure outperforms others used in the literature in predicting investment cuts following negative shocks. We split our sample into "Less" ("More") constrained firms based on their measure of financing constraints, estimated as of the year prior to the forecast year.[12]

Panel C of Table 6 presents these results. Consistent with our predictions and the evidence in prior *Learning* papers, the coefficient on *CAR* is larger (1.407) and significant at the 1% level in the less constrained sample, while it is 0.703 and insignificant in the more constrained sample.

[12] We thank Jerry Hoberg for making these data publicly available. We exclude firms that do not discuss financing-driven investment cuts from the sample. Our results are robust to treating such firms as unconstrained (see Hoberg and Maksimovic (2014) for more details).

A one standard deviation increase in *CAR* increases capex adjustments by a statistically significant 13.5% (statistically insignificant 6.7%) in less (more) financially constrained firms. We interpret these results as being consistent with the *Learning* channel, where lower financing constraints allow firm managers the flexibility of altering investment decisions in response to information gleaned from market reactions to capex forecasts.

5. Mutual fund outflows and the likelihood of making an investment forecast

5.1 Regression model and main results

While the self-selection of firms into forecasting/non-forecasting groups does not seem to affect our inferences, we further probe into why firms issue an investment forecast in the context of managerial learning. After all, prior studies posit that managerial disclosure crowds out outsider information acquisition and thus reduces how much managers can learn from stock prices (see for example, Gao and Liang (2013), Goldstein and Yang (2016), and Schneemeier (2017) for theoretical models).[13] Why then do firms issue investment forecasts?

Hypothesize II predicts that managers are likely to make investment forecasts during periods when non-fundamental price shocks inhibit their ability to learn from the stock price. In other words, we hypothesize that periods such as large mutual fund outflows (e.g., Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012)) reduce the ability of informed traders to impound private information into the stock price (see De Long et al. (1990) for an example of how noise-trading can reduce the equilibrium informativeness of stock prices). Managers respond to this reduced information content of their stock prices by issuing investment forecasts as a substitute mechanism to glean decision-relevant information. We focus on mutual fund outflow shocks as

[13] Arya, Mittendorf, and Ramanan (2017) present a theoretical model where disclosure enhances rather than mitigates managerial learning from the price. This occurs because disclosure in their model is backward-looking while prices reflect both historical and forward looking information. Thus, disclosure helps filter out the historical component, and enhances the role of stock prices in communicating (decision-relevant) forward-looking information.

these have been shown to be uncorrelated with underlying firm-characteristics. Additionally, we follow Edmans et al., (2012) and estimate a measure of price-pressure based on mutual funds' hypothetical trades mechanically induced by flows by their own investors. This helps circumvent the concern with using actual mutual fund trades, as these might be endogenously driven by mutual funds' private information about firm prospects. We assume, similar to Edmans et al., (2012) that following investor outflows, a mutual fund will be pressured to sell shares in proportion to its current holdings. We consider only mutual funds that have experienced outflows of at least 5% of total assets, because only extreme outflows are likely to have an impact on pricing. Hence, for each stock, this measure is the hypothetical (signed) net selling by all mutual funds that have experienced extreme shocks. We define *MF_OF* as an indicator variable that takes the value of 1 (0) for mutual fund outflows that are greater (smaller) than the overall sample median. We then augment the investment forecast likelihood model as follows:

$$\begin{aligned} Pr(TREAT_{i,a}=1) = {} & \alpha_j + \beta_y + \gamma_a + \eta_1 MF\_OF_{i,a-1} + \eta_2 LEV_{i,a-1} + \eta_3 MTB_{i,a-1} + \eta_4 SIZE_{i,a-1} \\ & + \eta_5 TANG_{i,a-1} + \eta_6 ROA_{i,a-1} + \eta_7 NEG\_ROA_{i,a-1} + \eta_8 ROA\_VOL_{i,a-1} + \varepsilon_{i,a} \end{aligned} \tag{2}$$

where, *TREAT* is an indicator for firm *i* in quarter *a*, that takes the value of 1 (0) for quarters when firms make (do not make) investment forecasts; α_j, β_y and γ_a represent 2-digit SIC industry, year and announcement quarter fixed effects respectively. We predict $\eta_1 > 0$, i.e., managers are more likely to issue investment forecasts immediately after periods when they have experienced a mutual fund outflows-driven negative price pressure shock.

We begin by examining changes in information asymmetry around capex forecasts. In particular, we define an "Event" window as days [-2, 2] and a "Non-event" window as days [-10, -3] and [3, 10] surrounding the capex forecast date. We then compare the daily relative bid-ask spread defined as the spread scaled by the mid-point (*SPREAD*) across these windows. Panel A of

Figure 1 presents these results. The vertical axis presents the orthogonalized (with respect to firm-level characteristics as well as firm and time fixed effects) spread while the horizontal axis denotes the non-event versus event periods. The figure indicates higher spreads over the event window as compared to the non-event window, consistent with greater information processing of the capex forecast by informed traders. Panel B splits the sample into periods following mutual-fund-outflows (MF_OF_{a-1}=1) versus all other periods (MF_OF_{a-1}=0). Several noteworthy facts emerge. First, non-event information asymmetry is much lower in periods following mutual-fund-outflows, consistent with a reduced scope for managerial learning from the regular stock price during these periods. Second, the increase in announcement window spreads is much larger in periods following mutual-fund outflows than other periods – consistent with the "informational leverage effect" of Dow, Goldstein, and Guembel (2017).

Panel A of Table 7 presents multivariate regression results, with daily *SPREAD* as the dependent variable. The positive and significant coefficient on *EVENT* (which denotes the average difference in daily spreads between non-event and event periods) corroborates the graphical evidence. This effect is robust to including firm and year-qtr fixed effects in model (2) and extant determinants of spreads such as firm size (*SIZE*), stock liquidity (*TURNOVER*) and return volatility (*RETVOL*) in model (3). The coefficient of 0.015 on *EVENT* in model (3) corresponds to a 20% increase in spreads around capex forecasts (given a median non-event spread of 0.073).

Model (4) distinguishes between mutual-fund-outflow and non-outflow periods. The negative and significant coefficient on *MF_OF* indicates lower non-event spreads in periods following mutual-fund outflows, suggesting diminished managerial learning from the regular stock price. While there is greater information processing around capex forecasts even during non-mutual-fund outflow periods (as seen by the positive and significant coefficient on *EVENT*), this effect intensifies during outflow periods (as indicated by the positive and significant coefficient on *EVENT*MF_OF*). In terms of economic significance, the coefficient of 0.009 on *EVENT* in model (4) corresponds to a 12% increase in information asymmetry (given a median non-event spread of 0.073) around capex forecasts during non-outflow periods. In contrast, the increase in information asymmetry during mutual fund outflow periods is 43%.[14]

While these results are suggestive of the "informational leverage effect" in Dow, Goldstein, and Guembel (2017), they are also consistent with voluntary disclosure models such as Demski and Feltham (1994) and McNichols and Trueman (1994) where informed traders have short-horizons and public disclosure encourages information acquisition by resolving uncertainty sooner. To differentiate between these potential explanations, we contrast between capex forecasts and regular earnings forecasts with the expectation that the "informational leverage effect" should be more relevant for capex forecasts. Model (5) presents results based on introducing an additional interaction term *CAPEX*. Consistent with the limited horizons models of Demski and Feltham (1994) and McNichols and Trueman (1994), the coefficient on *EVENT*MF_OF* is positive and significant indicating greater disclosure-period information asymmetry in periods following mutual-fund outflows. However, this is an incremental effect for capex forecasts as seen by the positive and significant coefficient on *EVENT*MF_OF*CAPEX*. Overall, we interpret these results as evidence of the "informational leverage effect" in Dow, Goldstein, and Guembel (2017).

Panel B of Table 7 presents results for the likelihood of making a capex forecast. In addition to probit (models (1) to (3)), we present OLS results (models (4) to (7)) since probit estimations are sensitive to the inclusion of high-dimensional fixed effects, and we would like to verify robustness to including firm fixed effects. Model (1) presents results of the probit estimation of

[14] Non-event period spreads during outflow periods are 0.051 (i.e., 0.073 – 0.022 (coefficient on *MF_OF*)). These increase by 0.022 (0.009 (*EVENT*) plus 0.013 (*EVENT*MF_OF*)), which corresponds to 43% (0.022/0.051).

equation (2) where we benchmark capex forecast quarters with all firm-quarters on Compustat without an investment forecast. Consistent with our prediction, the coefficient on *MF_OF* is positive (0.150) and significant (p<0.01) indicating that firms are more likely to make an investment forecast immediately after experiencing a negative price-pressure shock due to mutual fund outflows. The economic significance is also meaningful – the probability of firms making an investment increases from 6.6% in non-outflow periods to 8.2% during mutual-fund outflow periods – a relative increase of 24%.

Models (2) and (3) present results based on a propensity-score based matching technique where each forecast-quarter is matched to a non-forecasting quarter based on the non-forecasting firm's predicted propensity to issue an investment forecast given covariates. We re-define *MF_OF* based on the median mutual-fund outflows-based price pressure within this matched sample. Our results remain robust – the coefficient on *MF_OF* remains positive and significant whether we exclude the propensity-model covariates (model (2)) or include them (model (3)). The economic significance of *MF_OF* (as indicated by the reported marginal effects) is unchanged in this subsample – while the (within-sample) likelihood of issuing an investment forecast during non-mutual fund price-pressure periods is 0.449, it increases to 0.551 – a relative increase of 22.7% during price-pressure periods. Models (4) and (5) present results based on OLS rather than probit. The advantage is that it allows for the inclusion of firm fixed effects. While the economic magnitude of *MF_OF* diminishes in the presence of firm fixed effects (model (5)), it remains statistically significant.

These results indicate that managers issue capex forecasts during periods of price-pressure shocks that weaken learning from the equilibrium stock price – consistent with Hypothesis II.

5.2 Mutual fund outflows and investment-q sensitivity

While the above results are suggestive of managers issuing capex forecasts to substitute for the loss in managerial learning during fire-sales periods, they allow for alternative interpretations. For example, it could be that firms issue capex forecasts during periods of mutual fund outflows merely to signal that their growth prospects are intact and that the price-pressure is temporary. Thus, the forecasting behavior might have more to do with managers attempting to realign market expectations rather than managerial learning from the stock price.

To bolster our preferred interpretation, we rely on insights from the investment-*q* literature that shows that investments are more strongly correlated with *q* when managers learn more from the stock price (e.g., Chen, Goldstein and Jiang (2007), Bakke and Whited (2010), Edmans, Jayaraman and Schneemeier (2017)). If mutual fund outflows decrease the extent to which managers can learn from the price, and if managers issue capex forecasts to recoup (some of) the lost learning by learning from market reactions to these disclosures, then we predict that – (i) the correlation between investments and *q* should be *weaker* during periods of mutual-fund outflows driven price pressures, and (ii) especially so for firms that *do not make* capex forecasts. We test these predictions by augmenting the classic investment-*q* regression as follows:

$$\begin{aligned} INV_{i,t+1} = {} & \alpha_i + \gamma_t + \beta_1 q_{i,t} + \beta_2 CFO_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 MF\_OF_{i,t} + \beta_4 MF\_OF_{i,t} * q_{i,t} \\ & + \beta_5 MF\_OF_{i,t} * CFO_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

where *INV* denotes capex expenditures for firm *i* in year *t+1*, scaled by lagged PP&E, *q* represents the (end-of-year) market-to-book ratio, *CFO* denotes cash flow from operations (scaled by total assets), *SIZE* is the log of market value of equity, *MF_OF* is an indicator variable that takes the value of 1 for firm-years where the firm has experienced a large mutual fund outflow shock for the majority of the year (i.e., 3 or more quarters) and 0 otherwise.

We predict $\beta_4 < 0$, since investment should be less sensitive to *q* during periods when mutual fund outflows reduce the informativeness of stock prices in guiding managerial decisions. Table 8 presents the results. Model (1) presents results of the classical investment-*q* regression where investment correlates positively with *q* and also with cash flows. Model (2) presents results of the augmented investment-q regression of equation (3) – as predicted the coefficient on *q*MF_OF* is negative and significant at the 5% level. The coefficient of -0.015 on *q*MF_OF* indicates a 15% decrease (-0.015/0.1) in the reliance of investment on *q* during periods of mutual-fund-outflows based price-pressure shocks. Model (3) includes the interaction of *CFO* with *MF_OF* – which in contrast to the coefficient on *q*MF_OF* is statistically insignificant and indistinguishable from zero (coefficient = -0.002). This is not surprising since price-pressure shocks should only reduce the informativeness of *stock prices* and not cash flows.

Models (4) and (5) split the sample based on firm-years depending on whether firms issue an investment forecast. The results again support our hypothesis – the reduced sensitivity of investment to *q* during periods of price-pressure shocks is concentrated in non-investment forecast periods (as seen by the negative and significant coefficient on *q*MF_OF* in model (4)). In other words, the sensitivity of investment to *q* is not any different between price-pressure periods and regular periods for firms that make an investment forecast (as seen by the insignificant coefficient on *q*MF_OF* that is indistinguishable from zero (0.003) in model (5)). We interpret these results as evidence that managers issue investment forecasts as a substitute mechanism to the equilibrium price in gleaning information that helps them guide investment decisions.

6. Conclusion

We hypothesize that voluntary disclosure can be used as a vehicle by managers to invite investor feedback on firm strategic decisions. This soliciting-feedback role of voluntary disclosure is predicated on the assumption that information flows from the market to the manager (i.e., there is managerial learning). Analyzing a large sample of management investment forecasts from 2003 to 2015, we find evidence consistent with managers strategically issuing investment forecasts to elicit investor feedback and then using such feedback to guide firm real decisions.

Specifically, we study market reactions to managers' investment forecasts and find that favorable (unfavorable) price reactions foretell upward (downward) adjustments of subsequent actual investments relative to the initial forecasts. We further show that this effect is stronger for firms with more informed trading (greater scope for managerial learning), longer-term oriented CEOs (greater managerial incentives to learn), less financial constraint (greater freedom to pursue growth), consistent with managerial learning through market feedback. Forecasting future investment is a voluntary choice by the manager. If the benefits of receiving investor feedback factor into the disclosure decision as we believe, we would expect a manager's desire to learn from the market to affect her likelihood of making an investment forecast. Using mutual fund outflows as non-fundamental shocks to stock prices (which introduce noise into prices and hamper managerial learning), we find that firms experiencing large mutual fund outflows are more likely to issue investment forecasts, consistent with our expectation and with recent theories where cash flows are endogenous to informed trading via the managerial learning effect (e.g., Dow, Goldstein, and Guembel (2017).

We contribute to the voluntary disclosure literature by providing evidence that soliciting market feedback can be an important managerial motive for disclosure. This motive was conjectured in prior analytical work but has not been empirically demonstrated before. Our analysis brings together the learning and disclosure literatures and illustrates the real effects of managerial learning through disclosures. Our findings also highlight the distinction between mandatory and voluntary disclosures -- while mandatory disclosures may crowd out managerial learning, voluntary disclosures can be used strategically to promote learning.

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Appendix 1: Newfield Exploration anecdote

<u>Example 1:</u> April 2010 capex forecast (positive market reaction)

S&P Global
Platts

Newfield Exploration shifts spending to oil from gas

26 April 2010
Platts Commodity News
PLATT
English

New York (Platts)--26Apr2010/435 pm EDT/2035 GMT
Citing the "continued spread between crude oil and natural gas prices," the Houston-based independent producer said it now expects to invest about $700 million in oil projects this year, or about 45% of its $1.6 billion total budget. "Spending reductions in planned gas development programs will offset new oil investments," the company said.

<u>Example 2:</u> Nov 2014 capex forecast (negative market reaction)

Newfield Exploration Co at Bank of America Merrill Lynch Global Energy Conference - Final

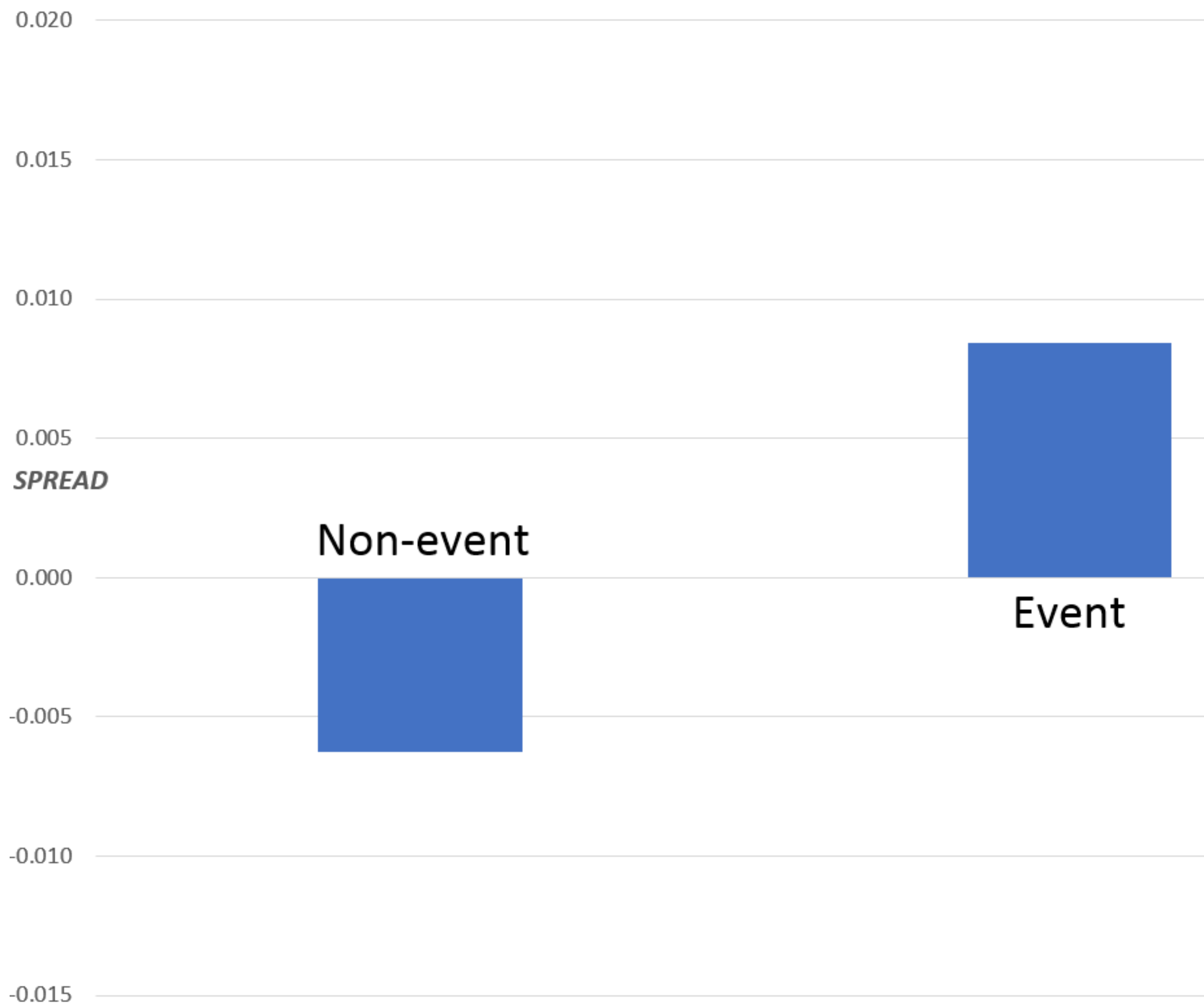
13 November 2014
CQ FD Disclosure
FNDW
English

We expect to show industry-leading liquids growth, and move toward a balanced budget in 2016. Our plan envision annual investment ranges of $1.6 billion to $1.8 billion. At $80 oil, we will likely migrate our investments to the lower end of this range. With the quality of the liquids inventory, especially in the Anadarko Basin, we will deliver on these key objectives.

Figure 1: Information asymmetry around capex forecasts

Panel A: Non-event period versus event-period

The vertical axis presents the orthogonalized (with respect to firm-level characteristics as well as firm and time fixed effects) spread across the two periods. “Event” denotes days [-2, 2] relative to the capex forecast date while “Non-event” denotes the average of days [-10, -3] and [3, 10].



Panel B: Mutual fund outflow periods (*MF_OF*=1) versus other periods (*MF_OF*=0)

The vertical axis presents the orthogonalized (with respect to firm-level characteristics as well as firm and time fixed effects) spread across the two periods. "Event" denotes days [-2, 2] relative to the capex forecast date while "Non-event" denotes the average of days [-10, -3] and [3, 10]. *MF_OF*=1 denotes periods following mutual fund outflows that are greater than the overall sample median. *MF_OF*=0 denotes all other periods.

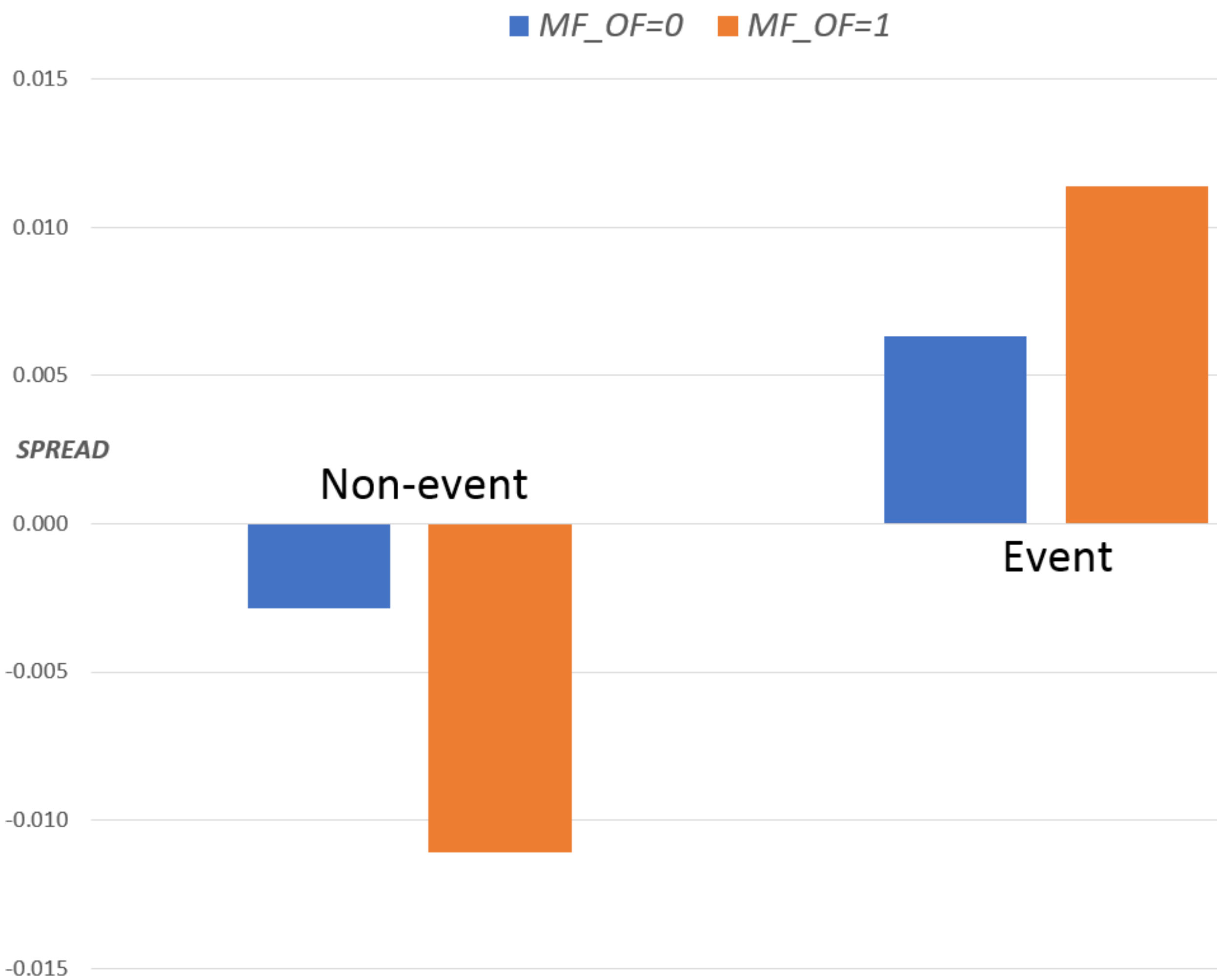


Table 1: Descriptive statistics

The sample comprises 17,577 firm-quarters where 1,790 unique firms make capital expenditure forecasts over the period 2003-2015, and 233,076 firm-quarters for 9,968 unique firms over the same period without forecasts. *CAPEX_FORE* denotes the value of the (annual) capex forecast made by the firm (in US$ millions). *CAPEX_ACT* denotes actual capital expenditures (in US$ millions) pertaining to the year for which the forecast was made. *CAPEX_ADJ* denotes the percentage deviation between actual capital expenditures (*CAPEX_ACT*) and forecasted capital expenditures (*CAPEX_FORE*) scaled by the latter. *CAR* denotes the cumulative abnormal stock market returns (defined as firm return minus S&P 500 index return) over the five-days (day -2 to day 2) surrounding the forecast date and expressed in percentage terms. *TREAT* is an indicator variable that takes the value 1 (0) for firm-quarters with (without) a capex forecast. *LEV* denotes book leverage defined as the ratio of short-term and long-term debt scaled by total assets. *MTB* denotes the market-to-book ratio defined as the market value of assets plus book value of debt scaled by the book value of assets. *SIZE* denotes firm size defined as the log of market value of equity (closing stock price times shares outstanding). *TANG* denotes asset tangibility, defined as the ratio of (net) PP&E to total assets. *ROA* is defined as income before extraordinary items scaled by total assets. *NEG_ROA* is an indicator that takes the value of 1 if *ROA* is negative. *ROA_VOL* denotes volatility defined as the standard deviation of ROA based on the current and past years (i.e., eight quarterly observations). All firm-specific characteristics (*LEV*, *MTB*, *SIZE*, *TANG*, *ROA*, *NEG_ROA* and *ROA_VOL*) are calculated as of the end of the quarter preceding the capex forecast quarter.

Panel A: Event-study variables

Variable	Obs.	Mean	Median	S.D.	Min	Max
CAPEX_FORE	17,577	586.539	120.000	1,318.429	2.000	8,000.000
CAPEX_ACT	17,577	654.077	123.512	1,527.146	0.000	9,496.000
CAPEX_ADJ (%)	17,577	10.447	1.400	51.217	-77.050	290.910
CAR (%)	17,577	-0.148	0.069	8.974	-31.359	25.350

Panel B: Firm-characteristics

	TREAT=1			*TREAT*=0		
Variable	**Obs.**	**Mean**	**Median**	**Obs.**	**Mean**	**Median**
LEV	17,577	0.286	0.264	233,050	0.190***	0.130***
MTB	17,577	1.686	1.373	233,050	1.923***	1.346***
SIZE	17,577	7.378	7.344	233,050	5.899***	5.768***
TANG	17,577	0.454	0.418	233,050	0.208***	0.103***
ROA	17,577	0.004	0.010	233,050	-0.012***	0.004***
NEG_ROA	17,577	0.246	0.000	233,050	0.333***	0.000***
ROA_VOL	17,577	0.022	0.010	233,050	0.031***	0.011***
PIN	7,822	0.108	0.095	149,460	0.197***	0.177***

Table 2: Capex forecasts by year

This panel presents the total number of capex forecasts made during each year of the sample, as well as the number of firms that do so for the first time that year.

Announcement year	Forecasts	First time forecasters
2003	22	22
2004	226	121
2005	488	181
2006	874	235
2007	841	197
2008	1,560	234
2009	2,064	225
2010	1,974	133
2011	2,048	122
2012	1,993	96
2013	1,931	87
2014	1,779	73
2015	1,777	64
Total	**17,577**	**1,790**

Table 3: Real effects of market reaction to capex forecasts

The dependent variable is capex adjustments (*CAPEX_ADJ*) defined as the percentage deviation of the actual capital expenditures from the forecasted expenditures scaled by the latter. *CAR* denotes the cumulative abnormal stock market returns (defined as firm return minus S&P 500 index return) over the five-days (day -2 to day 2) surrounding the forecast date and expressed in percentage terms. *CAR_PRE* denotes pseudo market reactions defined as the five-day market reaction around a non-forecast-date, defined as two weeks prior to the capex forecast date. *CAR* and *CAR_PRE* have been standardized to have zero mean and unit standard deviation. *SIZE* denotes firm size defined as the log of market value of equity (closing stock price times shares outstanding) and calculated as of the end of the quarter preceding the capex forecast quarter. Columns (1) to (6) present results for the entire sample of capex forecasts while model (7) and model (8) split the sample into forecasts with higher and lower bid-ask spreads in the event-window (i.e., days [-2, 2]) as compared to the pre-event window (i.e., days [-10, -3]) respectively. Table 1 contains detailed variable definitions. Robust standard errors are clustered by firm in models (1) to (4) and by industry in models (5) to (8) and are tabulated under the coefficients in parentheses. In addition, model (3) includes year-qtr fixed effects while models (4) to (8) include firm and year-qtr fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	***CAPEX_ADJ***							
Sample	**All forecasts**						**Higher spreads**	**Lower spreads**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CAR	**1.141*****	**1.150*****	**1.148*****	**0.868*****	**0.868*****	**0.870*****	**1.244****	**-0.333**
	(0.401)	**(0.400)**	**(0.405)**	**(0.322)**	**(0.322)**	**(0.322)**	**(0.503)**	**(0.563)**
CAR_PRE						0.278	0.252	0.318
						(0.327)	(0.473)	(0.548)
SIZE		0.960	0.903	0.257	0.257	0.092	0.813	-0.658
		(0.674)	(0.697)	(1.378)	(1.378)	(1.365)	(1.471)	(1.996)
p. value of diff. in:								
CAR							0.039	
CAR_PRE							0.930	
Clustering	Firm	Firm	Firm	Firm	Ind	Ind	Ind	Ind
Fixed effects	None	None	Yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr
Adj. R^2	0.000	0.001	0.005	0.515	0.515	0.515	0.520	0.508
Obs.	17,577	17,577	17,577	17,577	17,577	17,577	9,587	7,785

Table 4: Controlling for self-selection

This panel estimates the Heckman (1969) two-step correction for self-selection where the first stage (model (1)) estimates a probit model of the likelihood of issuing a capex forecast (Pr (*TREAT*=1)), where *TREAT* is an indicator variable that takes the value 1 (0) for firm-quarters with (without) a capex forecast, on firm-level covariates – leverage (*LEV*), market-to-book (*MTB*), firm size (*SIZE*), asset tangibility (*TANG*), performance (*ROA*, *NEG_ROA*) and volatility (*ROA_VOL*). All firm-specific characteristics (*LEV*, *MTB*, *SIZE*, *TANG*, *ROA*, *NEG_ROA* and *ROA_VOL*) are calculated as of the end of the quarter preceding the capex forecast quarter. The inverse-mills ratio (*INV_MILLS*) estimated from this stage is included as an additional explanatory variable in the second stage market reaction regression (models (2) and (3)). The dependent variable here is capex adjustments (*CAPEX_ADJ*). *CAR* denotes the cumulative abnormal stock market returns over the five-days surrounding the capex forecast date and expressed in percentage terms, and standardized to have zero mean and unit standard deviation. *SIZE* denotes firm size. *INV_MILLS* is the inverse Mills ratio from the first-stage probit model. Table 1 contains detailed variable definitions. All regressions include firm and year-qtr fixed effects and robust standard errors clustered by firm (tabulated under the coefficients in parentheses). (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

	First-stage	**Second stage**	
Dep. variable	**Pr (*TREAT*=1)**	***CAPEX_ADJ***	
	(1)	**(2)**	**(3)**
LEV	0.528***		
	(0.083)		
MTB	-0.055***		
	(0.015)		
SIZE	0.136***		
	(0.010)		
TANG	1.009***		
	(0.100)		
ROA	0.556***		
	(0.201)		
NEG_ROA	-0.079***		
	(0.027)		
ROA_VOL	-0.225		
	(0.275)		
CAR		**1.168*****	**0.899*****
		(0.398)	**(0.324)**
SIZE		-2.339***	1.439
		(0.815)	(1.653)
INV_MILLS		**-28.856*****	**11.224**
		(3.476)	**(8.817)**
Clustering	Firm	Firm	Firm
Fixed effects	Year, qtr	Yr-qtr	Firm, yr-qtr
Pseudo/Adj. R^2	0.285	0.039	0.515
Obs.	250,627	17,577	17,577

Table 5: Future performance

The dependent variable in models (1)-(2) is cash flow from operations (*CFO*), while that in models (3)-(4) and (5)-(6) is income before extraordinary items (*IBEI*) and net income (*NI*) respectively, all defined as of the subsequent year and scaled by total assets. *CAPEX* denotes capital expenditures as of the end of the year scaled by total assets. This is broken up into three components – forecasted capital expenditures (*CAPEX_FORE*), capex adjustments that correspond to the market reaction to capex forecasts (*CAPEX_ADJ_MKT*) and other capex adjustments (*CAPEX_ADJ_OTH*). *SIZE* denotes firm size defined as the log of market value of equity (closing stock price times shares outstanding) and calculated as of the end of the quarter preceding the capex forecast quarter. *INV_MILLS* is the inverse Mills ratio from the first-stage probit model. Table 1 contains detailed variable definitions. All regressions include firm and year-qtr fixed effects and robust standard errors clustered by firm (tabulated under the coefficients in parentheses). (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	***CFO_{t+1}***		***$IBEI_{t+1}$***		***NI_{t+1}***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CAPEX	0.004		0.009		0.009	
	(0.003)		(0.017)		(0.017)	
CAPEX_FORE		0.005*		0.003		0.002
		(0.003)		(0.018)		(0.018)
CAPEX_ADJ_MKT		**0.002*****		**0.009*****		**0.009*****
		(0.001)		**(0.002)**		**(0.002)**
CAPEX_ADJ_OTH		0.000		0.004		0.004
		(0.001)		(0.008)		(0.008)
SIZE	0.014***	0.014***	0.021	0.024	0.021	0.025
	(0.004)	(0.004)	(0.021)	(0.020)	(0.021)	(0.020)
INV_MILLS	-0.012	-0.011	0.147***	0.151***	0.138***	0.142***
	(0.016)	(0.016)	(0.053)	(0.053)	(0.053)	(0.053)
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Fixed effects	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr
Adj. R^2	0.708	0.708	0.253	0.254	0.264	0.266
Obs.	16,353	16,353	16,370	16,370	16,370	16,370

Table 6: Cross-sectional tests

The dependent variable is capex adjustments (*CAPEX_ADJ*) defined as the percentage deviation of the actual capital expenditures from the forecasted expenditures scaled by the latter. *CAR* denotes the cumulative abnormal stock market returns over the five-days surrounding the capex forecast date and expressed in percentage terms, and standardized to have zero mean and unit standard deviation. *INV_MILLS* denotes the inverse-mills ratio estimated from the first-stage of the self-selection correction model (i.e., model (1) of Table 4). All regressions control for *SIZE* (not tabulated for parsimony) calculated as of the end of the quarter preceding the capex forecast quarter. Table 1 contains detailed variable definitions. Robust standard errors clustered by firm are tabulated under the coefficients in parentheses. In addition, all models include firm and year-qtr fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Panel A: Informed trading (*PIN*)

This panel splits the forecasting sample into high and low informed trading sub-samples based on the probability of informed trading (*PIN*). Low (High) denotes firms with below (above) median *PIN*.

Dep. variable	***CAPEX_ADJ***	
	Low *PIN*	**High *PIN***
	(1)	**(2)**
CAR	**0.049**	**1.265****
	(0.773)	**(0.603)**
INV_MILLS	39.329*	5.211
	(23.565)	(15.178)
p. value of diff. in *CAR*	0.221	
Controls for *SIZE*?	Yes	Yes
Clustering	Firm	Firm
Fixed effects	Firm, yr-qtr	Firm, yr-qtr
Adj. R^2	0.526	0.573
Obs.	3,950	3,872

Table 6: Cross-sectional tests (continued…)

Panel B: CEO's long-term orientation

This panel splits the forecasting sample into less and more long-term oriented CEO sub-samples based on the total amount of restricted stock granted to the CEO. Less (More) denotes firms with zero (non-zero) restricted stock.

Dep. variable	***CAPEX_ADJ***	
	Less long-term oriented	**More long-term oriented**
	(1)	**(2)**
CAR	**-0.264**	**0.832****
	(0.898)	**(0.395)**
INV_MILLS	17.625	-7.196
	(17.456)	(11.942)
p. value of diff. in *CAR*	0.239	
Controls for *SIZE*?	Yes	Yes
Clustering	Firm	Firm
Fixed effects	Firm, yr-qtr	Firm, yr-qtr
Adj. R^2	0.469	0.519
Obs.	2,401	9,272

Panel C: Financing constraints

This panel splits the forecasting sample into less and more financially constrained sub-samples based on the financing constraints measure of Hoberg and Maksimovic (2015). Less (More) denotes firms with lower (higher) financing constraints than their peers (see Hoberg and Maksimovic (2014) for details).

Dep. variable	***CAPEX_ADJ***	
	Less constrained	**More constrained**
	(1)	**(2)**
CAR	**1.407*****	**0.703**
	(0.457)	**(0.697)**
INV_MILLS	10.545	26.125**
	(14.337)	(10.110)
p. value of diff. in *CAR*	0.350	
Controls for *SIZE*?	Yes	Yes
Clustering	Firm	Firm
Fixed effects	Firm, yr-qtr	Firm, yr-qtr
Adj. R^2	0.546	0.555
Obs.	6,567	6,322

Table 7: Mutual fund outflows and the likelihood of making an investment forecast

Panel A: Information asymmetry around voluntary disclosures

The unit of observation in this panel is an event-day. Models (1)-(4) present results for capex forecasts while model (5) presents results for capex and earnings forecasts. The dependent variable *SPREAD* denotes the daily relative bid-ask spread, defined as the spread scaled by the mid-point. *EVENT* is an indicator variable denoting the event-window around voluntary disclosure announcements, and takes the value of 1 (0) for days [-2, 2] (days [-10, -3] and [3, 10]) relative to the disclosure date. *MF_OF* is an indicator that denotes whether the previous firm-quarter experienced a large (i.e., above median) mutual-fund-based outflow shock. This shock is estimated as the hypothetical (signed) net selling by all mutual funds that have experienced extreme shocks (i.e., an outflow that is more than a 5% of total fund assets). *CAPEX* is an indicator variable that takes the value of 1 for capex forecasts and 0 for earnings forecasts. *SIZE*, *TURNOVER* and *RETVOL* denote firm size, stock turnover, and stock return volatility respectively, defined as of the pre-announcement period (i.e., days [-10, -3] relative to the disclosure date). Robust standard errors are clustered by firm. Models (2)-(5) include firm and year-qtr fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	***SPREAD***				
Sample	***CAPEX* forecasts**				***CAPEX* and *EPS* forecasts**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
EVENT	**0.014*****	**0.015*****	**0.015*****	**0.009*****	**0.009*****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
MF_OF				-0.022***	-0.022***
				(0.005)	(0.004)
*EVENT*MF_OF*				0.013***	0.007***
				(0.002)	(0.002)
CAPEX					-0.015**
					(0.006)
*EVENT*CAPEX*					0.001
					(0.002)
*MF_OF*CAPEX*					0.005
					(0.005)
EVENT*MF_OF*CAPEX					**0.006****
					(0.003)
SIZE			-0.131***	-0.132***	-0.133***
			(0.012)	(0.012)	(0.007)
TURNOVER			-5.700***	-5.780***	-7.899***
			(0.722)	(0.734)	(0.547)
RETVOL			3.961***	3.944***	4.557***
			(0.643)	(0.639)	(0.329)
Clustering	Firm	Firm	Firm	Firm	Firm
Fixed effects	None	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr	Firm, yr-qtr
Pseudo/Adj. R^2	0.000	0.571	0.616	0.616	0.549
Obs.	233,619	233,619	233,619	233,619	940,177

Panel B: Likelihood of making an investment forecast

The dependent variable *TREAT* denotes forecasting quarters. Models (1)-(3) use probit while models (4)-(7) use OLS. Model (1) uses all non-forecasting quarters while models (2)-(7) use a propensity-score based matched sample. Models (6) and (7) split into low and high *PIN* sub-samples. *MF_OF* is an indicator that denotes whether the previous firm-quarter experienced a large (i.e., above median) mutual-fund-based outflow shock. This shock is estimated as the hypothetical (signed) net selling by all mutual funds that have experienced extreme shocks (i.e., an outflow that is more than a 5% of total fund assets). All other variables are as defined in Table 4. Table 1 contains detailed variable definitions. Robust standard errors are clustered by firm. Models (1)-(4) include industry and year-qtr fixed effects while models (5)-(7) also include firm fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	***TREAT***				
Model	**Probit**		**OLS**		
Sample	**Full sample**	**Propensity-score based matched sample**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
MF_OF	**0.150*****	**0.256*****	**0.261*****	**0.103*****	**0.020****
	(0.024)	**(0.050)**	**(0.047)**	**(0.019)**	**(0.009)**
LEV	0.547***		0.187	0.074	0.013
	(0.084)		(0.118)	(0.047)	(0.044)
MTB	-0.053***		0.011	0.004	-0.009
	(0.015)		(0.022)	(0.009)	(0.008)
SIZE	0.138***		-0.008	-0.003	0.014
	(0.010)		(0.018)	(0.007)	(0.010)
TANG	1.017***		0.126	0.050	-0.124**
	(0.101)		(0.146)	(0.058)	(0.061)
ROA	0.559***		-1.478***	-0.580***	-0.198**
	(0.203)		(0.344)	(0.133)	(0.083)
NEG_ROA	-0.073***		-0.120***	-0.048***	-0.005
	(0.027)		(0.039)	(0.016)	(0.009)
ROA_VOL	-0.126		-0.948**	-0.368**	-0.149
	(0.274)		(0.462)	(0.177)	(0.143)
Marginal effect at:					
OUTFLOW=0	0.066	0.449	0.448		
OUTFLOW=1	0.082	0.551	0.552		
Clustering	Firm	Firm	Firm	Firm	Firm
Fixed effects	Ind, yr-qtr	Ind, yr-qtr	Ind, yr-qtr	Ind, yr-qtr	Firm, yr-qtr
Pseudo/Adj. R^2	0.291	0.004	0.007	0.008	0.597
Obs.	250,627	35,150	35,150	35,150	35,150

Table 8: Mutual fund outflows and investment-*q* sensitivity: the role of capex forecasts

The dependent variable is investment (*INV*) defined as capital expenditures as of year *t+1* scaled by fixed assets as of year *t*. *q* denotes Tobin's Q as of year *t*, defined as the market value of equity plus book value of debt scaled by book value of assets. *CFO* denotes cash flows as of year *t*, defined as earnings before extraordinary items plus depreciation and amortization scaled by total assets. *SIZE* denotes firm size. *MF_OF* is an indicator (defined in year *t*) that denotes whether the firm experienced a large (i.e., above median) mutual-fund-based outflow shock. This shock is estimated as the hypothetical (signed) net selling by all mutual funds that have experienced extreme shocks (i.e., an outflow that is more than a 5% of total fund assets). All regressions contain firm and year fixed effects and robust standard errors clustered by firm. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	$INV_{i,t+1}$				
Sample	**Full sample**			**Sub-samples**	
				***TREAT*=0**	***TREAT*=1**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
q	0.098***	0.100***	0.100***	0.099***	0.114***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.023)
CFO	0.049***	0.049***	0.050***	0.050***	0.013
	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)
SIZE	0.017***	0.017***	0.017***	0.017***	0.021**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)
MF_OF		-0.010**	-0.010*	-0.011*	0.029
		(0.004)	(0.005)	(0.006)	(0.018)
q*MF_OF		**-0.015****	**-0.015****	**-0.016****	**0.003**
		(0.007)	**(0.008)**	**(0.008)**	**(0.031)**
*CFO*MF_OF*			-0.002	-0.002	-0.032
			(0.010)	(0.010)	(0.027)
p. value of diff. in:					
*Q*MF_OF*				0.506	
*CFO*MF_OF*				0.258	
Clustering	Firm	Firm	Firm	Firm	Firm
Fixed effects	Firm, year	Firm, year	Firm, year	Firm, year	Firm, year
Adj. R^2	0.339	0.339	0.339	0.331	0.642
Obs.	63,683	63,683	63,683	60,067	3,616