Living up to Analyst Expectations: A Quantitative Analysis of Corporate Short-Termism*

Edward Shore†

Columbia University

January 9, 2024

Abstract

I investigate how external analyst forecasts influence managerial earnings decisions. Using shifts in analyst composition effected by brokerage mergers as a source of exogenous variation, I establish a one-to-one response of firm earnings to analyst forecasts. This response is driven by accounting accruals, consistent with short-termist earnings management. I find that the market perceives these accruals as costly to the firm. I present a model where this behavior emerges as a rational equilibrium, confirmed by a calibration that mirrors a one-to-one forecast-earnings relationship. Calibration outcomes align with real-world earnings and forecast patterns.

*JEL Codes: G17, G24, G30

†Email: edward.shore@columbia.edu; I am very grateful to my PhD advisers, Hassan Afrouzi and Harrison Hong, and my dissertation committee members, Matthieu Gomez and Jennifer La'O, for all of their help and support throughout my PhD. I also want to thank Sandra Black, Matthias Breuer, Alwyn Clarke, Mark Dean, Andres Drenik, Lukas Fischer, Bruno Furtado, Adam Lovett, Andrew Olenski, Noémie Pinardon-Touati, Jose Scheinkman, Michael Woodford, the Cognition and Decision Lab at Columbia University, and seminar participants at the Trans-Atlantic Doctoral Conference for helpful suggestions and advice.

1 Introduction

To what extent does the pressure to achieve short-term goals affect the efficiency of resource allocation within firms? To answer this question, I study the responsiveness of managers to arbitrary shocks in the sell-side analyst forecasts that they face. If earnings respond to random fluctuations in forecasts, and managers prioritize financial appearances over long-term value creation/sustainability to achieve this earnings response, then this is good evidence of short-termism.

A sizeable literature has suggested that managers face pressures to meet analyst forecasts, and that they may act on these pressures.[1] However, causal claims on the relationship between earnings and forecasts are limited by identification strategies that focus on observed bunching in the distribution of earnings relative to forecasts (the so-called 'earnings surprise' distribution), where a greater mass is observed just above zero than just below. This bunching is taken as evidence that managers modify their earnings so as to 'just beat' the forecast.

This approach has four major drawbacks: firstly, as shown by Durtschi and Easton (2009), the shape of earnings surprise distributions is often driven by sample selection bias and scaling, rather than explicit earnings management. Secondly, these specifications only explain local characteristics of the earnings surprise distribution around zero. Thirdly, these approaches are not robust to the problem of 'Guidance', i.e. the process in which managers try to 'guide' analyst forecasts through direct communication. Finally, it is difficult to arrive at quantitative measures of the size of the direct relationship between forecasts and earnings using this approach.

In this paper I develop a new empirical strategy, designed to identify causal responses of earnings to analyst forecasts, that does not suffer from the problems identified above. I implement an instrumental variable approach that utilises brokerage mergers as a source of exogenous and continuous variation in consensus analyst forecasts. When brokerage mergers occur, and the merging firms have multiple analysts covering the same stock, the target firm

[1]See, for example: Burgstahler and Dichev (1997), Bartov, Givoly, and Hayn (2002), Bergstresser and Philippon (2006), Bhojraj et al. (2009), Terry (2015), Almeida, Fos, and Kronlund (2016), Bird, Karolyi, and Ruchti (2019)

analysts are often fired. This generates plausibly exogenous variation in the set of analysts that cover a given firm.

Whilst the use of brokerage mergers as a source of exogenous variation in the set of analysts that cover a firm is not new (Hong and Kacperczyk (2010), He and Tian (2013), Kelly and Ljungqvist (2012), Kim, Lu, and Yu (2018)), my method of operationalizing these merger events is. Rather than focusing on discrete changes in the quantity of analysts covering a firm, as is typical in previous literature, I instead focus on the qualitative changes induced by the brokerage mergers.

I do this by first estimating an analyst fixed effect from forecast data, particular to a given analyst, and fixed over time. Roughly, this fixed effect can be thought of as a measure of the analyst's 'optimism'. I then determine, for each firm in my sample, how the composition of analyst fixed effects of analysts that cover that firm changes in the wake of brokerage mergers. I then use this compositional change as an instrument for variation in the forecast the firm faces. This approach is similar in spirit to the use of judge fixed effects in Dobbie, Goldin, and Yang (2018).

I find that the changes in analyst fixed effects effected by brokerage mergers have significant and economically sensible implications for consensus earnings forecasts. I document a clear and intuitive downward sloping relationship between my instrument and the change in the consensus forecast: when more 'positive' analysts leave a firm's coverage, the subsequent consensus earnings forecast is lower, and vice versa.

I then implement this continuous variation in an instrumental variable regression model to identify the plausibly causal relationship between analyst forecasts and earnings. I find evidence that earnings not only respond directly to analyst forecasts, but that the relationship is roughly one-to-one. After controlling for firm and year fixed effects, plus a battery of firm-level controls, I find evidence of a causal 1.04 standard deviation response in firm-level earnings to a 1 standard deviation sell-side analyst forecast shock, significant at the 1% level. This effect is symmetric, with both positive and negative forecast shocks inducing positive/negative earnings responses respectively.

To the best of my knowledge, my paper is the first to arrive at a measure of the size of the explicit causal relationship between earnings and forecasts. Furthermore, that measure is strikingly large, suggesting a very strong relationship between forecasts and earnings.

I then establish the accounts responsible for the increase in earnings. I decompose earnings into cash flows and accruals, using the comprehensive definition of accruals outlined in Larson, R. Sloan, and Zha Giedt (2018).[2] I find that the earnings response comes entirely through the accruals channel. In contrast to several findings in the literature (He and Tian (2013), Terry (2015)), I find mixed evidence that managers adjust real expenditures like R&D. I conclude that the principal channel of earnings management in response to consensus forecast shocks is through accruals.

The literature is unsettled on whether earnings manipulation via accruals is costly to firms.[3] I shed light on this issue by directly examining the stock market reaction to the consensus forecast shock. Here I assess whether the market views these adjustments as neutral or harmful to firm health. Looking at the entire sample, I find a negative relationship between the consensus forecast shock and monthly stock returns, albeit with limited statistical significance.

The literature remains divided on the cost implications of earnings manipulation through accruals.[4] Given this ambiguity, I use the same framework as before to test for a stock market reaction to the consensus forecast shock. The results indicate a mild negative relationship between consensus forecast shocks and monthly stock returns, though with limited statistical significance.

One concern here is that the forecast shock is likely to have two countervailing effects on the stock price. The first is the direct effect: if forecast shocks are not perfectly revealed to be arbitrary, then they should move market expectations upwards about the underlying quality of the firm. The second is the indirect effect: if forecast shocks encourage accruals-based earnings management, and this harms the firm, then the price should go down. The interaction of these two effects could plausibly 'wash out' the cost of accruals-based earnings management in the overall sample.

To parse out the costs associated with the indirect effect, I take advantage of the relative

[2]Accruals are accounting adjustments for revenues and expenses that have been incurred but not yet recorded in the financial statements.

[3]See Christensen et al. (2022) for a summary of recent papers on accruals.

[4]For a summary of recent papers on the cost implications of accruals, see Christensen et al. (2022).

strength of each channel for large vs. small firms. Specifically, I look at the stock market effect of a consensus forecast shock on a restricted sample of larger firms.[5] The intuition for this approach is that arbitrary forecast shocks are more likely to be identified as arbitrary for larger firms compared to smaller firms, simply because the market is already paying more attention to these firms.

Consistent with this idea, I find that smaller firms experience a positive though statistically insignificant price response to the forecast shock, whereas larger firms experience a negative response. In terms of magnitude, the size is considerable: a one standard deviation shock to the consensus forecast lowers average monthly returns by around 1.82% in the restricted sample of large firms (the standard deviation of average monthly returns in the sample is 2.65%), significant at the 10% level. This finding is robust to several additional exercises that use different assumptions about the size of relative channels.

In summary, my reduced form findings: (i) are consistent with managers engaging in costly earnings management in response to arbitrary forecast shocks; (ii) suggest that the earnings response is symmetric with respect to positive vs. negative shocks; and (iii) indicate that the market views these adjustments as costly. These results naturally prompt the question: if the market is punishing managers for engaging in forecast-based earnings management, why do they go through with it?

In the second part of my paper, I answer precisely this question by building a model of short-termism that rationalizes all three of my reduced form findings. My model is based on the model in Stein (1989). At its core, the Stein model is one of asymmetric information. Managers face a wedge that separates their interests from the interests of their firm: a short-term pressure to maximize the contemporaneous stock price. Managers can engage in costly and unobservable 'borrowing' in an attempt to fool the market into believing the firm is doing well, and hence raise the stock price. This 'borrowing' involves moving future earnings forward to today whilst paying an increasing and convex cost for doing so. In equilibrium managers engage in manipulation, yet the market is not fooled, and the managers are trapped into behaving myopically.

[5] I initially define a 'larger' firm as a firm with total assets in the top quintile of the distribution, though in robustness tests I use several alternative definitions for 'large'.

I modify the model in Stein (1989) for two reasons. Firstly, there are no analysts in Stein's framework. Secondly, there is no co-movement between the model's underlying shocks and the level of earnings management. Given that my results suggest that managers influence their firm's earnings in response to arbitrary forecast shocks, this lack of co-movement is a problem.

Addressing the first concern is simple: I include in the framework an analyst forecast that acts as an additional signal of firm performance. These forecasts are subject to an i.i.d. random shock that is uncorrelated with any other shock in the model, which I take to be isomorphic to the consensus analyst forecast shocks I identify in my reduced form exercise.

Dealing with the second concern is less trivial. In Stein (1989), the lack of co-movement between shocks and earnings management is a direct result of the assumption that there is a linear relationship between some underlying and evolving state of the business and the observed earnings of that business. To break this result in Stein (1989), I generalize the model to allow for a convex relationship between the underlying quality of the business and the earnings that the firm generates. Intuitively, this is isomorphic to assuming increasing returns to scale. Under this assumption, earnings management is increasing in arbitrary analyst forecast shocks, consistent with my empirical findings. Significantly the responsiveness is also symmetric. An additional advantage of the assumption of increasing returns to scale is that this results in an earnings distribution that has positive skew, which is in line with the data.

In the third part of my paper, I calibrate the parameters of my model to match real world data moments. Here my goal is to show that my model is able to generate a one-to-one relationship between earnings management and forecast shocks, whilst also matching key features of the earnings and forecast distributions, all without relying on outlandish parameter values. I find that it is possible to match the data more or less exactly, with parameter values well within bounds suggested by the literature.

I then perform two counterfactual exercises. In the first, I consider a framework in which there is no short-termism. Here my goal is to give some indication to the aggregate efficiency losses associated with short-termism. Under this parameterization, the mean of the earnings-per-share distribution increases by 0.80 standard deviations. This significant efficiency loss comes from the fact that managers are consistently engaging in sizable amounts of earnings management in the model. Removing short-termism eliminates these inefficient allocations.

In the second, I assess whether the presence of analyst forecasts as an additional signal of firm level performance increases or decreases the inefficiencies associated with short-termism. I find that under this new framework, the costs of short-termism are greatly muted. Mean earnings-per-share are 0.62 standard deviations higher once analysts are removed. This result is driven by the fact that the informative signal of analyst forecasts induces greater certainty in the market's beliefs over the firm's underlying state, which in turn increases the incentives of the manager to modify earnings in an attempt to 'trick' the market into believing that the underlying state is high.

Related Literature My paper contributes to three main strands of literature. The first strand concerns the endogeneity of firm earnings to external analyst forecasts (see, e.g., Burgstahler and Dichev (1997), Bhojraj et al. (2009), Almeida, Fos, and Kronlund (2016), Bird, Karolyi, and Ruchti (2019)). This literature typically focuses on the presence of bunching in the earnings surprise distribution (earnings minus the consensus forecast) to identify a causal relationship between earnings and forecasts. I instead use an instrumental variable design that avoids three problems with these existing approaches: (i) I avoid the data concerns related to spurious inferences from earnings surprise distribution bunching (Durtschi and Easton (2009)), (ii) I focus on the entire distribution rather than observations local to the bunching region, and (iii) my approach is robust to the presence of 'Guidance', i.e. the process by which managers attempt to 'guide' forecasts by communicating with analysts directly. I am also able to directly quantify the responsiveness of earnings to forecast shocks, which is not possible using a bunching approach.

The second strand concerns the quantification of corporate short-termism. Here the paper closest to mine is Terry (2015). In that paper, Terry builds a dynamic stochastic general equilibrium model where R&D acts as the principal channel for managerial short-termism. Although this short-termism is endogenised, it is done so in the context of an exogenously assumed payment scheme that punishes managers for falling short of forecasts. He also allows for accruals that induce a private cost to the manager. My contribution differs from

Terry (2015) in three key ways: (i) consistent with my reduced form findings that earnings management plausibly occurs through multiple accruals-based channels, I do not restrict to any specific mechanisms and maintain a general channel for intertemporal borrowing; (ii) to match my finding that the market views accruals-based earnings management as damaging, I model 'accruals' as costly to the firm, not just the manager; and (iii) I do not assume a payment structure to managers that explicitly incorporates a discontinuity around failing to meet forecasts.

This final point is significant, as it relates to my empirical finding that the response to the forecast shock is symmetric for both positive and negative shocks. Under the assumption of a discontinuity in payoffs to the manager for failing to meet the forecast, we would not expect to observe this kind of symmetric response in the data. Rather, this modelling framework seems designed to be consistent with the 'bunching' evidence commonly reported in the literature. As I discuss above, this evidence is hard to interpret, so I see it as a strength of my model that I do not require this assumption, and that my model predictions are additionally able to explain the symmetric response of earnings to forecast shocks.

The third strands relates to the use of analyst forecasts in studies of expectations. In Coibion and Gorodnichenko (2015), the authors develop a test of full information rational expectations, motivated by theory, that involves regressions of macro forecasts on realized macro variables. This methodology has since been applied to analyst level forecasts (see, e.g. Bordalo et al. (2019), Ham, Kaplan, and Lemayian (2022)). Whereas macro forecasters are unlikely to play a significant role in shaping macro variables, the results in this paper suggest that the same is not true for analyst forecasts. Awareness and mitigation of the endogeneity present in analyst forecasts and firm level is essential to avoid bias in estimates of expectation formation using this data.

Roadmap. Section 2 describes the data that I use for my reduced form and structural exercises. This data is a combination of readily available firm level data and some hand collected evidence on brokerage mergers. Section 3 describes my reduced form exercise and findings. Section 4 outlines my theoretical model. Section 5 discusses the model calibration, and outlines counterfactuals. Section 6 discusses my findings. Section 7 concludes.

2 Data

I use publicly available data on forecasts, earnings, and other firm fundamentals. For my identification strategy, I also require data on brokerage mergers, which requires hand collection. The details of my data collection on brokerage mergers, which is based on the work in Gibbons, Iliev, and Kalodimos (2020), can be found in Section 2.3.

2.1 Forecast Data

I use the IBES database as my source for analyst forecasts. IBES is a standard database of analyst forecasts, with wide use across the literature. It also has the highest coverage across alternatives. For these reasons, I focus on IBES forecasts.

IBES Detail is a historical forecast database that collates analyst estimates on a number of forecast measures. The dataset offers comprehensive coverage of US publicly traded firms, from 1982 through to the 2020. I use the diluted, annual earnings-per-share (EPS) forecast as my measure of Wall Street earnings forecasts. Diluted EPS forecasts are the most well-populated in the IBES Detail dataset, and also the variable typically used when reporting earnings performance relative to forecast (So (2013), Kothari, So, and Verdi (2016)).

Whilst EPS forecasts are available across a fairly long horizon, by far the most represented of these forecasts are the 'F1' and 'F2' forecasts —these are forecasts of annual earnings-per-share for the upcoming year and the year after respectively. To maximize the number of observations, and hence the precision of the estimation, I use both 'F1' and 'F2' forecasts to estimate analyst fixed effects. In total, there are around 3.7 million 'F1' and 3.5 million 'F2' EPS forecasts, covering 16,521 unique firms for forecast period end-dates from 1989-2023. Using both 'F1' and 'F2' forecasts means I have, on average, 311.3 forecasts for each analyst. Using only 'F1' would drop that number to 167.1 forecasts.

I also make use of the IBES Summary dataset to collect the IBES consensus forecasts; this is the consensus forecast that is typically used for market tests (Brown (2001), Lim (2001), Bartov, Givoly, and Hayn (2002)). I use the most recent consensus forecast prior to the forecast period end-date as the measure that earnings performances are compared against; again, this is because market tests are typically performed relative to this measure. I use the change to the mean forecast (IBES Summary item 'MEANEST') in my main analysis, although the results are near identical if I instead use the change to the median forecast (IBES Summary item 'MEDEST').

2.2 Firm Fundamentals and Earnings

For firm fundamentals, I use the CRSP-COMPUSTAT merged database. CRSP-Compustat is a standard and comprehensive database containing annual fundamental financial and market information for US publicly traded firms across the same time period as IBES estimates.

For my measure of earnings, I use Compustat item 'EPS-FX' —that is diluted earnings per share excluding extraordinary items —and also subtract special items (Compustat item 'SPID'). Philbrick and Ricks (1991) show that IBES earnings data is often unreliable, which motivates the use of the Compustat data. I follow the example of Bradshaw and R. G. Sloan (2002) and So (2013), in excluding extraordinary and special items; IBES earnings and analyst forecasts often exclude non-recurring items that are included in Generally Accepted Accounting Principles (GAAP), and would therefore appear in the Compustat data under earnings. Excluding extraordinary or special items then ensures that earnings and earnings forecasts are directly comparable.

For controls, I follow the guidelines in So (2013). Specifically, I control for the one-year lagged values of: the log of assets, the log of market-to-book ratio, the log of the end-of-year stock price, the dividends-per-share, the return on assets, and the leverage. I also control for the contemporaneous number of analysts covering the firm.

2.3 Brokerage Mergers

In the past, the process of identifying brokerage mergers was simple, as IBES tracked analyst and brokerage names. In 2018, these were anonymized. To meet this challenge, I follow the methodology in Gibbons, Iliev, and Kalodimos (2020). This method allows me to identify 27 brokerage mergers across the 1990-2020 sample period.

I first link the IBES Recommendations database to link analyst names to forecasts[6]. I

[6] IBES Recommendations is an accompanying database containing buy/hold/sell recommendations for IBES tracked companies that still includes analyst names

Table 1: Identified Mergers

This table presents the 27 mergers that I identify in the data. Since 2018, brokerage names have been anonymised by the owners of the IBES dataset, Thomson Reuters. To get around this problem, I follow the strategy in Gibbons, Iliev, and Kalodimos (2020), using IBES Recommendations to identify analyst names, and then finding these analysts on Bloomberg to identify the name of the brokerages they work at. I then validate that mergers occur by searching Factiva for evidence that a merger took place.

Brokerage	Closure Date	Merger	No. Analysts Dropped	No. Firms Affected
Advest	September 19th 2005	Merrill Lynch	2	11
Alex Brown	April 8th 1997	Bankers Trust New York Corp	8	35
Ferris Baker Watts	February 14th 2008	RBC Dain Rauscher	11	92
JC Bradford	May 1st 2000	PaineWebber Group	6	37
Natwest Equities	November 23rd 1997	Bankers Trust New York Corp	3	8
CRT Capital	March 22nd 2016	Cowen	11	114
Dahlman Rose	February 1st 2013	Cowen	6	91
Dain Rauscher Wessels	September 28th 2000	RBC	18	132
Donaldson, Lufkin and Jenrette	August 30th 2000	Credit Suisse	33	253
AG Edwards	May 31st 2007	Wachovia Securities	17	172
Equitable Securities	September 26th 1997	SunTrust Banks, Inc.	6	26
Fox Pitt Kelton Cochran Caronia Waller	September 30th 2009	Macquarie Group	3	4
Soundview Technology Group	December 3rd 2003	Charles Schwab	9	74
Hamilton Investments Inc.	January 13th 1995	New York Bancorp	2	3
ISI Group	October 31st 2014	Evercore	2	26
Josephthal Lyon and Ross	September 18th 2001	Fahnestock Viner Holdings Inc.	1	21
Kemper Securities	April 11th 1995	Zurich Insurance	5	26
Kidder Peabody	October 18th 1994	PaineWebber Group	16	142
Legg Mason	November 10th 2005	Citigroup	4	42
Morgan Keegan	April 5th 2012	Raymond James Financial	5	69
Parker/Hunter	February 23rd 2005	Janney Montgomery Scott	1	6
Dean Witter Reynolds	February 6th 1997	Morgan Stanley	11	90
Sandler O'Neill	July 9th 2019	Piper Jaffray	3	20
Volpe Brown	December 13th 1999	Prudential Securities	4	30
Thomas Weisel	April 26th 2010	Stifel Financial	5	28
Wertheim	July 7th 1994	Schroders plc.	37	151
Wunderlich Securities	May 18th 2017	B. Riley Financial	3	28
Total			232	1,419

then search for these analyst names on Bloomberg to identify the name of the brokerage firm the analyst was working for at the time of each reported forecast.

I then identify brokerage mergers by finding the date of the last forecast registered to that brokerage in the IBES dataset. I then search on Factiva for any news reports regarding brokerage closures around this date. If the brokerage was part of a merger, I note the date of the merger, and include it in my dataset. For any closures that are not related to a merger, I do not include the brokerage closure in the dataset.

I identify analysts who exit the sample due to brokerage mergers as those who posted their last forecast between six months before, and one month after the brokerage merger date.

This process results in 27 mergers, and 232 analyst exits due to mergers. Table 1 offers more detail, including the number of analysts that exit in the wake of the merger, and the

Table 2: Summary Statistics of Firms with Exiting vs. No Exiting Analysts

In this table I show summary statistics of the firms in my sample that experience an analyst exit from a brokerage merger, compared to those firms that do not experience an exit. Firms experiencing exits are larger in asset size, have higher earnings, income, and sales, and employ more people.

Analyst Exit?	No				Yes				
Variable	N	Mean	SD	Median	N	Mean	SD	Median	Test
EPS	11,200	0.34	1.3	0.31	1,006	1.2	1.2	1.2	F= 386.869***
Sales	11,199	1,448	7,548	197	1,006	6,185	16,943	1,183	F= 272.798***
Cost of Goods Sold	11,193	987	5,924	101	1,006	4,086	12,624	671	F= 195.567***
Net Income	11,200	62	437	4	1,006	391	1,176	63	F= 345.124***
Total Assets	11,194	5,098	49,237	381	1,006	10,494	34,743	2,268	F= 11.565***
Plant, Property, and Equipment (Net)	10,976	707	4,693	33	981	2,536	7,865	312	F= 119.213***
Market Value	9,029	1,993	8,615	359	944	10,178	28,951	1,962	F= 390.973***
Stock Price	11,195	20	20	15	1006	32	19	30	F= 367.892***
Employees	10,846	5.2	20	0.74	1,005	21	64	4.6	F= 326.465***
Total Dividends	11,157	40	266	0.08	1,006	177	578	13	F= 186.568***
Common Shares Outstanding	11,172	80	280	28	1,006	246	632	70	F= 242.759***
Shareholder Equity	11,183	899	5,023	140	1,006	3,001	7,686	751	F= 145.557***

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

number of firms affected by these exits. In total, 1,437 firms were affected by changes in the analyst set effected by mergers.[7]

2.4 Merging the datasets

Merging IBES and Compustat data is non-trivial —no simple, one-to-one mapping of the two datasets exists. I implement Python code available on the Wharton Research Data Services (WRDS), known as 'IClink', that maps IBES 'Ticker' identifiers to CRSP 'PERMNO' identifiers. These linkages are scored from 0 to 6 based on their accuracy, with 0 being the most accurate and 6 the least. The scores are computed by comparing information on company name and Exchange Ticker symbol corresponding to linkages. Using this link, I can match IBES data with Compustat data using the CRSP/Compustat merged database. In the main analysis, I restrict to linkages that score the highest (score of 0). As a consequence, I experience some loss of data —my final dataset consists of an unbalanced panel of 102,435 firm-year observations, for 12,342 unique firms, from 1990 to 2020, with 1,099 unique firms affected by brokerage mergers.

Table 2 shows some summary statistics of firms who experience an analyst exit due to a brokerage merger, versus those that don't. Unsurprisingly, firms that experience an exit are

[7]Note that the sum of the firms affected by each individual merger does not sum to the total number of unique firms affected (it sums to 1,759). This is because some mergers affect the same firms.

larger, more valuable, have higher earnings, and pay out more total dividends. Given that these variables all correlate with analyst coverage, and given that the identification strategy supposes a plausibly random change to coverage, we would expect to see such firms affected more often than their smaller counterparts.

3 Reduced-Form Estimation of Earnings Response to Analyst Forecast Shocks

3.1 Identification and Methodology

Here I outline a novel identification strategy for estimating causal earnings responses to analyst forecasts. I look at the change in the composition of analyst 'fixed effects' induced by brokerage mergers. When brokerage mergers occur, they do so for reasons plausibly exogenous to the firms that they cover. Mergers typically result in analyst job loss, inducing plausibly exogenous variation in the set of analysts covering a firm. It is this variation that I use to identify my results.

My approach is based on Hong and Kacperczyk (2010). Where my strategy differs from Hong and Kacperczyk (2010) is that, rather than a discrete change in coverage, I estimate a continuous and qualitative dimension to the change in the set of analysts. This setup allows me to implement an instrumental variable (IV) estimation design.

3.1.1 Model Specification

I want to study the causal impact of analyst forecasts on firm earnings. A major concern is that forecasts are clearly endogenous to earnings. A simple OLS regression will result in biased coefficients, because the error term will contain factors that correlate with both earnings and forecasts. To get around this problem, I propose using an instrumental variable approach using qualitative changes in the set of analysts that cover a firm in the wake of brokerage mergers.

Suppose that the set of analysts that cover firm i at time t is denoted by $A_{i,t}$. This set of analysts produce forecasts of earnings-per-share, $EPS_{i,t}$, for firm i at time t. Denote by $\mathbb{F}_{t-1}[EPS_{i,t}]$ the *consensus* forecast, i.e. the average of all individuals analyst forecasts, $\mathbb{F}_{a,t-1}[EPS_{i,t}]$, in the set of analysts covering firm i at time t, $A_{i,t}$. Then:

$$\mathbb{F}_{t-1}[EPS_{i,t}] = \frac{1}{|A_{i,t}|} \sum_{a \in A_{i,t}} \mathbb{F}_{a,t-1}[EPS_{i,t}] \tag{1}$$

My goal is to estimate regressions of the following form:

$$\Delta EPS_{i,t} = \phi_i + \tau_t + \beta \Delta \mathbb{F}_{t-1}[EPS_{i,t}] + \Gamma X_{i,t} + \nu_{i,t} \tag{2}$$

where $\Delta EPS_{i,t}$ is the change in actual earnings-per-share of firm i at time t, $\Delta \mathbb{F}_{t-1}[EPS_{i,t}]$ is the change in the consensus forecast of earnings-per-share, where the consensus is defined as in Equation 1, ϕ_i and τ_t are firm and time fixed effects respectively, and $X_{i,t}$ is a vector of firm-level controls.

My hypothesis is that exogenous changes to $\mathbb{F}_{t-1}[EPS_{i,t}]$ could cause firms to modify their earnings. A clear concern is apparent: changes in $\mathbb{F}_{t-1}[EPS_{i,t}]$ are endogenous to firm characteristics by construction. I resolve this problem by looking at changes in $\mathbb{F}_{t-1}[EPS_{i,t}]$ around a small window in which $A_{i,t}$ changes. This creates a new concern (changes in $A_{i,t}$ may also be endogenous) that I address by looking at changes in $A_{i,t}$ that are induced by brokerage mergers.

Changes in $A_{i,t}$ induce at least two important effects on firms. Firstly, after exit, the number of analysts is lower. It is this component of the brokerage merger effect that was first considered in Hong and Kacperczyk (2010), and has seen broad application in subsequent papers (for example, Kelly and Ljungqvist (2012), He and Tian (2013)). Secondly, the *composition* of analysts covering the firm has also changed. To illustrate, suppose that each analyst's forecast is composed of an analyst fixed effect, a firm-year fixed effect, and some error term:

$$\mathbb{F}_{a,t-1}[EPS_{i,t}] = \alpha_a + \tilde{\phi}_{i,t} + u_{a,i,t} \tag{3}$$

Then consider the following decomposition of the consensus forecast:

$$\begin{aligned}\mathbb{F}_{t-1}[EPS_{i,t}] &= \frac{1}{|A_{i,t}|}\sum_{a\in A_{i,t}}[\alpha_a+\phi_{i,t}+u_{a,i,t}] \\ &= \left[\frac{1}{|A_{i,t}|}\sum_{a\in A_{i,t}}\alpha_a\right]+\phi_{i,t}+U_{i,t}\end{aligned} \tag{4}$$

The term in square brackets contains the average fixed effects of the analysts that cover firm i, i.e. all analysts in the set $A_{i,t}$. When analysts exit, this component of the consensus forecast changes, and its change will be related to the underlying α_a of the exiting analysts. To see this, note that the change in the consensus forecast can be expressed as:

$$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] = \left(\left[\frac{1}{|A_{i,t}|}\sum_{a\in A_{i,t}}\alpha_a\right]-\left[\frac{1}{|A_{i,t-1}|}\sum_{a\in A_{i,t-1}}\alpha_a\right]\right)+\Delta\phi_{i,t}+\Delta U_{i,t} \tag{5}$$

The goal is therefore to identify changes to the analyst fixed effect component that are exogenous to the change in firm productivity, as captured by $\Delta\phi_{i,t}$. I propose to use changes in this composition of analyst fixed effects, induced by brokerage mergers.[8]

3.1.2 Estimating Analyst Fixed Effects

A key component of my identification is the estimation of analyst 'fixed effects'. An analyst fixed effect is a unique, time-invariant descriptor of that analyst's forecast behavior, which I estimate using standard techniques. I focus on a holistic fixed effect that describes the analyst in general, rather than an analyst-firm fixed effect, as this increases the number of observations I can use in my estimation by a factor of 10. I also restrict to analysts with at least 30 forecasts to avoid extreme values of the fixed effects (Breuer and Schütt (2021)).

I isolate the analyst-specific variation in forecasts by estimating the following regression

[8]Throughout the paper, I focus on changes in the forecast, rather than levels. The reason for this is that my identification strategy rests on changes in the composition of analyst fixed effects, rather than levels. In the appendix, I also include results for levels. The final conclusions are the same, though the first stage is slightly weaker.

using my entire dataset of diluted EPS forecasts from the IBES dataset:

$$\mathbb{F}_{a,t-1}[EPS_{i,t}] = \alpha_a + \psi_{FPI} + \phi_{i,t} + u_{a,i,t} \tag{6}$$

Here, α_a is an analyst fixed effect, ψ_{FPI} is a Forecast Period Indicator that identifies whether the forecast is an 'F1' or 'F2' forecast (one year or two years ahead respectively), and $\phi_{i,t}$ is a firm-time fixed effect designed to pick up any firm or time-specific variation within the forecasts. As discussed in Section 2.1, I use both 'F1' and 'F2' forecasts as this roughly doubles the number of observations I can use to estimate analyst fixed effects (from an average of 160.1 forecasts per analyst to 311.3).

3.1.3 Constructing the instrument

In this subsection I outline how I construct the novel instrument. I argue that brokerage mergers induce changes in the composition of analyst fixed effects, and that these changes have plausibly significant consequences for subsequent consensus forecasts.

To run an instrumental variable regression, I need to convert the variation in analyst fixed effects, α_a, into an actual instrument. I use the average fixed effects of exiting analysts that cover a firm, minus the average fixed effect of all analysts that cover that firm. In plain English, this measure tells us how optimistic the exiting analysts were. I label this instrument $\partial AFE_{i,t}$. Let $A_{i,t}^{exit}$ be the set of analysts that no longer cover firm i at time t, due to their exit after time $(t-1)$ due to a brokerage merger. Then the instrument I use is defined by the following expression:

$$\partial AFE_{i,t} = \frac{1}{|A^{exit}|} \sum_{a \in A_{i,t}^{exit}} \alpha_a - \frac{1}{|A|} \sum_{a \in A_{i,t}} \alpha_a \tag{7}$$

Note that for the majority of the observations, the value of the instrument, $\partial AFE_{i,t}$, is equal to zero. This is because most observations do not contain an analyst exit.

My identification argument rests on two claims: (i) that the term $\partial AFE_{i,t}$ is correlated with a firm's consensus forecast; and (ii) that $\partial AFE_{i,t}$ is orthogonal to firm earnings, i.e. uncorrelated with the error term, ν_t, in Equation 2. This identification argument can be summarized as follows:

$$cov(\partial AFE_{i,t}, \mathbb{F}_{t-1}[EPS_{i,t}]) \neq 0 \tag{8}$$

$$cov(\partial AFE_{i,t}, \nu_{i,t}) = 0 \tag{9}$$

where Equation 8 is the standard relevance condition, and Equation 9 is the exogeneity condition, where $\nu_{i,t}$ is the error in the second stage regression as described in Equation 2. I now discuss how my instrument achieves both of these conditions.

Relevance of the Instrument —Equation 8. A crucial feature of an instrument is that it explains variation in the endogenous variable. To demonstrate that this is the case, I estimate a local linear regression of the standardized changes in the consensus forecast on the constructed instrument, using only observations that involve an analyst exit effected by a brokerage merger. This approach provides an illustrative impression of the relationship between the instrument and the consensus forecast, and its localized structure avoids results that are driven purely by outliers. Figure 1 shows the result of this exercise, overlaid on a histogram of the instrument.

Figure 1 shows a clear, and economically meaningful relationship between the change in the analyst fixed effects and the change in the consensus forecast. When optimistic analysts exit, i.e. when $\partial AFE_{i,t}$ is positive, then the change to the consensus forecast in the subsequent period is negative. Note further that when the instrument takes a value of zero, then the change in the consensus forecast ought also to be zero. As indicated by the dashed line at zero, this is indeed what we see from running the local linear regression.

I also present results from the standard linear first stage in Table 3. The specification for that regression is shown in Equation 10:

$$\Delta\mathbb{F}_{t-1}[\mathrm{EPS}_{i,t}] = \phi_i + \tau_t + \theta\partial AFE_{i,t} + \Delta X_{i,t} + \epsilon_{i,t} \tag{10}$$

where θ is the coefficient of interest, and $X_{i,t}$ is a vector of firm-year controls. The same basic intuition emerges: when more ‘optimistic’ analysts leave the set, the subsequent consensus forecast is lower. In a robustness check, I run the same regression but using placebo cases

Figure 1: Local Linear Regression of Change in Analyst Fixed Effects on Change in Consensus Analyst Forecast

In this figure, I plot a local linear estimation of the effect of changes in the composition of analyst fixed effects that cover a given firm in the wake of a brokerage merger on the subsequent change to their consensus earnings forecast. I overlay this plot on a histogram of the distribution of those analyst fixed effect changes. Confidence intervals are shown at the 95% level. The downward slope indicates that when more 'optimistic' analysts leave the set, the subsequent consensus forecast is lower, and vice versa.

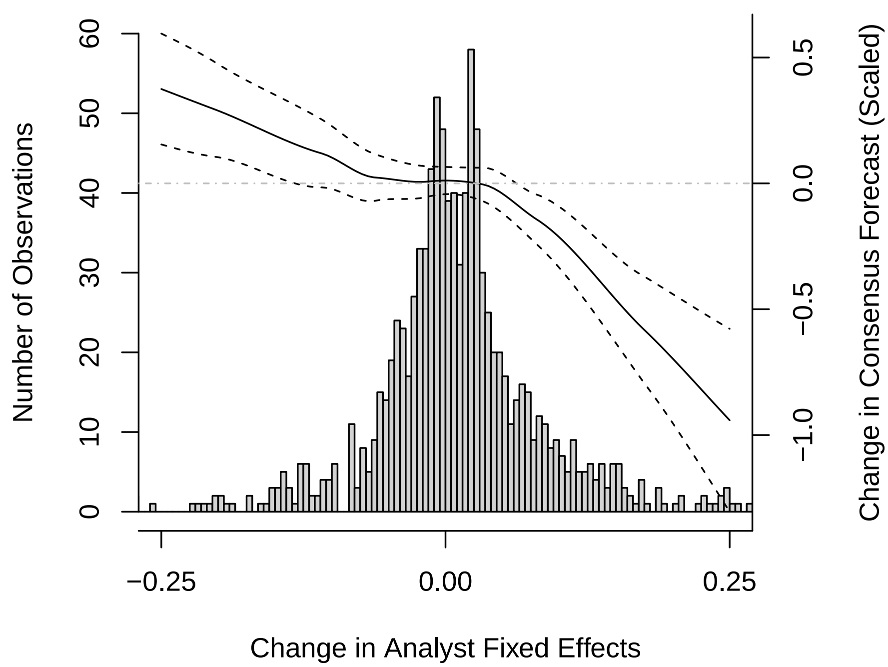


Table 3: First Stage Results of the Change in the Consensus Forecast on the Instrument, $\partial AFE_{i,t}$

This table presents the first stage regression of my IV approach. Regression outputs come from specification: $\Delta\mathbb{F}_{t-1}[EPS_{i,t}] = \phi_i + \tau_t + \beta\partial AFE_{i,t} + \Gamma X_{i,t} + u_{i,t}$, where $\partial AFE_{i,t}$ is the constructed instrument that roughly captures how optimistic exiting analysts were. The change to the consensus forecast is scaled by the standard deviation of the firm's earnings. Standard errors are clustered at the 'Firm' level. Consistent with the economic intuition, the negative estimate for β suggests that when optimistic analysts cease coverage due to a brokerage merger, the subsequent consensus forecast is lower.

Dependent Variable:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$\partial AFE_{i,t}$	-1.871***	-1.951***	-1.944***	-1.946***	-1.940***	-1.933***	-1.933***
	(0.4159)	(0.4234)	(0.4248)	(0.4249)	(0.4237)	(0.4301)	(0.4309)
log(lag_at)	-0.1729***	-0.1048***	-0.0831***	-0.0826***	-0.0814***	-0.0441***	-0.0309***
	(0.0080)	(0.0082)	(0.0090)	(0.0090)	(0.0088)	(0.0091)	(0.0096)
log(mtb)		0.2705***	0.2850***	0.2846***	0.2869***	0.3134***	0.3150***
		(0.0086)	(0.0096)	(0.0096)	(0.0095)	(0.0095)	(0.0096)
log(price)			-0.0502***	-0.0477***	-0.0499***	-0.0757***	-0.0714***
			(0.0083)	(0.0084)	(0.0084)	(0.0086)	(0.0087)
dvps				-0.0279***	-0.0288***	-0.0262***	-0.0257***
				(0.0085)	(0.0085)	(0.0086)	(0.0086)
roa					0.0452*	0.0435*	0.0436*
					(0.0269)	(0.0251)	(0.0252)
lev						-0.7421***	-0.7466***
						(0.0387)	(0.0387)
num							-0.0009***
							(0.0002)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	66,629	64,277	64,274	64,051	64,051	63,793	63,793
R^2	0.15484	0.18155	0.18236	0.18272	0.18405	0.19009	0.19046
Within R^2	0.00953	0.03648	0.03740	0.03769	0.03925	0.04578	0.04621
F-test (1st stage)	32.290	36.238	36.012	36.096	35.942	35.796	35.816

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Comparison of Exiting and Non-Exiting Analysts

This table presents summary statistics of analysts working at brokerages that experience mergers, split into those who subsequently exit the sample and those that do not. I fail to find statistically significant differences in the average error, average squared error, estimated analyst fixed effect (AFE), estimated analyst fixed effect using only pre-merger forecasts (AFE Pre-Merger), or the number of firms that the analyst covers. If I restrict to only the last 20 forecasts that analyst produces before the merger (labelled 'Recent'), I also fail to find statistically significant differences in mean or squared errors.

Treatment	Exiting				Non-Exiting				
Variable	N	Mean	SD	Median	N	Mean	SD	Median	Test
Mean Error	158	0.36	1.1	0.24	1575	0.46	1.9	0.19	F= 0.439
Squared Error	158	9.2	21	3.1	1575	10	43	2.3	F= 0.102
Mean Error (Recent)	158	0.54	1.4	0.27	1575	0.46	2	0.17	F= 0.255
Squared Error (Recent)	158	7.9	16	2.1	1575	11	50	1.6	F= 0.589
AFE	158	0.077	0.11	0.083	1575	0.087	0.082	0.082	F= 1.944
AFE Pre-Merger	158	0.075	0.11	0.079	1575	0.085	0.092	0.081	F= 1.643
Number of Firms Covered	158	13	9.6	12	1575	12	11	10	F= 1.196

Statistical significance markers: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

where analysts did not leave the set. I consistently find a positive coefficient, consistent with the fact that these analysts are still contributing to the forecast.[9]

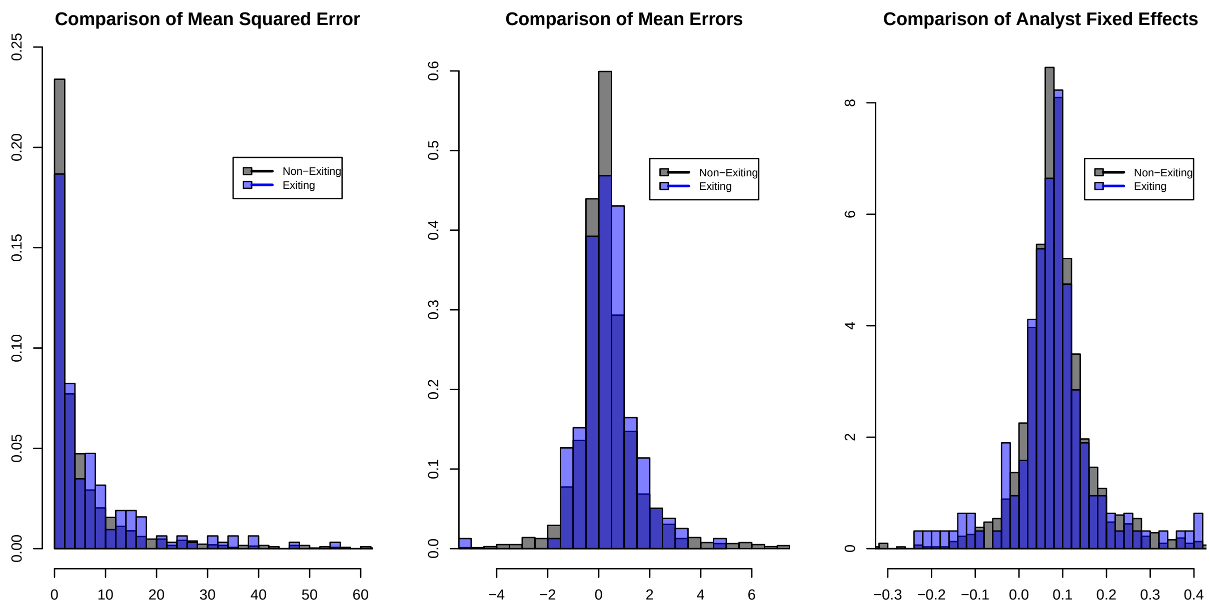
Exogeneity Condition—Equation 9. Aside from the requirement that brokerage mergers occur for reasons orthogonal to the business conditions of the firms that the brokerage covers, I also require that exiting analysts are not systematically different from non-exiting analysts. If more positive/negative analysts consistently exit due to brokerage mergers, then the change in analyst fixed effect composition is plausibly correlated with underlying features of the analyst and hence could also be correlated with underlying features of the firm they cover.

Previous work has shown that analysts who exit due to mergers are not systematically different from those who keep their jobs (Hong and Kacperczyk (2010)). To confirm this finding, I compare the distributions of exiting analysts fixed effects with those of all analysts at the merging brokerages that *didn't* lose their job in the wake of the merger. For robustness, I also compare the distributions of a different set of analysts fixed effects estimated using only data from before the merger occurs. This avoids the problem that non-exiting analysts continue to produce forecasts after the merger, whereas the exiting analysts do not. For

[9]Details are presented in Appendix A.

Figure 2: Histograms of Distributions of Exiting v.s Non-Exiting Analysts

In this figure, I plot histograms of the mean squared error, mean error, and analyst fixed effects (AFE) of analyst working at brokerages that experience a merger. I plot two separate histograms for analysts who exit in the wake of the merger (blue), and those that do not (red).



completeness, I also compare their mean errors, mean squared errors, and the number of firms they cover.

Table 4 shows the average values for each of these variables of the two groups, alongside an F-test of group differences.[10] I fail to reject the null that the analyst fixed effects of exiting analysts is systematically different than those of non-exiting analysts. I also fail to reject the null that the two groups are not statistically different along all other dimensions. For further clarity, I present histograms of the distributions of estimated analyst fixed effects, mean errors, and mean squared errors in Figure 2. Again, these distributions appear consistent with exiting analysts being close to a random sample.

[10]Note that in my main analysis, I restrict to analysts with at least 30 forecasts. I also lose some observations in the IBES-Compustat merge. For these two reasons, the number of exiting analysts that make it to my final sample is slightly lower (158) than the total number I identify here.

3.2 Results of Reduced-Form Estimation

In this section I describe my main results. I find evidence that earnings not only respond directly to analyst forecasts, but that the relationship is roughly one-to-one. This finding holds under several robustness checks that I outline. I also conduct analysis into the mechanism by which earnings increase. I find that accruals play the most significant role.

3.2.1 Earnings Response

The first stage of my IV regression explores the relationship between the instrumental variable, $\partial AFE_{i,t}$, and the change in the consensus earnings forecast, $\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}]$. I specify this relationship as:

$$\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}] = \phi_i + \tau_t + \theta\partial AFE_{i,t} + \Phi X_{i,t} + \epsilon_{i,t} \tag{11}$$

where $\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}]$ is the change in the consensus earnings forecast; ϕ_i represents firm-specific fixed effects. τ_t is the time-specific fixed effect; $\partial AFE_{i,t}$ is our instrumental variable; $\Delta X_{i,t}$ is a vector of control variables; and $\epsilon_{i,t}$ is the error term.

Having retrieved the predicted values of $\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}]$ from the first stage ($\Delta\widehat{\mathbb{F}_{t-1}[\text{EPS}}_{i,t}]$), we proceed to the second stage to examine the causal impact of $\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}]$ on ΔEPS. The model is:

$$\Delta\text{EPS}_{i,t} = \phi_i + \tau_t + \beta\Delta\mathbb{F}_{t-1}[\text{EPS}_{i,t}] + \Gamma X_{i,t} + \nu_{i,t} \tag{12}$$

To account for problems of scale, I standardize earnings and the consensus forecast. That is, I subtract the firm-level mean and divide by the standard deviation for each variable respectively. As such, these coefficients can be interpreted as standard deviation changes. I take this approach as opposed to running a log regression, because both earnings and forecasts are systematically negative, which log regressions cannot interpret.

I find that firm-level earnings respond roughly one-to-one to plausibly exogenous variation in analyst forecasts. As Table 5 shows, the coefficient on the change in the consensus forecast is roughly invariant to the inclusion of several firm-level controls.

Table 5: Earnings Response to Consensus Forecast Shock

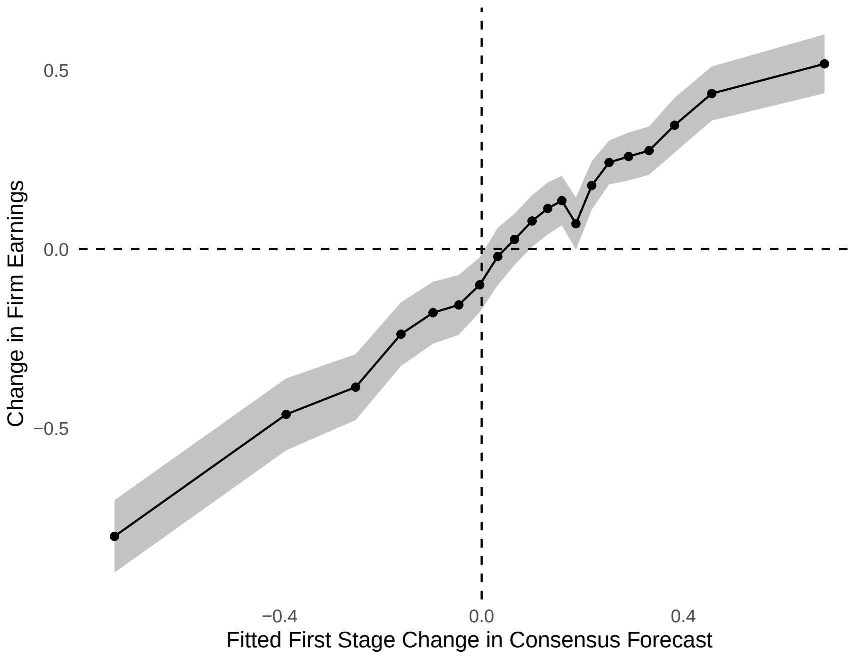
This table presents the second stage regression of my IV approach. Regression outputs come from specification: $\Delta[EPS_{i,t}] = \phi_i + \tau_t + \beta\Delta\mathbb{F}_{t-1}[EPS_{i,t}] + \Gamma X_{i,t} + u_{i,t}$, where $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$ is instrumented by the variable $\partial AFE_{i,t}$, which roughly captures how optimistic exiting analysts were. The changes to the consensus forecast and earnings are scaled by the standard deviation of the firm's earnings. Standard errors are clustered at the 'Firm' level. I consistently find a highly significant and positive causal relationship between forecasts and earnings, that is not statistically distinguishable from one. The F-test statistics for the first stage are comfortably above the thresholds set in Stock and Yogo (2002).

Dependent Variable:	$\Delta EPS_{i,t}$						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	1.068***	1.058***	1.039***	1.039***	1.036***	1.039***	1.039***
	(0.2965)	(0.2830)	(0.2883)	(0.2881)	(0.2887)	(0.2911)	(0.2911)
log(lag_at)	-0.0331	-0.0565*	0.0553**	0.0549**	0.0556**	0.0730***	0.0721***
	(0.0518)	(0.0305)	(0.0253)	(0.0252)	(0.0250)	(0.0159)	(0.0135)
log(mtb)		-0.0759	0.0041	0.0047	0.0074	0.0180	0.0179
		(0.0773)	(0.0831)	(0.0830)	(0.0838)	(0.0922)	(0.0926)
log(price)			-0.2604***	-0.2615***	-0.2635***	-0.2752***	-0.2755***
			(0.0178)	(0.0173)	(0.0178)	(0.0247)	(0.0237)
dvps				0.0167	0.0159	0.0171	0.0171
				(0.0129)	(0.0131)	(0.0126)	(0.0125)
roa					0.0388*	0.0379*	0.0379*
					(0.0228)	(0.0220)	(0.0220)
lev						-0.3335	-0.3332
						(0.2189)	(0.2201)
num							6.36×10^{-5}
							(0.0003)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	66,629	64,277	64,274	64,051	64,051	63,793	63,793
R^2	0.12409	0.13611	0.16110	0.16178	0.16390	0.16268	0.16268
Within R^2	0.02857	0.03820	0.06600	0.06670	0.06906	0.06709	0.06710
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	32.290	36.238	36.012	36.096	35.942	35.796	35.816
Wu-Hausman, p-value	0.01191	0.00955	0.01085	0.01095	0.01114	0.00993	0.00990

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 3: Quantile Bin Scatter Plot of Second Stage

In this figure, I plot a quantile bin scatter plot of the change in firm earnings on the fitted change in consensus earnings forecasts. I use twenty bins with an equal number of observations in each bin. I show the average value for each bin with 95% confidence intervals. I produce the fitted change using the specification outlined in Equation 11.



Testing for Asymmetry. Ex-ante, it is not obvious whether the earnings response would be symmetric for positive vs. negative shocks. If prior to the shock the firm is in some neutral state, positive shocks to the forecast may drive managers to respond, whereas negative shocks could be ignored. Alternatively, if managers are always engaged in earnings management, then when the forecast shock is negative, managers may engage in less costly manipulation. To establish which narrative explains my results, I plot a quantile bin scatter of the change in firm earnings on the fitted values of the change in the consensus earnings forecast. Figure 3 shows the details. I fail to uncover evidence that the effect is asymmetric. This feature of my reduced form results is a key driving force behind the model I develop in Section 4, as frameworks that introduce an asymmetric payoff to just beating the consensus forecast will struggle to generate earnings responses with the symmetry I document in Figure 3.

Robustness. To test the robustness of my main result, I perform a series of additional estimations under varying specifications. The first set of exercises are designed to eliminate the possibility that outliers, crisis periods, or data from the Pre Sarbanes-Oxley act are driving my results. I look at pre- and post-Sarbanes-Oxley as this was a major piece of US legislation that specifically addressed concerns around analyst forecast manipulation.[11]

I perform six additional estimations where I: (i) include an industry-year fixed effect, (ii) restrict to firms over $200m in asset value, (iii) restrict to observations before passage of the Sarbanes-Oxley Act in 2001, (iv) restrict to observations after passage of the Sarbanes-Oxley Act in 2001, (v) remove data from the Great Recession (2008 and 2009), and (vi) remove any year that includes an NBER defined recession. Table 6 shows the results. In all cases, I find a significant and positive coefficient that is not statistically different from one.

As Table 2 demonstrates, firms that experience an analyst exit are systematically different from firms that do not experience an exit. In an additional exercise, I also restrict the sample to only contain firms that experience an analyst exit at some point in my panel. My findings are reported in Table 7; my point estimates are essentially unchanged by estimating only on this restricted sample.

3.2.2 Mechanism for Earnings Result

I now investigate which accounts drive the earnings response to the consensus forecast shock. I begin by decomposing earnings into the sum of cash flows and accruals. I then estimate which channel is responsible for the increase in earnings. I find that accruals make up the entirety of the total earnings response. In the appendix, I perform two robustness checks to validate this result that broadly support accruals as the key channel for earnings management in response to consensus forecast shocks.

Accruals Based Earnings Management. A common approach to earnings management is to make use of accruals. Accruals constitute a set of judgments managers make when recording expenses and earnings. These include adjusting the timing of transactions, the estimation of uncertain amounts (i.e. bad debt provision, warranty provision, etc.), and

[11] See Bartov and Cohen (2009) for an excellent summary.

Table 6: Robustness Checks of Earnings Response to Consensus Forecast Shock

This table presents a series of robustness checks of my main earnings response result. For all seven cases, I use the same set of controls as in column (7) of my main earnings response result. In column (Industry), I include an industry-year fixed effect rather than just a year effect; in column (Large), I restrict to firms with over $200m in total assets; in column (Pre SOX), I restrict to data before the passage of the Sarbanes-Oxley Act (SOX) in 2001; in column (Post SOX), I restrict to data after the passage of SOX; in column (08-09), I remove observations in 2008 and 2009 to avoid results being driven by the Great Recession; in column (Crisis), I remove all years that contain an NBER defined recession. In all six of these robustness tests, I uncover a point estimate for the causal response of a shock to forecasts on earnings that is significant and statistically indistinguishable from one.

Dependent Variable:	$\Delta EPS_{i,t}$					
Model:	(Industry)	(Large)	(Pre SOX)	(Post SOX)	(08-09)	(No Crisis)
Variables						
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	1.179**	1.142**	1.091**	1.004***	0.8638***	0.7814**
	(0.4788)	(0.4565)	(0.4369)	(0.3698)	(0.2592)	(0.3578)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry:Year	Yes					
Year		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	63,793	48,623	20,336	43,457	59,144	69,675
R^2	0.23374	0.12483	0.20717	0.20154	0.25105	0.29008
Within R^2	-0.08081	0.03361	0.02339	0.10906	0.15650	0.19473
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	18.248	18.243	15.316	25.579	28.514	13.636
Wu-Hausman, p-value	0.01719	0.01446	0.04197	0.04861	0.13235	0.45024

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Earnings Response to Consensus Forecast Shock on Restricted Sample containing only Firms that experience an Analyst Exit.

This table presents results of the second stage of my main IV regression with a sample restricted to only the firms that experience an analyst exit in the wake of a brokerage merger at some point during the panel period. This restriction minimally impacts the size of my coefficient compared to the main results.

Dependent Variable:	$\Delta EPS_{i,t}$						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	1.035***	1.024***	1.044***	1.041***	0.9162***	0.9238***	0.9230***
	(0.2491)	(0.2365)	(0.2452)	(0.2473)	(0.2741)	(0.2755)	(0.2776)
log(lag_at)	-0.0467*	-0.0687***	0.0383**	0.0379**	0.0652***	0.0693***	0.0715***
	(0.0254)	(0.0131)	(0.0162)	(0.0159)	(0.0147)	(0.0155)	(0.0180)
log(mtb)		-0.0673	0.0395	0.0408	0.0275	0.0297	0.0299
		(0.0629)	(0.0631)	(0.0631)	(0.0587)	(0.0624)	(0.0628)
log(price)			-0.3213***	-0.3213***	-0.3794***	-0.3827***	-0.3820***
			(0.0197)	(0.0210)	(0.0208)	(0.0218)	(0.0214)
dvps				-0.0018	0.0012	0.0028	0.0028
				(0.0187)	(0.0173)	(0.0173)	(0.0173)
roa					2.113***	2.068***	2.069***
					(0.5833)	(0.5751)	(0.5791)
lev						-0.1449	-0.1469
						(0.1076)	(0.1110)
num							-0.0001
							(0.0004)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	15,491	15,108	15,108	15,059	15,059	15,000	15,000
R^2	0.11132	0.12226	0.13530	0.13529	0.20983	0.20668	0.20701
Within R^2	0.06123	0.07139	0.08518	0.08506	0.16393	0.16066	0.16100
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	55.641	62.502	62.236	61.304	49.860	49.766	49.075
Wu-Hausman, p-value	0.00615	0.00514	0.00352	0.00396	0.02204	0.01974	0.02066

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

determining whether financial details warrant noting (known as 'materiality'). Whilst tightly regulated by GAAP and IFRS, there is still substantial discretion on the part of managers as to how they construct accruals. As a consequence, accrual adjustments have long been considered a prime candidate for earnings management (Jones (1991), Roychowdhury (2006), Bergstresser and Philippon (2006)).

I begin by noting the following decomposition of earnings, which is an accounting identity linking earnings to cash flows and accruals:

$$NI = CashFlow + Accruals \tag{13}$$

where NI is net income, cash flow is the flow of cash in and out of the business, and accruals are defined as in Larson, R. Sloan, and Zha Giedt (2018):

$$Accruals = \Delta CEQ - \Delta CHE \tag{14}$$

where CEQ is common equity, and CHE is cash balances. My main variable of interest is diluted earnings-per-share, which is simply net income, adjusted for extraordinary items, over the current number of shares outstanding, plus adjustments that take into account all the securities that can be converted into shares, and thereby dilute the earnings per existing share. To increase earnings-per-share, it is therefore necessary to either increase cash flows, increase accruals, or decrease the number of shares outstanding.

I test whether the per-share values of cash flows or accruals increase in response to the consensus forecast shock by performing a decomposition of my earnings result. To do this, I take the accounting identity in Equation 13 and express all terms as per-share variables using the appropriate diluted share number (Compustat item: CSHFD). I winsorize the accruals variable to avoid results driven by outliers. Note that I include the extraordinary items in the decomposition of my earnings result to ensure consistency with the accounting identity.

My findings are reported in Table 8. I find that accruals dominate the earnings-per-share result, accounting for essentially the entire earnings response. The coefficients on cash flows and extraordinary items are not statistically different from zero.

Table 8: Decomposition of Earnings into Cash Flow and Accruals

This table presents my findings from an IV estimation exercise of the impact of a consensus forecast shock on a decomposition of the earnings result. My earnings variable is Net Income (NI) less any extraordinary items, where (NI) is equal to the sum of cash flows (CF) and accruals (ACC). I define accruals according to the definition in Larson, R. Sloan, and Zha Giedt (2018), that $ACC = \Delta CEQ - \Delta CHE$, where CEQ is common equity, and CHE is cash balances. In column (1) I showcase the earnings result. In column (2) I show the result for changes in accruals, in column (3) for changes in cashflows, and in column (4) for changes in extraordinary items. Note that the coefficients in columns (2)-(4) sum to the coefficient in column (1).

Dependent Variables: Model:	$\Delta EPS_{i,t}$ (1)	$\Delta ACC_{i,t}$ (2)	$\Delta CF_{i,t}$ (3)	$\Delta EXTRA_{i,t}$ (4)
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	1.140***	1.607**	-0.3879	0.0788
	(0.3088)	(0.6878)	(0.6126)	(0.1690)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	45,316	45,316	45,316	45,316
R^2	0.13162	-0.01575	0.05752	0.10108
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	35.148	35.148	35.148	35.148
Wu-Hausman, p-value	0.00299	0.03235	0.36462	0.70132

Clustered (Firm) standard-errors in parentheses

Which Accruals? To shed light on what type of accrual adjustments react to achieve the earnings response, I first test whether earnings revert in the year after the shock. If the entire response is driven by changes in the timing of transactions, we should see a mechanical reversion in the year after the adjustments are made.

I estimate the following two expressions, as in my main analysis:

$$\Delta \mathbb{F}_{t-1}[\text{EPS}_{i,t}] = \phi_i + \tau_{t+1} + \theta \partial AFE_{i,t} + \Phi X_{i,t+1} + \epsilon_{i,t+1} \tag{15}$$

$$\Delta \text{EPS}_{i,t+1} = \phi_i + \tau_{t+1} + \beta \Delta \mathbb{F}_{t-1}[\text{EPS}_{i,t}] + \Gamma X_{i,t+1} + \nu_{i,t+1} \tag{16}$$

Note that the only difference here is that the earnings term is one period ahead, and the time fixed effect and controls are shifted one year forward to match the earnings response time period.

Details of my findings can be found in Table 9, where I show the first and second stage both of the main result, and the result of estimating Equations 15 and 16. I find a significant drop in earnings in the year after the consensus forecast shock, though not as sizable as the initial increase. This reversion is consistent with some, but not all, of the accrual response being driven by changes in the timing of transactions, which naturally revert in the subsequent period.

To further establish which accruals are adjusted to achieve the earnings response, I perform a decomposition using the framework outlined in Larson, R. Sloan, and Zha Giedt (2018). Details can be found in Appendix C. My findings cannot rule out that managers engage in multiple channels to achieve the accrual response, i.e. not just adjustments to the timing of transactions.

Robustness Checks I perform two robustness checks. In the first, I construct measures of so-called 'discretionary' accruals to use as my dependent variable. These 'discretionary' accruals are designed to capture accrual behavior not otherwise explicable by the ordinary function of the firm and is a typical candidate for identifying earnings management in the literature (Jones (1991), Roychowdhury (2006), Breuer and Schütt (2021)). The details of this exercise can be found in Appendix D. I find that discretionary accruals respond to the

Table 9: Earnings Drop After Forecast Shock

This table shows the impact of the forecast shock on the change in earnings the year after the shock occurs. In the first two columns, I repeat the first and second stage results from the main analysis. In columns (3) and (4), I report the first and second stage results when shifting the dependent variable and all controls forward by one year.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta EPS_{i,t}$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta EPS_{i,t+1}$
IV stages	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
$\partial AFE_{i,t}$	-1.933***		-1.962***	
	(0.4309)		(0.3890)	
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		1.039***		-0.6273***
		(0.2911)		(0.2287)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes		
Lead Year			Yes	Yes
Fit statistics				
Observations	63,793	63,793	55,826	55,826
R^2	0.19046	0.16268	0.17628	0.06832
F-test (1st stage)	35.816		36.467	
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	35.816		36.467	
Wu-Hausman, p-value		0.00990		0.05342

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

forecast shock, bolstering the claim that accruals are responsible for the earnings response.

In the second robustness check, I investigate whether managers engage in 'real activities' based earnings management. Typical measures of 'real' earnings management include lowered R&D expenditures, lowered selling and general expenses, and sales price reductions (Roychowdhury (2006)). All of these components affect net income (NI) through cashflows, and hence plausibly influence my earnings result. I also investigate whether managers engage in share buybacks. I find mixed evidence, with some supportive and some contradictory estimates. A major problem throughout is a lack of precision. Taken collectively, these results do not rule out real activities based earnings management, but do support the notion that accruals are the key driving force behind the earnings result.

3.2.3 Stock Market Response to the Forecast Shock

How costly are these accruals-based earnings responses? The literature is unsettled on how costly accruals are for the long-run health of firms (Christensen et al. (2022)). To shed light on this issue, I test the impact of the consensus forecast shock on firm stock prices.

In theory, the forecast shock could have two countervailing implications for prices. Suppose we label the forecast shock as ξ_t, and the amount of accruals-based earnings management as b_t. Then the total impact of the forecast shock on prices is given by the following decomposition:

$$\frac{dP_t}{d\xi_t} = \frac{\partial P_t}{\partial \xi_t} + \frac{\partial P_t}{\partial b_t}\frac{\partial b_t}{\partial \xi_t} \tag{17}$$

Note that the first term, the direct effect, ought to be weakly positive; at worst, the impact of the shock is zero if it is fully interpreted as arbitrary by the market. The second term, the indirect effect, is negative if the market views accruals-based earnings management as costly.

In practice, it is not possible to directly estimate the components of this decomposition, and so establish the cost of accruals-based earnings management. To get around this problem, I take advantage of the relative size of these two channels for large vs. small firms. Given that the market pays closer attention to larger firms, then we should expect that arbitrary shocks to forecasts are more likely to be identified as arbitrary, at least compared to smaller firms. By looking at the differential response of large firms relative to small firms, we can better isolate the impact of the second term in the decomposition.

Overall Market Response. I first test the overall stock market response to the consensus forecast shock. I set up my estimation as in my earnings response estimation in Section 3.2.1, though I use monthly data on stock returns rather than annual data on firm earnings. I also construct abnormal returns by calculating rolling firm level β's using the standard Carhart (1997) four factor model, and adjusting returns to account for those factor loadings. I use a rolling window of 60 months when estimating the β's. Finally, I also control for an industry-month fixed effect, and the log of the volatility of the stock, in addition to the firm level controls used in my earnings specification. My final second stage regression specification takes the following form:

$$r_{i,m} = \phi_i + \tau_{j,m} + \beta_0 \Delta \mathbb{F}_{t-1}[EPS_{i,t}] + \Gamma X_{i,m} + \epsilon_{i,m} \tag{18}$$

where $r_{i,m}$ is the monthly return of firm i in month m, ϕ_i is a firm fixed effect, $\tau_{j,m}$ is an industry-month fixed effect for industry j, $\Delta \mathbb{F}_{t-1}[EPS_{i,t}]$ is the change in the consensus forecast, instrumented as before, and $X_{i,m}$ is a set of firm-month controls, including estimated risk $\beta_{i,m}$'s constructed with a Carhart (1997) four factor model, the volatility of the stock in the previous year, and all firm-level controls from the main earnings regression. Note that because our consensus forecast is defined at the annual level, the coefficient, β_0, captures the impact of the forecast shock on average monthly returns across the entire year.

My findings are reported in Table 10, where I also include OLS estimates. Whilst the point estimates in the IV case are negative, I fail to reject the null that the stock market response to the forecast shock is zero.

Testing for differential responses. My finding for the overall market response is consistent with two explanations. On the one hand, it is possible that both components of the decomposition in Equation 17 are zero, i.e. the accruals response is fully interpreted by the market and has no long-term impact on the health of firms. On the other hand, it is also possible that the two effects are non-zero, yet roughly cancel one another out.

Table 10: Stock Market Response to Consensus Forecast Shock

This table presents the results from my estimation of the impact of consensus forecast shocks on monthly stock market returns. Columns (1)-(4) contain IV first and second stage findings on raw returns (Columns (1) and (2)) and abnormal returns (Columns (3) and (4)), where the abnormal returns are calculated using the four-factor model of Carhart (1997), with β's estimated using a rolling 60 month window. In Columns (5) and (6) I report OLS regressions of consensus forecasts on stock returns. In all cases, I control for the four estimated β's, the previous year's dividends-per-share, and the one-year lagged log of: (i) market-to-book ratio, (ii) total assets, (iii) fiscal year end stock price, (iv) cash holdings, and (v) volatility. I also control for an industry-month fixed effect, as well as a firm fixed effect.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Raw Returns	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Abnormal Returns	Raw Returns	Abnormal Returns
IV stages	First	Second	First	Second		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\partial AFE_{i,t}$	-1.225***		-1.218***			
	(0.1483)		(0.1483)			
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		-0.0120		-0.0018	0.0067***	0.0053***
		(0.0174)		(0.0163)	(0.0002)	(0.0002)
Fixed-effects						
Industry-Month	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	440,088	440,088	440,088	440,088	440,088	440,088
R^2	0.25386	0.25575	0.25360	0.12777	0.27290	0.13113
F-test (1st stage)	67.008		66.215			
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		67.008		66.215		
Wu-Hausman, p-value		0.21794		0.62024		

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Differential Stock Market Response to Consensus Forecast Shock for Different Firm Size.

In this table I report the first and second stage results from IV estimations of Equation 17, where I restrict the sample to firms in the bottom four quintiles of the total assets distribution (Columns (1) and (2)), and to firms in the top quintile (Columns (3) and (4)). The dependent variable is abnormal stock market returns, adjusted using a four factor model as in Carhart (1997). I find a negative and statistically significant coefficient in my restricted sample of firms in the top quintile of assets.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Abnormal Returns	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Abnormal Returns
IV stages	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
$\partial AFE_{i,t}$	-0.7662***		-2.326***	
	(0.2018)		(0.2488)	
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		0.0605		-0.0182*
		(0.0369)		(0.0109)
Fixed-effects				
Industry-Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	335,372	335,372	104,634	104,634
R^2	0.27392	-0.04913	0.35983	0.25916
F-test (1st stage)	12.834		139.31	
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		12.834		139.31
Wu-Hausman, p-value		0.10995		0.01098

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

To rule out the former possibility, I run another set of regressions where I restrict attention to large firms. As I argue above, if the market is better able to parse out the arbitrary nature of the forecast shock for larger firms, then we should expect to see a relatively more negative coefficient when restricting to these firms if accruals-based earnings management is costly.[12]

Specifically, I rerun the estimation specification in Equation 17 on a restricted sample of firms in the top quintile of the total asset distribution. I use abnormal returns as the dependent variable. I also run the estimation on the bottom four quintiles for comparison. Details can be found in Table 11.

I find that the stock market reaction to the consensus forecast shock for the restricted

[12] I check whether the earnings response for large and small firms is the same to help with the validity of the comparison. Details are presented in Appendix F; I find no evidence that the earnings response differs significantly for large vs. small firms.

sample of firms in the bottom four quintiles is positive, though without statistical significance. By contrast, when I restrict the sample to large firms (those in the top quintile), I find a negative and statistically significant stock market response. The coefficient implies that a one standard deviation increase in the consensus forecast causes a drop in average monthly returns of 1.82%. Given that the standard deviation of average monthly returns in this restricted sample is 2.65%, this is a sizable drop, and suggests that the market views the accruals-based earnings management in response to the forecast shock as doing significant damage to the firm.

To confirm that my result is not driven by this specific slicing of the data, I conduct a series of additional exercises for robustness. I use raw excess returns instead of abnormal returns, I use quartiles instead of quintiles, I use the median split, I estimate a differential interaction using all the data together, and I split the sample based on analyst coverage. I also use a measure of the cumulative abnormal returns (CAR) across the entire year as a final check. In all six cases, the same basic result emerges. Details of these robustness tests can be found in Appendix G.

4 Theoretical Model of Short-Termism with Analyst Forecasts

In the second part of my paper, I build a theoretical model of short-termism. The findings in Section 3 suggest that managers engage in earnings management in response to forecast shocks. Here I develop a framework that explains why managers might react this way, even when the market is not fooled by their earnings manipulation activities.

In my model, as in the classic Stein (1989) paper on corporate short-termism, I implement a wedge that separates the interests of managers from those of their firm: a short-term pressure to maximize the contemporaneous stock price.[13]

[13] There are many intuitions for this assumption. In Stein (1989), managers are unable to fully insure against takeovers, which force them to tender their shares at the market price. As such, they face a pressure to maximize the contemporaneous stock price as a form of self-insurance. Other potential intuitions for a manager wanting to maximize the contemporaneous stock price include funding requirements necessitating that managers go to the market to issue new stock, or that managers may be acting on behalf of shareholders (possibly also including themselves) facing liquidity needs and who must consequently sell off some stock

The stock price is a measure of market beliefs over discounted future earnings, which is influenced by the history of a firms earnings, and the history of the forecasts that the manager has faced. As such, the manager can attempt to influence the stock price by bringing future earnings forward to today, i.e. performing earnings management. The goal of the manager is to trick the market into thinking that higher earnings today imply that the underlying state of the business has improved. However in truth, this activity is independent of the underlying business, is inefficient, and harms the firm.

In equilibrium, the market is not fooled, though the manager is trapped into behaving 'myopically' (Stein (1989)). This is because the market correctly conjectures that the manager cannot credibly deviate from attempting to manage earnings, given the pressures they face. The size of the problem is a function of the magnitude of the concern over incomplete contracts, but also the features and histories of the earnings and forecast variables.

Crucially, my model generates earnings management that varies with arbitrary shocks to the forecasts the manager faces. This is because, unlike in Stein (1989), the amount of earnings management is a function of beliefs about the underlying state of the business. This is achieved by the introduction of a convex relationship between the underlying state of the business and earnings. In the linear case, the marginal value of increasing earnings today is always the same, no matter what the state is. In the convex case, understanding the current underlying quality of the business matters for how to interpret the effect of an increase in earnings on the beliefs about that quality.

The intuition for why this matters can be explained with the following analogy. Imagine you're climbing a hill. In a linear world, this hill is just a straight incline. Every step you take, you rise by the same amount. But in a convex world, the hill starts off gentle and then becomes steeper. If you're halfway up (meaning the business is doing reasonably well), a small step can make you rise much more than when you were at the bottom. So, when someone from afar (the market) sees you take a step halfway up, they believe you've achieved more than if they saw you take the same step at the bottom. Your decision on how big a step to take depends on where you believe you are on the hill, and if someone yells (i.e. there

in each period, or even simply that perhaps managers' compensation in each period is a function of that period's stock price. I abstract from a lengthy discussion of the source of this pressure, as the purpose of the model is not to establish what causes short-termism, but rather to assess its consequences.

is a shock to the forecast) that you're actually higher up than you thought, you might adjust your next step accordingly.

A benefit of the assumption of a convex relationship is that this guarantees that the earnings distribution has positive skew. This is a big advantage of the model over the linear case, as the data on US earnings displays positive skew, allowing the model to more closely match real world data.

4.1 Setting up the model

In the model there are three players: the manager, the analyst, and the market. The manager makes choices about how to allocate resources intertemporally. The analyst produces forecasts, though enters as a degenerate player and does not act strategically. The market forms expectations about the firm's future earnings based on their observations of past earnings and past forecasts. The manager's optimal response depends critically on market expectations, as these determine the stock price.

The Manager's Problem. Managers can influence earnings by inefficiently reallocating earnings intertemporally. I model this by constructing observable earnings as the sum of three components:

$$e_t = e_t^n + b_t - c(b_{t-1}) \tag{19}$$

where e_t^n is some exogenous process I will label 'natural earnings' that is outside of the manager's control, b_t is the amount managers reallocate from future earnings to today, and $c(.)$ is a cost function that captures the inefficiency of this reallocation.[14] Note that this inefficiency cost only bites in the subsequent period. I assume the following features for the cost function:

$$c(0) = 0, c'(0) = (1 + r), c'' > 0 \tag{20}$$

[14] Here we can think of e_t^n as being the earnings of the firm post-optimization. As such, I am not claiming that all intertemporal earnings management is costly, but am instead focusing on purely inefficient and unnecessary manipulation by the manager after optimal financial decisions have been made.

The process that governs natural earnings is a potentially non-linear state space model of the following form:

$$\alpha_t = \alpha_{t-1} + \eta_t, \eta_t \sim N(0, \sigma_\eta^2) \tag{21}$$

$$e_t^n = h(\alpha_t) + \epsilon_t, \epsilon_t \sim N(0, \sigma_\epsilon^2) \tag{22}$$

Here α_t is some underlying state that evolves according to a random walk, and enters into the process of natural earnings through the generic function $h(.)$. These natural earnings can be thought of the earnings of the firm after optimization.

Manager's face a tradeoff between maximizing the discounted sum of future earnings, and maximizing the contemporaneous stock price. Given that the borrowing term, b_t, is a jump variable, and only relevant to period t and $(t+1)$, we can model the per-period utility of the manager in the following way:

$$U_t = e_t + \pi P_t + (1-\pi)\frac{e_{t+1}}{1+r} \tag{23}$$

where e_t are firm earnings, r is the discount rate, π is a measure of short-termism capturing the presence of incomplete contracts[15], and P_t is the stock price, defined as the market's expectation of discounted future earnings:

$$P_t = \mathbb{E}_t \left[\sum_{j=1} \frac{e_{t+j}}{(1+r)^j} \right] \tag{24}$$

The manager does not observe e_t^n, and, crucially, both of b_t *and* e_t^n are unobservable to the market.

The Analyst's Problem. Analysts are a degenerate player in this game. I assume that analyst forecasts are generated by a process that is near identical to earnings, save for an independent and arbitrary shock, labelled ξ_t. Analysts do not behave strategically, but instead produce a single forecast in a mechanical fashion, which is isomorphic to the consensus

[15]The measure of short-termism, π, could be thought of as the probability that the firm experiences a takeover, and hence the manager is required to exercise their options.

forecast in my reduced form exercise. Let ϕ_t be the consensus forecast. Then the process that generates this forecast is given by the following

$$\phi_t^n = h(\alpha_t) + \xi_t, \xi_t \sim N(0, \sigma_\xi^2); \xi_t \perp\!\!\!\perp \epsilon_t \tag{25}$$

$$\phi_t = \phi_t^n + b_t - c(b_{t-1}) \tag{26}$$

The key shock, ξ_t, is the theoretical analogue of the shock I explore in my reduced form exercise. Note that although I identify this shock in the reduced form by looking at changes in individual analysts, the ultimate goal is to construct a plausibly random shock to the *consensus* forecast, akin to ξ_t. Here I abstract from how this shock might be generated for simplicity, and just assume it is an i.i.d. shock unrelated to any aspects of the actual business.

The Market's Problem. The market does not observe e_t^n, ϕ_t^n, or b_t, only e_t and ϕ_t. On the basis of these observations, the market forms expectations about future earnings, $\{e_{t+j}\}$. Without knowledge of b_t or e_t^n, it is necessary for the market to make some conjecture.[16] Suppose this conjecture is over the path of borrowing, which I will label $\{\hat{b}_t\}$. The goal of the market is to choose a conjecture that minimizes the gap between their conjecture and actual borrowing:

$$\min_{\{\hat{b}_t\}} \mathbb{E}_t \left[\sum_{j=0}^{\infty} (\hat{b}_j - b_j)^2 \right] \tag{27}$$

For a given conjecture, the market's beliefs over future earnings is determined by the following non-linear state space model:

$$\alpha_t = \alpha_{t-1} + \eta_t, \eta_t \sim \mathbf{N}(0, \sigma_\eta^2) \tag{28}$$

$$\begin{bmatrix} e_t^n \\ \phi_t^n \end{bmatrix} = \mathbf{h}(\alpha_t) + \begin{bmatrix} \epsilon_t \\ \xi_t \end{bmatrix}, \begin{bmatrix} \epsilon_t \\ \xi_t \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\epsilon^2 & 0 \\ 0 & \sigma_\xi^2 \end{bmatrix} \right) \tag{29}$$

[16]Note that a conjecture of b_t is sufficient to establish a conjecture over e_t^n, as they are jointly determined by Equation 19

4.2 Outline of Solution

The solution mechanism is a 'signal-jamming equilibrium'. The basic idea is as follows: we suppose that the 'market' has some conjecture over borrowing, $\{\hat{b}_t\}$. On the basis of this conjecture, the market constructs observations of natural earnings/forecasts by backing out conjectured borrowings from observed actual earnings/forecasts. The manager treats the market's conjecture over borrowing as fixed, and therefore concludes that changes in observable earnings will be interpreted as changes to natural earnings. The manager derives their best response under this assumption.

However, as the market understands the manager's problem, and there is no asymmetric information in regard to the underlying state, the market's optimal conjecture over borrowing will coincide with actual borrowing. In equilibrium, b_t is known to all, and there is no asymmetric information whatsoever; both manager and market have identical beliefs over the hidden state, α_t.[17]

Defining Equilibrium. Formally, we define an equilibrium in the following way:

Definition 1. *For a given exogenous sequence of natural earnings/forecasts, $\{e_t^n, \phi_t^n\}$, and exogenous parameters $\{\pi, r\}$, an equilibrium of the model is a path for borrowing, $\{b_t\}$, a conjecture over borrowing, $\{\hat{b}_t\}$, and observable earnings/forecasts, $\{e_t, \phi_t\}$, such that:*

- *The choice of $\{b_t\}$ is an optimal response to a given path of earnings, $\{e_t\}$, and conjectures over borrowing, $\{\hat{b}_t\}$; i.e. $b_t = \arg\max e_t + \pi P_t + (1-\pi)\frac{e_{t+1}}{1+r}$, subject to borrowing conjecture $\{\hat{b}_t\}$.*

- *The conjecture over borrowing is equal to actual borrowing; $b_t = \hat{b}_t$, $\forall t$.*

Finding Equilibrium. We begin by finding the optimal borrowing conditional on the manager's conjecture. First note the first order condition of their problem:

$$c'(b_t^*) = \frac{1+r}{1-\pi}\left(1 + \pi\frac{\partial P_t}{\partial b_t}\right) \tag{30}$$

[17]The classic implementation of this solution mechanism is in Harris and Holmstrom (1982), and is also used in Holmström (1999).

Now we have to establish $\partial P_t/\partial b_t$. In Stein (1989), this expression drops out of the application of a Kalman filter to the linear state space model. Introducing non-linearities creates a fundamental problem with applying the Kalman filter, as the Kalman filter is the optimal linear estimator only for linear system models. To deal with this problem, I implement an Extended Kalman filter framework that can handle non-linearities.

The Extended Kalman filter (EKF) is a *near*-optimal estimator, that can perform state estimation of nonlinear dynamic systems by implementing a local linearization of the non-linearities.[18] Note that the introduction of $h(.)$ does not change the first order condition of the manager, though it will change $\frac{\partial P_t}{\partial b_t}$. Application of the Extended Kalman Filter leads to the following result:

Theorem 1. *When natural earnings/forecasts, $\{e_t^n, \phi_t^n\}$, are determined by Equations 29 and 28, then:*

$$\frac{\partial P_t}{\partial b_t} = \frac{K_t \boldsymbol{h}'(\mathbb{E}_t[\alpha_t])}{r} \tag{31}$$

where K_t is the Kalman gain in the Extended Kalman filter. Consequently, optimal borrowing is given by:

$$c'(b_t^*) = \frac{1+r}{1-\pi}\left(1 + \frac{\pi}{r} K_t \boldsymbol{h}'(\mathbb{E}_t[\alpha_t])\right) \tag{32}$$

Proof. See Appendix H $\square$

Optimal Borrowing. Given the result in Theorem 1, we can say that optimal borrowing is given by Equation 32. For a given pair of exogenous sequences of $\{e_t^n, \phi_t^n\}$, and parameters $\{\pi, r\}$, then:

- $b_t = c'^{-1}\left(\frac{1+r}{1-\pi}\left(1 + \frac{\pi}{r} K_t \mathbf{h}'(\mathbb{E}_t[\alpha_t])\right)\right)$, $\forall t$
- $\hat{b}_t = b_t$, $\forall t$

[18] The Extended Kalman Filter was developed by NASA Ames in their attempts to apply filtering techniques to nonlinear systems (Smith, Schmidt, and McGee (1962), McElhoe (1966)). It is the 'de facto' standard in nonlinear state estimation, and is implemented in, for example, navigation systems and GPS (Wan (2006)).

which gives us the equilibrium of the model. Note that the borrowing is directly proportional to the slope of the function $h(\mathbb{E}_t[\alpha_t])$. When the slope is high, borrowing will be high, and vice versa. The intuition for this result is that when the slope of $h(.)$ is large, it requires a significantly greater change in earnings to move market beliefs about the underlying state, α_t. As the manager wants to increase the value of that belief today due to short-term pressure to maximize the share price, they will be forced into borrowing more in order to do this.

4.3 Theoretical Consequences of Solution

State-Dependence of Borrowing. Note that optimal borrowing is time-varying, and depends on beliefs about the state, α_t. This is in contrast to Stein (1989), where borrowing is fixed and state independent.

Why state dependence emerges is because the slope of the response of the stock price to borrowing is no longer constant. In the linear case, $\partial P_t/\partial b_t$ is fixed, because the changes in beliefs about the state, α_t, from changes in earnings is linear. By contrast, once changes in earnings have non-linear effects on beliefs over the state, the slope of $\partial P_t/\partial b_t$ is no longer fixed. To understand how a change in earnings would influence a change in beliefs about the state, it is necessary to know where on that non-linear function you are, because the gradient is changing across the domain. Hence, $\partial P_t/\partial b_t$ in Equation 31 is no longer constant, but varies with beliefs over the current value of the state, α_t.

Note that in my setup, the Kalman gain term, K_t, which is a one-by-two vector, is also time-varying, unlike the case in Stein (1989). This lack of convergence is a direct feature of the linearizations involved in the Extended Kalman Filter (EKF) procedure, and is neither an economically nor quantitatively meaningful source of state dependence.

The impact of forecast shocks on earnings management. When natural earnings/-forecasts, $\{e_t^n, \phi_t^n\}$, are determined by Equations 29 and 28, then we arrive at the following result:

Theorem 2. *If, and only if, $h(.)$ is convex, then:*

$$\frac{\partial b_t}{\partial \xi_t} > 0$$

i.e. optimal borrowing is increasing in arbitrary variation in analyst forecasts.

Proof. We know that

$$b_t^* = c'^{-1}\left(\frac{1+r}{1-\pi}\left(1+\frac{\pi}{r}K_t\mathbf{h}'(\mathbb{E}_t[\alpha_t])\right)\right)$$

Given $c'(.) > 0, c''(0) > 0$, it follows that c'^{-1} is an increasing function. Thus it is enough to show that $\frac{\partial K_t \mathbf{h}'(\mathbb{E}_t[\alpha_t])}{\partial \xi_t} > 0$. Let $K_{2,t}$ be the component of K_t that corresponds to ϕ_t. Then note that:

$$\frac{\partial K_t \mathbf{h}'(\mathbb{E}_t[\alpha_t])}{\partial \xi_t} = h''(\mathbb{E}_t[\alpha_t])(K_{2,t})^2$$

which is positive iff $h''(.) > 0$ □

To understand why convexity delivers this result, recall that the slope of the function $h(\mathbb{E}_t[\alpha_t])$ determines the level of borrowing in the model. For a convex function, this figure is high when the underlying state is high, and low when the underlying state is low. For a concave function, the opposite is true.

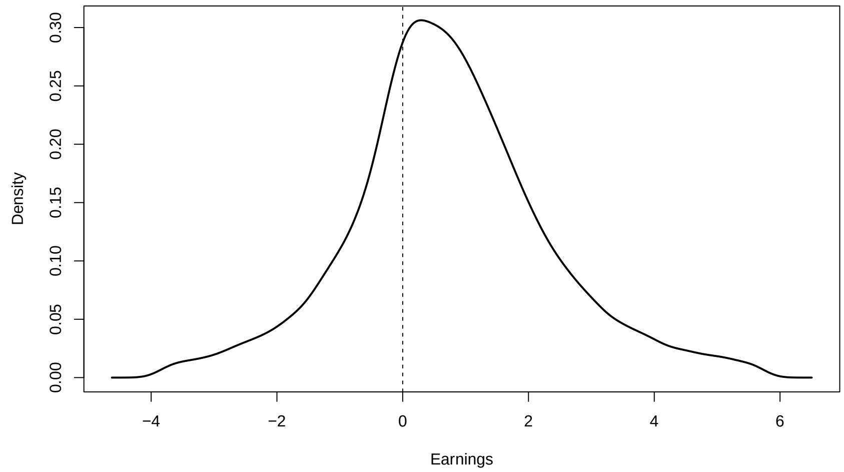
The reason convexity matters here relates to the central trade-off that the manager faces. Managers wish to influence the contemporaneous stock price, but also care about long-term earnings. When forecasts indicate the earnings will be high, beliefs about the underlying state go up. As such, managers need to conduct relatively more earnings management to influence beliefs about the underlying state, because the slope of $h(\mathbb{E}_t[\alpha_t])$ is now steeper.

The reason one gets the opposite intuition if the function $h(.)$ is concave also relates to this relative cost argument. When forecasts indicate the earnings will be high, beliefs about the underlying state go up, but managers need to conduct relatively *less* earnings management to influence beliefs about the underlying state, because the slope of $h(\mathbb{E}_t[\alpha_t])$ is now flatter.

Symmetry in earnings response. This theoretical result achieves a symmetric response in earnings to positive and negative forecast shocks. This is a key feature of my model, as this result is consistent with my reduced form findings in Section 3.2.1 in that I observe no meaningful asymmetry in actual earnings response to forecast shocks. This result is very difficult to achieve using a modelling framework that just incorporates a discontinuity in payoffs for 'just beating' the forecast.

Figure 4: Binned Kernel Density Estimation of the Earnings-per-share Distribution.

In this figure, I plot a binned kernel density estimation of the distribution of the earnings-per-share variable I use as my principal measure of earnings in Section 3. The mean and skewness of this distribution are positive (0.74 and 0.23 respectively).



Convexity as a reasonable assumption. Assuming convexity ensures that the earnings distribution of the model matches the skewness of real world data. As shown in Figure 4, the distribution of earnings-per-share has positive skew. A convex function loading on the state, which is distributed symmetrically, will also result in positive skew by amplifying the value of higher positive states.

Impact on Stock Prices. I now show that my model is able to capture the results on stock prices in my reduced form section. Recall that stock prices are the sum of expected discounted future earnings. We can decompose these earnings in the following way:

$$\begin{aligned} P_t &= \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[e_{t+j}] \\ &= \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[e^n_{t+j}] + \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[b_{t+j}] - \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[c(b_{t+j-1})] \\ &= \underbrace{\sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[h(\alpha_{t+j})]}_{(i)} + \underbrace{\sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[b_{t+j}]}_{(ii)} - \underbrace{\sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[c(b_{t+j-1})]}_{(iii)} \end{aligned} \tag{33}$$

We want to establish the value of $dP_t/d\xi_t$ in equilibrium, i.e. the total derivative. As the forecast shock affects both beliefs and borrowing, we can decompose this total derivative into the sum of two components, the direct effect through changes in beliefs about the state, and the indirect effect through increased borrowing:

$$\frac{dP_t}{d\xi_t} = \frac{\partial P_t}{\partial \xi_t} + \frac{\partial P_t}{\partial b_t}\frac{\partial b_t}{\partial \xi_t} \tag{34}$$

The first term, $\partial P_t/\partial \xi_t$, will be positive; absent borrowing, a positive forecast shock will increase the value of term (i) in Equation 33. The second term will be negative, as the shock will drive borrowing up, and greater borrowing is always inefficient, implying lower total discounted earnings; i.e. the term (ii) is larger than (iii) in Equation 33. Which effect dominates will depend on the specific parameterization of the model.

5 Model Calibration

In the third part of my paper, I calibrate my theoretical model. Here my goal is to show that, using reasonable parameter values, I can generate the estimated reduced form response of earnings to forecast shocks, as well as produce distributions over earnings and forecasts that match closely to those in the data. I begin this section by establishing a set of assumptions on functional forms. I then establish the parameters I calibrate, and the moments in the data I attempt to match. Finally, I consider some counterfactual exercises.

5.1 Functional Form Assumptions

My theoretical model contains two generic functions that require a form assumption: $c(b_t)$, and $h(\alpha_t)$. I assume the following functional forms for these general functions:

$$c(b_t) = (1 + r)b_t + \frac{\chi}{2}b_t^2 \tag{35}$$

$$h(\alpha_t) = \alpha_t + \psi e^{\alpha_t} \tag{36}$$

Equation 35, which represents the cost of borrowing function, assumes a simple quadratic cost, where the parameter χ is a measure of the degree of convexity. This simple functional form captures the three key theoretical features required of the cost function as outlined in Section 4, namely: (i) $c(0) = 0$, (ii) $c'(0) = (1 + r)$, and (iii) $c''(.) > 0$ for all $\chi > 0$. Further, because borrowing is never negative for any $\pi \geq 0$, this function displays monotonicity across the support of feasible b_t.[19]

Equation 36, which represents the non-linear function mapping the state variable to earnings/forecasts, includes the standard linear case, plus an exponent term scaled by ψ that captures the degree of non-linearity. This functional form has the advantage of both nesting the linear case ($\psi = 0$), and displaying monotonicity in the value of the state, α_t, with no upper or lower bound to the function output. In this latter respect, the assumption of an exponent is preferable to a quadratic assumption that would necessarily introduce a lower bound to the function.

Together, these functional form assumptions imply the following form for the key optimal borrowing condition:

$$b_t^* = \frac{1}{\chi}\left(\frac{1+r}{1-\pi}\left(\pi + \frac{\pi}{r}K_t\begin{bmatrix}1 + \psi e^{\mathbb{E}_t[\alpha_t]} \\ 1 + \psi e^{\mathbb{E}_t[\alpha_t]}\end{bmatrix}\right)\right) \tag{37}$$

As well as these two functional form assumptions, I also relax the assumption that transitory shocks to earnings/forecasts (ϵ_t/ξ_t) are mean zero. I allow these two shocks to have differing means, which I label μ_ϵ and μ_ξ respectively.

5.2 Parameters and Moments

I calibrate seven parameters using seven moments. Details of the parameters and moments involved in the estimation can be found in Table 12.

Parameters. My model contains nine parameters in total: π, the degree of short-termism; χ, the convex cost of borrowing; ψ, the degree of non-linearity in the state loading function

[19]See Equation 32: the functional form of the function $h(\alpha_t)$ implies that $h'(.)$ is strictly positive, and the Kalman gain term, K_t is also non-negative. Hence, for any $\pi \geq 0$, $c'(b_t^*) \geq 0$, which implies that $b_t \geq 0$.

$h(\alpha_t)$; σ_η, the standard deviation of the shocks to the underlying state, η_t; $\{\mu_\epsilon, \sigma_\epsilon\}$, the mean and standard deviation of the transitory shocks to earnings, ϵ_t; $\{\mu_\xi, \sigma_\xi\}$, the mean and standard deviation of the transitory shocks to forecasts, ξ_t; and r, the discount rate.

Of these nine parameters, I calibrate all but σ_ξ and r. For σ_ξ, I assume the value of the standard deviation of the forecast shocks identified in my reduced form exercise, which is 0.16. For r, I assume an 8% rate, roughly in line with the equity premium produced by the average stock return (Fama and French (2002)).

Moments. To calibrate my seven parameters, I select seven moments to match: the mean, the standard deviation, and skewness of earnings, the mean and skewness of forecasts, the correlation between earnings and forecasts, and the responsiveness of earnings through borrowing to a forecast shock.

The final moment is lifted from my reduced form analysis where I show that the relationship between forecast shocks and earnings is one-to-one. In my model, this moment is the slope of borrowing with respect to the forecast shock, ξ_t. Note that this slope is equivalent to that of the slope of earnings with respect to the forecast shock, as borrowing enters linearly to earnings. Under the functional form assumptions listed above, this slope takes the following form:

$$\frac{\partial e_t}{\partial \xi_t} = \frac{1}{\chi}\left(\frac{\pi(1+r)}{r(1-\pi)}\psi e^{\mathbb{E}_t[\alpha_t]} K_{2,t}^2\right) \tag{38}$$

As my model generates two distributions, one for earnings and one for forecasts, I select moments that are designed to map these distributions directly to those observed in the data. I also attempt to match the elasticity of earnings to the borrowing shock to show that it is possible to generate responses in line with my reduced form estimates. Ideally, I would also match to the price response I document in Section 3.2.3. However, due to the non-linearities in my model, beliefs are evolving in a very sophisticated way; figuring out the expected value for earnings in the future depends on the history of shocks that the firm will draw going forward.

To construct my data moments, I use the same sample as in my reduced form exercise. I first take the average of earnings and the consensus forecast across the entire sample. I then remove an industry-year fixed effect from both variables, before re-adding the previously calculated means.

5.3 Final Calibration

The details of my calibrated parameters, data moments, and model moments can be found in Table 12. I find that I am able to match the moments very closely, including the responsiveness of earnings to arbitrary forecast shocks.

I calibrate the short-termism parameter, π, at 0.0160. One interpretation of short-termism in the model is as self-insurance against the risk of takeover. The empirical frequency of takeovers typically ranges from about 3-8% annually (Edmans, Fang, and Lewellen (2017)), so my calibrated value here is roughly in line with those estimates. Further, note that this calibration shows it is possible to generate sizable reactions to forecast shocks in my model without unrealistically high levels of short-termism; a π value of 0.0160 suggests managers are very close to acting as though they do not face pressure to maximize the contemporaneous stock price.

I calibrate the borrowing cost parameter, χ, at 0.0235. This parameter does not have a real-world analogue, but this parameterization suggests that the cost of borrowing function can be relatively close to the costless case, yet still generate sensible distributions of earnings/forecasts.

I calibrate the non-linearity parameter, ψ, at 0.6875. It is necessary for ψ to be greater than zero to generate skewness in the data, and to achieve responsiveness of earnings to forecast shocks. I find that a relatively high value for this parameter generates moments that match this data well.

The remaining calibrated parameters are chosen naturally to fit the associated moments, i.e. μ_ϵ to fit the mean of earnings, μ_ξ to fit the mean of forecasts, etc. All of these parameters take reasonable values that roughly coincide with the data moment analogues.

Removing Short-Termism. My first counterfactual exercise is to set the short-termism parameter, π, to zero. This means managers do not face a short-term pressure to maximize the contemporaneous stock price. Table 13 shows the simulated moments: I find that the mean of earnings and forecasts increase, and the slope of borrowing falls to zero. Specifically,

Table 12: Calibrated Baseline Model

This table presents the calibrated parameters and moments from my baseline model, including data moments as reference. Panel B's data moments are constructed using my reduced-form sample, covering a Compustat-IBES panel of 12,432 unique firms for 63,773 firm-year observations, from 1990 to 2020. Model moments use twenty samples of 40-year simulated panels of 1,000 firms.

Panel A: Estimated Parameters	Notation	Calibrated Value
Short-Termism	π	0.0160
Borrowing Cost	χ	0.0235
Non-linearity	ψ	0.6875
Standard Deviation of State Shocks	σ_η	0.1110
Standard Deviation of Earnings Shocks	σ_ϵ	1.1350
Mean of Earnings Shocks	μ_ϵ	1.1050
Mean of Forecast Shocks	μ_ξ	1.2600
Panel B: Assumed Parameters	**Notation**	**Value**
Discount rate	r	0.08
Standard Deviation of Forecast Shocks	σ_ξ	0.16
Panel C: Moments	**Data**	**Model**
Mean of Earnings	0.7413	0.7408
Standard Deviation of Earnings	1.4516	1.4564
Skewness of Earnings	0.2544	0.2673
Correlation of Earnings and Forecasts	0.6399	0.6164
Mean of Forecasts	0.8953	0.8968
Skewness of Forecasts	1.1718	1.0632
Slope of Borrowing	1.0000	0.9844

Table 13: Counterfactual Results

This table presents the simulated moments from my counterfactual exercises. I repeat the data and baseline model moments as reference. The 'No Short-Termism' column corresponds to a counterfactual where I set $\pi = 0$, and the 'No Analyst Forecasts' column corresponds to a counterfactual where analyst forecasts are entirely uninformative (the shock to the forecast has arbitrarily high variance ($\sigma_\xi > c$, where c is some arbitrarily large number). I again use twenty simulated 40-year panels of 2,000 firms to construct these moments.

	Data	Model	No Short-Termism	No Analyst Forecasts
Mean of Earnings	0.741	0.741	1.909	1.636
Standard Deviation of Earnings	1.452	1.456	1.520	1.517
Skewness of Earnings	0.254	0.267	0.326	0.328
Correlation of Earnings and Forecasts	0.634	0.616	0.656	—
Mean of Forecasts	0.895	0.897	2.064	—
Skewness of Forecasts	1.172	1.063	1.089	—
Slope of Borrowing	1.0000	0.984	0	—

when $\pi = 0$, earnings increase by 0.80 standard deviations, compared to the baseline model. This increase in earnings/forecasts is a result of no inefficient borrowing when $\pi = 0$; $b_t = 0$ for all t, as can be seen from Equation 37. Other moments are mostly unchanged.

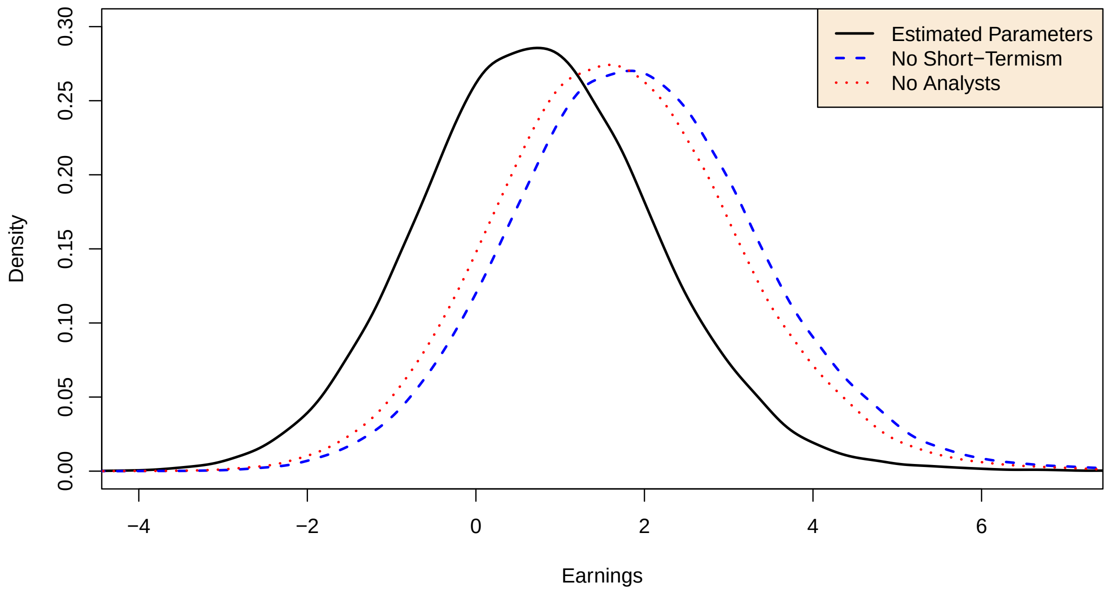
For illustrative purposes, I present Figure 5, where I show a plot of a simulated distribution of earnings from the baseline model (solid black line) alongside a plot of a simulated distribution of earnings from the counterfactual case where $\pi = 0$ (dashed blue line). What we notice is a positive shift with a slight spread in the overall distribution. These findings indicate that short-termism results in a non-trivial cost, at least with respect to firm level earnings.

Removing Analyst Forecasts. I assess whether analyst forecasts amplify or reduce the costs associated with short-termism. I do this by setting the standard deviation of the forecast to an arbitrarily high value, making the signal entirely uninformative. I keep all other parameters the same as in the baseline model. Table 13 shows the simulated moments under this framework. I also plot the simulated distribution under this framework in Figure 5 as the dotted black line. Both the Table and the Figure confirm that the earnings distribution is closer to the counterfactual of no short-termism than it is to the baseline when analyst forecasts are uninformative.

This finding is driven by the informative nature of the analyst forecast in the baseline

Figure 5: Counterfactual Exercises

In this figure, I plot the earnings distributions from simulated 40-year panels of 2,000 firms under the baseline, the 'No Short-Termism' counterfactual, and the 'No Analyst Forecasts' counterfactual. The baseline case is represented by a solid line, the 'No Short-Termism' by the dashed line, an the 'No Analyst Forecasts' by the dotted line.



case; recall that optimal borrowing is driven by the implied effect of borrowing on price, which in turn is simply a function of how much borrowing moves beliefs over the underlying state. With two informative signals, borrowing moves beliefs over the state more than with a single earnings signal.

The mechanism that operates here is best seen by considering the Kalman gain term in Equation 37. The Kalman gain in the baseline case is defined by the following expressions:

$$\underbrace{K_t}_{1\times 2} = P_{t|t-1} H_t^T S_t^{-1} \tag{39}$$

$$\underbrace{S_t}_{2\times 2} = H_t P_{t|t-1} H_t^T + R$$

$$\underbrace{H_t}_{2\times 1} = \left.\frac{\partial \mathbf{h}}{\partial \alpha}\right|_{\mathbb{E}_{t-1}[\alpha_t]}$$

$$\underbrace{P_{t|t-1}}_{1\times 1} = P_{t-1|t-1} + \sigma_\eta^2$$

In the absence of analyst forecasts, the Kalman gain term reduces down to:

$$\underbrace{\hat{K}_t}_{1\times 1} = \hat{P}_{t|t-1}\hat{H}_t\hat{S}_t^{-1} \tag{40}$$

$$\underbrace{\hat{S}_t}_{1\times 1} = \hat{H}_t^2\hat{P}_{t|t-1} + \sigma_\epsilon^2$$

$$\underbrace{\hat{H}_t}_{1\times 1} = \left.\frac{\partial h}{\partial \alpha}\right|_{\mathbb{E}_{t-1}[\alpha_t]}$$

$$\underbrace{\hat{P}_{t|t-1}}_{1\times 1} = \hat{P}_{t-1|t-1} + \sigma_\eta^2$$

It is simple to show that $(1+\psi e^{\mathbb{E}_t[\alpha_t]})(K_{1,t}+K_{2,t})$ is greater than $(1+\psi e^{\mathbb{E}_t[\alpha_t]})\hat{K}_t$, which directly leads to a lower b_t^*. By reducing the confidence of the market in the underlying firm-level state, managerial incentives to 'fool' the market are commensurately reduced.

6 Discussion

In this section, I discuss some implications of my paper's findings. I begin by emphasizing that my reduced form findings suggest caution when interpreting regressions of earnings on analyst forecasts. I then discuss my structural results along two dimensions: the impact that analysts have on the US economy, and potential policy designs that limit the inefficiencies associated with short-termism.

Endogeneity of Analyst Forecasts and Firm Earnings. A common test of Rational Expectations in the literature, first developed by Coibion and Gorodnichenko (2015) is to run regressions of the following kind:

$$x_{t+h} - \mathbb{F}_t[x_{t+h}] = c + \beta\left(\mathbb{F}_t[x_{t+h}] - \mathbb{F}_{t-1}[x_{t+h}]\right) + error_t \tag{41}$$

Theory suggests that $\beta = 0$ in the case of Full Information Rational Expectations (FIRE), but is non-zero otherwise. In the original specification, Coibion and Gorodnichenko (2015) look at professional forecasters of macroeconomic variables. It seems unlikely that there is a meaningful endogeneity problem in this case. However, more recent papers have applied this methodology to external analyst earnings forecasts; examples include Bordalo et al. (2019) and Ham, Kaplan, and Lemayian (2022).

The reduced form findings in this paper give us reason to think carefully about how we interpret the results in these papers. If it is the case that earnings are endogenously linked to analyst forecasts, then results from these regression specifications are likely to be biased. If we think that earnings are *positively* endogenously related to analyst forecasts, for example, then observations of positive values of β (as is the case in Bordalo et al. (2019)) could simply be capturing this endogeneity. A logical future extension of this paper is to quantify the size of this endogeneity bias.

Impact of Analysts on the US Economy. As well as finding that analyst forecasts causally drive earnings management, I also find that their presence negatively impacts the earnings distribution. In a structural counterfactual exercise with no analyst forecasts, simulated mean earnings are significantly higher compared to the baseline case.

These findings are consistent with a sizable literature that documents that analyst forecasts are not simply informative signals about future firm performance, but sources of distortion and inefficiency (Terry (2015), Almeida, Fos, and Kronlund (2016), Bhojraj et al. (2009), Hong and Kacperczyk (2010)). The typical approach here is to assume that forecasts act as 'targets', and that there exists some discontinuity effect around failing to meet analyst forecasts. By contrast, in my model, analysts amplify the incentives of managers to modify earnings by lowering the degree of uncertainty over the underlying state. Hypothetical borrowing then plausibly moves market expectations more from the perspective of the manager, though of course in equilibrium this is not the case, and the market is not fooled. I do not require any assumptions about discontinuities to arrive at this result.

Increased 'Borrowing' Costs to Curb Short-Termism. A sizable literature has argued in favor of increased financial flexibility for firms (Denis (2011)). Typically the argument relates the presence of financial frictions with respect to cash flows as a source of inefficient investments. The findings in my paper suggest a counterbalance to this position by noting that fewer frictions in the intertemporal substitution of earnings result in greater earnings management, and more inefficient earnings allocations.

7 Conclusion

This paper attempts to quantify the degree of short-termism in the US economy. I begin by developing a novel empirical test of short-termism that identifies causal responses of firm-level earnings to forecasts. I find that earnings and consensus analyst forecasts move one-to-one. This earnings response is driven by accounting accruals, which the market views as costly.

I then construct a theoretical model of short-termism based on the classic work in Stein (1989) that reconciles my reduced form findings. I show that costly earnings management that responds to arbitrary shocks in forecasts can emerge as a fully rational equilibrium, even when the market is not fooled by earnings manipulations.

I then perform a calibration exercise designed to show that the magnitudes of my reduced form results are consistent with plausible specifications of the model parameters. I am able to match key moments from the data, and the one-to-one relationship between forecast shocks and earnings.

References

Almeida, Heitor, Vyacheslav Fos, and Mathias Kronlund (Jan. 2016). "The real effects of share repurchases". en. In: *Journal of Financial Economics* 119.1, pp. 168–185. ISSN: 0304-405X.

Bartov, Eli and Daniel A. Cohen (Oct. 2009). "The "Numbers Game" in the Pre- and Post-Sarbanes-Oxley Eras". en. In: *Journal of Accounting, Auditing & Finance* 24.4. Publisher: SAGE Publications Inc, pp. 505–534. ISSN: 0148-558X.

Bartov, Eli, Dan Givoly, and Carla Hayn (June 2002). "The rewards to meeting or beating earnings expectations". en. In: *Journal of Accounting and Economics* 33.2, pp. 173–204. ISSN: 0165-4101.

Bergstresser, Daniel and Thomas Philippon (2006). "CEO incentives and earnings management". In: *Journal of Financial Economics* 80.3, pp. 511–529. ISSN: 0304-405X.

Bhojraj, Sanjeev et al. (2009). "Making Sense of Cents: An Examination of Firms That Marginally Miss or Beat Analyst Forecasts". en. In: *The Journal of Finance* 64.5, pp. 2361–2388. ISSN: 1540-6261.

Bird, Andrew, Stephen A. Karolyi, and Thomas G. Ruchti (Nov. 2019). "Understanding the "numbers game"". en. In: *Journal of Accounting and Economics* 68.2, p. 101242. ISSN: 0165-4101.

Bordalo, Pedro et al. (2019). "Diagnostic Expectations and Stock Returns". en. In: *The Journal of Finance* 74.6, pp. 2839–2874. ISSN: 1540-6261.

Bradshaw, Mark T. and Richard G. Sloan (2002). "GAAP versus The Street: An Empirical Assessment of Two Alternative Definitions of Earnings". en. In: *Journal of Accounting Research* 40.1, pp. 41–66. ISSN: 1475-679X.

Breuer, Matthias and Harm H. Schütt (Oct. 2021). "Accounting for uncertainty: an application of Bayesian methods to accruals models". en. In: *Review of Accounting Studies*. ISSN: 1573-7136.

Brown, Lawrence D. (2001). "A Temporal Analysis of Earnings Surprises: Profits versus Losses". en. In: *Journal of Accounting Research* 39.2, pp. 221–241. ISSN: 1475-679X.

Burgstahler, David and Ilia Dichev (Dec. 1997). "Earnings management to avoid earnings decreases and losses". en. In: *Journal of Accounting and Economics*. Properties of Accounting Earnings 24.1, pp. 99–126. ISSN: 0165-4101.

Carhart, Mark M. (1997). "On Persistence in Mutual Fund Performance". In: *The Journal of Finance* 52.1, pp. 57–82.

Christensen, Theodore E et al. (2022). "Accruals earnings management proxies: Prudent business decisions or earnings manipulation?" In: *Journal of Business Finance & Accounting* 49.3-4, pp. 536–587.

Coibion, Olivier and Yuriy Gorodnichenko (Aug. 2015). "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts". en. In: *American Economic Review* 105.8, pp. 2644–2678. ISSN: 0002-8282.

Denis, David J (2011). "Financial flexibility and corporate liquidity". In: *Journal of corporate finance* 17.3, pp. 667–674.

Dobbie, Will, Jacob Goldin, and Crystal S. Yang (Feb. 2018). "The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges". en. In: *American Economic Review* 108.2, pp. 201–240. ISSN: 0002-8282.

Durtschi, Cindy and Peter Easton (2009). "Earnings Management? Erroneous Inferences Based on Earnings Frequency Distributions". en. In: *Journal of Accounting Research* 47.5, pp. 1249–1281. ISSN: 1475-679X.

Edmans, Alex, Vivian W Fang, and Katharina A Lewellen (2017). "Equity vesting and investment". In: *The Review of Financial Studies* 30.7, pp. 2229–2271.

Fama, Eugene F and Kenneth R French (2002). "The equity premium". In: *The Journal of Finance* 57.2, pp. 637–659.

Gibbons, Brian, Peter Iliev, and Jonathan Kalodimos (May 2020). "Analyst Information Acquisition via EDGAR". In: *Management Science* 67.2. Publisher: INFORMS, pp. 769–793. ISSN: 0025-1909.

Ham, Charles G., Zachary R. Kaplan, and Zawadi R. Lemayian (Mar. 2022). "Rationalizing forecast inefficiency". en. In: *Review of Accounting Studies* 27.1, pp. 313–343. ISSN: 1573-7136.

Harris, Milton and Bengt Holmstrom (1982). "A Theory of Wage Dynamics". In: *The Review of Economic Studies* 49.3, pp. 315–333. ISSN: 00346527, 1467937X.

He, Jie (Jack) and Xuan Tian (Sept. 2013). "The dark side of analyst coverage: The case of innovation". en. In: *Journal of Financial Economics* 109.3, pp. 856–878. ISSN: 0304-405X.

Holmström, Bengt (Jan. 1999). "Managerial Incentive Problems: A Dynamic Perspective". In: *The Review of Economic Studies* 66.1, pp. 169–182. ISSN: 0034-6527.

Hong, Harrison and Marcin Kacperczyk (Nov. 2010). "Competition and Bias*". In: *The Quarterly Journal of Economics* 125.4, pp. 1683–1725. ISSN: 0033-5533.

Jones, Jennifer J. (1991). "Earnings Management During Import Relief Investigations". In: *Journal of Accounting Research* 29.2. Publisher: [Accounting Research Center, Booth School of Business, University of Chicago, Wiley], pp. 193–228. ISSN: 0021-8456.

Kelly, Bryan and Alexander Ljungqvist (May 2012). "Testing Asymmetric-Information Asset Pricing Models". In: *The Review of Financial Studies* 25.5, pp. 1366–1413. ISSN: 0893-9454.

Kim, Jeong-Bon, Louise Yi Lu, and Yangxin Yu (Sept. 2018). "Analyst Coverage and Expected Crash Risk: Evidence from Exogenous Changes in Analyst Coverage". In: *The Accounting Review* 94.4, pp. 345–364. ISSN: 0001-4826.

Kothari, S. P., Eric C. So, and Rodrigo S. Verdi (Mar. 2016). *Analysts' Forecasts and Asset Pricing: A Survey*. en. SSRN Scholarly Paper ID 2748072. Rochester, NY: Social Science Research Network.

Larson, Chad R, Richard Sloan, and Jenny Zha Giedt (2018). "Defining, measuring, and modeling accruals: a guide for researchers". In: *Review of Accounting Studies* 23, pp. 827–871.

Lim, Terence (2001). "Rationality and Analysts' Forecast Bias". en. In: *The Journal of Finance* 56.1, pp. 369–385. ISSN: 1540-6261.

McElhoe, Bruce A (1966). "An assessment of the navigation and course corrections for a manned flyby of mars or venus". In: *IEEE Transactions on Aerospace and Electronic Systems* 4, pp. 613–623.

Philbrick, Donna R. and William E. Ricks (1991). "Using Value Line and IBES Analyst Forecasts in Accounting Research". In: *Journal of Accounting Research* 29.2. Publisher: [Accounting Research Center, Booth School of Business, University of Chicago, Wiley], pp. 397–417. ISSN: 0021-8456.

Roychowdhury, Sugata (Dec. 2006). "Earnings management through real activities manipulation". en. In: *Journal of Accounting and Economics* 42.3, pp. 335–370. ISSN: 0165-4101.
Smith, Gerald L, Stanley F Schmidt, and Leonard A McGee (1962). *Application of statistical filter theory to the optimal estimation of position and velocity on board a circumlunar vehicle*. Vol. 135. National Aeronautics and Space Administration.
So, Eric C. (June 2013). "A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?" en. In: *Journal of Financial Economics* 108.3, pp. 615–640. ISSN: 0304-405X.
Stein, Jeremy C. (Nov. 1989). "Efficient Capital Markets, Inefficient Firms: A Model of Myopic Corporate Behavior*". In: *The Quarterly Journal of Economics* 104.4, pp. 655–669. ISSN: 0033-5533.
Stock, James H. and Motohiro Yogo (Nov. 2002). *Testing for Weak Instruments in Linear IV Regression*. Working Paper 284. Series: Technical Working Paper Series. National Bureau of Economic Research.
Terry, Stephen (June 2015). *The Macro Impact of Short-Termism*. Discussion Paper 15-022. Stanford Institute for Economic Policy Research.
Wan, Eric (2006). "Sigma-point filters: An overview with applications to integrated navigation and vision assisted control". In: *2006 IEEE Nonlinear Statistical Signal Processing Workshop*. IEEE, pp. 201–202.

A Placebo Exercise of First Stage using instrument constructed from Analyst Fixed Effects of Non-exiting Analysts

As a sense check of my identification strategy, I conduct a placebo exercise. Specifically, I run my first stage regression using analyst-level fixed effects for analysts that I know did *not* exit the sample, which I label $\partial AFE_{i,t}^{placebo}$. Under this framework, I should find a positive coefficient on the fixed effect variable, because the analysts are still contributing to the forecast if they have not exited. My results are outlined in Table A1; I consistently find a positive and statistically significant coefficient on $\partial AFE_{i,t}^{placebo}$.

Table A1: Placebo Exercise using Analysts that did not exit the sample as the instrument.

This table presents the first stage of my IV regression using analysts that I know did not leave the sample. Specifically, I consider the same set of analysts that do leave, but lag the change in the fixed effect composition that they induce to a year in which they did not leave. I consistently find a significant and positive coefficient, consistent with the fact that these analysts continue to contribute to the forecast.

Dependent Variable:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$\partial AFE_{i,t}^{placebo}$	0.9216**	0.9596**	0.9581**	0.9618**	0.9638**	0.9614**	0.9481**
	(0.4430)	(0.4513)	(0.4475)	(0.4474)	(0.4468)	(0.4450)	(0.4450)
log(lag_at)	-0.1690***	-0.0998***	-0.0749***	-0.0740***	-0.0729***	-0.0330***	-0.0163
	(0.0088)	(0.0092)	(0.0100)	(0.0100)	(0.0097)	(0.0101)	(0.0106)
log(mtb)		0.2699***	0.2858***	0.2858***	0.2888***	0.3170***	0.3186***
		(0.0093)	(0.0103)	(0.0103)	(0.0102)	(0.0102)	(0.0103)
log(price)			-0.0552***	-0.0522***	-0.0546***	-0.0825***	-0.0770***
			(0.0089)	(0.0090)	(0.0090)	(0.0093)	(0.0093)
dvps				-0.0318***	-0.0329***	-0.0297***	-0.0290***
				(0.0097)	(0.0098)	(0.0097)	(0.0098)
roa					0.0454	0.0439	0.0440
					(0.0295)	(0.0276)	(0.0277)
lev						-0.7584***	-0.7643***
						(0.0414)	(0.0414)
num							-0.0011***
							(0.0002)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	58,510	56,470	56,469	56,280	56,280	56,051	56,051
R^2	0.14661	0.17273	0.17369	0.17410	0.17547	0.18197	0.18257
Within R^2	0.00849	0.03527	0.03638	0.03679	0.03839	0.04529	0.04599
F-test (1st stage)	7.5433	8.2700	8.2542	8.3175	8.3662	8.3757	8.1505

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Estimation of Earnings Response to Consensus Forecast shocks using levels rather than changes.

In my main analysis, I focus on the changes in the consensus forecast, instrumented using analyst exits due to brokerage mergers. The decision to use changes rather than levels is motivated by the identification strategy I implement, which considers the *change* in the analyst fixed effects after the merger. For completeness, I also run my estimation on levels. Details of the first and second stage can be found in Tables B1 and B2.

As expected, the first stage under this specification is weaker compared to the main specification. The sign of the coefficient is consistent with the intuition that underlies the identification. The second stage is positive, highly significant, and not statistically distinguishable from one.

Table B1: First Stage Results with Levels

This table presents the first stage regression of my IV approach using levels instead of differences. Regression outputs come from specification: $\mathbb{F}_{t-1}[EPS_{i,t}] = \phi_i + \tau_t + \beta \partial AFE_{i,t} + \Gamma X_{i,t} + u_{i,t}$, where $\partial AFE_{i,t}$ is the constructed instrument that roughly captures how optimistic exiting analysts were. The consensus forecast is scaled by the standard deviation of the firm's earnings. Standard errors are clustered at the 'Firm' level. Consistent with the economic intuition, the negative estimate for β suggests that when optimistic analysts cease coverage due to a brokerage merger, the consensus forecast is lower.

Dependent Variable:				$\mathrm{F}_{t-1}[EPS_{i,t}]$			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$\partial AFE_{i,t}$	-0.7540*	-0.8159**	-0.8580**	-0.8780**	-0.8712**	-0.8500**	-0.8511**
	(0.3922)	(0.3916)	(0.3643)	(0.3640)	(0.3628)	(0.3695)	(0.3695)
log(lag_at)	0.3201***	0.4246***	0.2274***	0.2258***	0.2272***	0.2688***	0.2402***
	(0.0135)	(0.0143)	(0.0144)	(0.0143)	(0.0143)	(0.0144)	(0.0148)
log(mtb)		0.3943***	0.2646***	0.2646***	0.2673***	0.2963***	0.2929***
		(0.0130)	(0.0115)	(0.0116)	(0.0117)	(0.0116)	(0.0115)
log(price)			0.4531***	0.4486***	0.4460***	0.4174***	0.4081***
			(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0113)
dvps				0.0372***	0.0364***	0.0389***	0.0380***
				(0.0106)	(0.0104)	(0.0108)	(0.0107)
roa					0.0522	0.0505	0.0502
					(0.0382)	(0.0363)	(0.0361)
lev						-0.8321***	-0.8224***
						(0.0582)	(0.0582)
num							0.0020***
							(0.0003)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	66,879	64,502	64,499	64,266	64,266	64,008	64,008
R^2	0.20113	0.25861	0.31817	0.31951	0.32121	0.32800	0.32966
Within R^2	0.03104	0.08786	0.16113	0.16151	0.16360	0.17168	0.17373
F-test (1st stage)	5.3542	6.6670	8.0176	8.4024	8.2932	7.9400	7.9812

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B2: Second Stage Results with Levels

This table presents the second stage regression of the IV approach using levels instead of differences. Regression outputs come from specification: $[EPS_{i,t}] = \phi_i + \tau_t + \beta \mathbb{F}_{t-1}[EPS_{i,t}] + \Gamma X_{i,t} + u_{i,t}$, where $\mathbb{F}_{t-1}[EPS_{i,t}]$ is instrumented by the variable $\partial AFE_{i,t}$, which roughly captures how optimistic exiting analysts were. The consensus forecast and earnings are scaled by the standard deviation of the firm's earnings. Standard errors are clustered at the 'Firm' level. I consistently find a highly significant and positive causal relationship between forecasts and earnings, that is not statistically distinguishable from one. Unlike in the 'differences' case, the F-test statistics for the first stage are below the thresholds set in Stock and Yogo (2002), motivating the use of differences over levels.

Dependent Variable:				$EPS_{i,t}$			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$F_{t-1}[EPS_{i,t}]$	1.611**	1.602**	1.567**	1.533**	1.529**	1.537**	1.535**
	(0.7473)	(0.6861)	(0.6338)	(0.6085)	(0.6123)	(0.6318)	(0.6303)
log(lag_at)	-0.5181**	-0.5840**	-0.4348***	-0.4264***	-0.4251***	-0.4181**	-0.3702**
	(0.2393)	(0.2914)	(0.1447)	(0.1380)	(0.1396)	(0.1702)	(0.1523)
log(mtb)		-0.2524	-0.1503	-0.1418	-0.1397	-0.1362	-0.1299
		(0.2709)	(0.1682)	(0.1615)	(0.1641)	(0.1876)	(0.1850)
log(price)			-0.3084	-0.2916	-0.2912	-0.3003	-0.2840
			(0.2873)	(0.2731)	(0.2732)	(0.2639)	(0.2574)
dvps				0.0010	0.0007	0.0010	0.0026
				(0.0243)	(0.0239)	(0.0261)	(0.0254)
roa					0.0227	0.0221	0.0226
					(0.0354)	(0.0354)	(0.0350)
lev						-0.1556	-0.1737
						(0.5303)	(0.5230)
num							-0.0033**
							(0.0013)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
	66,879	64,502	64,499	64,266	64,266	64,008	64,008
R^2	-0.32567	-0.27714	-0.20090	-0.15694	-0.15246	-0.16225	-0.15491
F-test (1st stage), $F_{t-1}[EPS_{i,t}]$	7.6417	5.3542	6.6670	8.0176	8.4024	8.2932	7.9400
7.9812							
Wu-Hausman, p-value	0.01701	0.00931	0.00679	0.00751	0.00782	0.00780	0.00794

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Accruals Breakdown

In this appendix, I break down the accruals result using the decomposition outlined in Larson, R. Sloan, and Zha Giedt (2018). Using the expression in that paper, I decompose accruals into working capital accruals, long-term operating accruals, and financial accruals:

$$ACC = \underbrace{WCACC + LTACC}_{OPACC} + FINACC \tag{C1}$$

These components are defined in the following way:

$$WCACC = (\Delta ACT - \Delta CHE) - (\Delta LCT - \Delta DLC) \tag{C2}$$

$$OPACC = (\Delta AT - \Delta CHE - \Delta IVAEQ - \Delta IVAO) - \tag{C3}$$

$$(\Delta LT - \Delta DLC - \Delta DLTT) \tag{C4}$$

$$LTACC = OPACC - WCACC \tag{C5}$$

$$FINACC = ACC - OPACC \tag{C6}$$

Working capital accruals affect current assets, so incorporate changes in accounts receivable/payable and the provision for bad debt of those accounts. Long-term operating accruals involve changes in depreciation of long term assets, both tangible and intangible, revaluations of long-term investments, deferred tax assets/liabilities, changes in the carrying value of long-term debt, and provisions for long-term liabilities like warranties, litigation, restructuring, etc. Finally, financial accruals concern any changes in investment accounts, debt accounts, and equity accounts other than common equity.

Having constructed these variables, I then estimate the impact of the consensus forecast shock on each component of the accruals response. Table C1 shows the results of this decomposition. Note that I lose a lot of observations by restricting to a sample that contains complete data on all four components, and consequently the point estimates are highly imprecise. Nonetheless, no one component of the accruals channels dominates.

To address the problem of limited data, I also perform the same exercise, but interpolate for missing values of $OPACC$ and $WPACC$. The results are shown in Table C2. This interpolation restores the significance of the accruals channel as a whole, but does not lead to any one channel emerging as the driver behind the response.

Table C1: Decomposition of Accruals Response

This table shows the results of decomposing the accruals response into working capital accruals ($WCACC$), long-term operating accruals ($LTACC$) and financia accruals ($FINACC$). The sum of the coefficients in columns (2) through (4) equal the coefficient in column (1). Although limited by precision issues, no one component appears responsible for driving the accruals response.

Dependent Variables:	$\Delta ACC_{i,t}$	$\Delta WCACC_{i,t}$	$\Delta LTACC_{i,t}$	$\Delta FINACC_{i,t}$
Model:	(1)	(2)	(3)	(4)
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	2.005	0.6731	0.3243	1.008
	(1.307)	(0.5454)	(2.528)	(2.532)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	35,262	35,262	35,262	35,262
R^2	-0.12012	0.14490	0.23540	0.23549
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	12.256	12.256	12.256	12.256
Wu-Hausman, p-value	0.08319	0.60266	0.96772	0.73210

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C2: Decomposition of Accruals Response

This table shows the results of decomposing the accruals response into working capital accruals ($WCACC$), long-term operating accruals ($LTACC$) and financial accruals ($FINACC$), whilst interpolating for missing values of $OPACC$ and $WPACC$. The sum of the coefficients in columns (2) through (4) equal the coefficient in column (1). Whilst interpolation restores the significance of the overall accruals channel, no one component of the decomposition emerges as the sole driver of that response.

Dependent Variables: Model:	$\Delta ACC_{i,t}$ (1)	$\Delta WCACC_{i,t}$ (2)	$\Delta LTACC_{i,t}$ (3)	$\Delta FINACC_{i,t}$ (4)
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	2.150**	0.5805	-0.1507	1.720
	(0.9580)	(0.3989)	(1.731)	(1.778)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	38,463	38,463	38,463	38,463
R^2	-0.17440	0.13965	0.22238	0.20724
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	22.832	22.832	22.832	22.832
Wu-Hausman, p-value	0.01034	0.56044	0.91860	0.45183

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

D Tests of Discretionary Accruals

In the body of the paper, I run a regression on standard accruals. In this robustness test, I construct an additional test using 'discretionary' accruals. Discretionary accruals are the portion of total accruals that management can influence that represent the difference between reported earnings and cashflow not due to normal business operations (Jones (1991)), and are often viewed as evidence of managers engaging in earnings manipulation.

To construct discretionary accruals, I use the non-discretionary accruals estimated in Breuer and Schütt (2021). These are constructed using a Bayesian estimation method that incorporates parameter and model uncertainty into the estimation of normal accruals.

My findings are reported in Table D1. Using non-discretionary accruals from Breuer and Schütt (2021), I find that roughly 90% of the accrual response is 'discretionary', and that the coefficient is significant at the 5% level. Note that my sample here is considerably smaller, as the non-discretionary accruals estimated in Breuer and Schütt (2021) do not cover my entire panel, leading to data loss.

Table D1: Tests for Discretionary Accruals

This table presents my findings from an IV estimation exercise of the impact of a consensus forecast shock on discretionary accruals ($ACC_{i,t}^{disc}$). I use the non-discretionary accruals estimated in Breuer and Schütt (2021), $ACC_{i,t}^{non-disc}$, to back out discretionary accruals from total accruals, $ACC_{i,t}$. These are constructed using a Bayesian estimation method that incorporates parameter and model uncertainty into the estimation of normal accruals. I express all variables in per-share terms, and scale by the firm-level standard deviation of earnings. I control for a firm and year fixed effect, plus the same set of controls that I include in my estimation of the Earnings effect in Table 5.

Dependent Variables:	$\Delta ACC_{i,t}$	$\Delta ACC_{i,t}^{Disc}$	$\Delta ACC_{i,t}^{non-disc}$
Model:	(1)	(2)	(3)
Variables			
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	2.444**	2.200**	0.2443
	(0.9643)	(0.9997)	(0.2789)
Controls	Yes	Yes	Yes
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	26,753	26,753	26,753
R^2	-0.18963	-0.17719	0.13332
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	18.487	18.487	18.487
Wu-Hausman, p-value	0.01942	0.03096	0.80262

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

E Real Activities Earnings Management

In this appendix, I explore whether 'real activities' based earnings management accounts react to the consensus forecast shock. I find mixed evidence of earnings management through these channels, with limited statistical significance.

To perform this exercise, I perform an alternative decomposition to the accruals-based approach in Section 3 that identifies whether managers also make use of 'real activities'-based earnings management:

$$Earnings = SALE - COGS - \underbrace{ADJ}_{(XSGA-RECD)-XRD-RECD-Other} \tag{E1}$$

where NI is net income, $SALE$ is sales, $COGS$ is cost-of-goods-sold, ADJ are additional adjustments that influence net income and hence earnings, $XSGA$ is selling and general expenses, $RECD$ is the provision for bad debt, XRD is Research and Development expense, and $Other$ captures additional accounting items that go into the calculation of $Earnings$. I subtract $RECD$ from $XSGA$ as $RECD$ is a component of $XSGA$, yet is a commonly identified channel of accruals-based earnings management documented in the literature.

I first decompose earning into just sales ($SALE$), cost-of-goods-sold ($COGS$), and adjustments (ADJ). My results are reported in columns (1) to (4) Table E1. I do not find that adjustments react sizably to the consensus forecast shock, with sales dominating the decomposition.

One common channel for real activities based earnings is to engage in price reductions and/or over production to boost sales. Roychowdhury (2006) notes that such strategies typically result in high production costs relative to sales. To see if this channel is supported by my estimation, I also run a regression using the same specification as before on production costs over sales. Production costs are defined as the cost-of-goods-sold plus the change in inventories, so I take this value and divide it by total sales. My findings are reported in column (5) of Table E1. Although statistically insignificant, the coefficient is consistent with the consensus forecast shock inducing strategies like sales price reductions/overproduction to generate sales.

I then unpack the adjustments (ADJ) component of the decomposition to investigate specific accounts common to the earnings management. My findings are reported in Table E3. In column 1 I look at selling and general expenses less the provision for bad debt ($XSGA - RECD$), in column 2 I look at research and development expenses (XRD), in column 3 I look at the provision for bad debt ($RECD$) (note that changes in the provision for bad debt would be an example of accruals-based manipulation), and in column 4 I look at any other adjustments not encompassed by these variables ($Other$). I find limited statistical evidence that these variables are affected by the forecast shock, though the sign of the coefficients for selling and general expenses less the provision for bad debt. Further note that the sign for the provision for bad debt regression is also consistent with this channel, though this would constitute accruals based rather than real activities based manipulation.

Share Buybacks Another common route for modifying earnings is to engage in share buybacks (Bhojraj et al. (2009)). As the key variable forecasted by analysts is earnings-per-

Table E1: Earnings Decomposition into Sales and Cost of Goods Sold

This table presents my findings from a decomposition of my earnings result into sales ($SALE$), cost-of-goods-sold ($COGS$), and adjustments (ADJ). I find that adjustments are not a major factor in the earnings result. In column (5) I also include a regression on the ratio of the change in production costs, defined as cost-of-goods-sold plus the change in inventories, to the change in sales. Excessive values of this measure are often indicative of sales price reductions and/or over production.

Dependent Variables:	$\Delta EPS_{i,t}$	$\Delta SALE_{i,t}$	$\Delta COGS_{i,t}$	$\Delta ADJ_{i,t}$	$\frac{\Delta PROD_{i,t}}{\Delta SALE_{i,t}}$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	1.334***	1.794	0.8247	0.3645	0.7710
	(0.3777)	(1.398)	(1.065)	(0.4129)	(0.7808)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	49,988	49,988	49,988	49,988	43,563
R^2	-0.03068	0.45261	0.42473	0.52338	0.20113
Within R^2	-0.15865	0.00396	0.00142	-0.00935	0.00030
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	26.466	26.466	26.466	26.466	32.891
Wu-Hausman, p-value	0.00045	0.76460	0.87085	0.50052	0.85202

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table E2: Tests for Real Activities Based Earnings Management

This table presents my findings from an additional set of tests of earnings management that are prominent in the literature, using my main IV approach. Here $XSGA$ is selling and general expenses, XRD is research and development expense, $RECD$ is the provision of bad debt, and $Other$ is a catch all of all adjustments to earnings not covered by the preceding variables. I estimate on $XSGA$ less $RECD$, as $RECD$ is a component of $XSGA$, and a common culprit for earnings management. I therefore wish to isolate out any specific effect on $XSGA$ through $RECD$.

Dependent Variables:	$\Delta(XSGA_{i,t} - RECD_{i,t})$	$\Delta XRD_{i,t}$	$\Delta RECD_{i,t}$	$\Delta Other_{i,t}$
Model:	(1)	(2)	(3)	(4)
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	-0.2057	0.1399	-0.0558	0.1473
	(0.3782)	(0.1317)	(0.0469)	(0.4811)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	34,200	30,379	36,335	22,103
R^2	0.52642	0.67260	0.84745	0.70654
Within R^2	-0.00438	-0.11812	-0.05634	0.01771
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	9.9625	13.795	12.775	5.4186
Wu-Hausman, p-value	0.77480	0.20629	0.41277	0.67121

Clustered (permno) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

share, this measure can be increased by lowering the denominator as well as increasing the numerator.

I use two different measures of company share buybacks, COMPUSTAT items PRSTKC and CSHFD, which are the purchase of common and preferred stock and the number of common shares used to calculate fully diluted earnings-per-share respectively. In column 1, I look at the log change in PRSTKC and find a positive, though statistically insignificant coefficient. overproduction. In column 2, I look at the change in the percentage change of CSHFD (a double change because this is a stock not a flow variable), and again find a negative though statistically insignificant coefficient. These coefficients are therefore consistent with the use of share buybacks, though the lack of precision of the estimates means these findings should be viewed with caution.

Table E3: Tests for Share Buybacks

This table presents my findings from a test of whether managers engage in share buybacks to modify their earnings. I use two measures for share buybacks: $PRSTKC$ is a measure of the purchase of common and preferred stock, and $CSHFD$ is the number of common shares used to calculate fully diluted earnings-per-share. As the first variable is a flow and the second a stock, I have to ake double difference for the latter, whereas just a single difference is appropriate for $PRSTKC$.

Dependent Variables:	$\Delta PRSTKC_{i,t}$	$\Delta\Delta CSHFD_{i,t}$
Model:	(1)	(2)
Variables		
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	0.2142	-0.1051
	(0.2163)	(0.1444)
Controls	Yes	Yes
Year	Yes	Yes
Fixed-effects		
Firm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	44,570	44,178
R^2	0.29177	0.14019
Within R^2	-0.00550	0.00406
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	23.363	31.838
Wu-Hausman, p-value	0.65072	0.64829

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

F Testing the earnings response for Large vs. Small firms.

As part of my strategy to identify the stock price effects of the consensus forecast shock, I draw on the idea that large firms are likely to be better understood by the market, and so forecast shocks are less likely to influence beliefs about underlying performance. Instead, the shock should affect prices through the indirect and costly channel of the loss of earnings due to accrual based earnings management.

For the comparison to be fair, it is necessary that there is no little to no difference in the actual earnings response between small and large firms. I test this possibility by estimating my main specification, as in Equation 19, on the same restricted sample of large firms as in Section 3.2.3. I also run an additional regression in which I include an interaction term between the consensus forecast and an indicator taking a value of one if the firm is in the top quintile of the total asset distribution.

My findings are reported in Table F1. I fail to identify a significant difference in the earnings response of large vs. small firms. I therefore conclude that the differential response in the stock market is not driven by differences in the earnings response to the forecast shock.

Table F1: Testing for a differential earnings response for Large and Small firms

In this table I present the results from two IV estimations, where I test whether large firms earnings response to the consensus forecast shock differs to those of smaller firms. The dependent variable is the change in earnings. In the first test, I account for differential effects by interacting the consensus forecast on an indicator that captures whether a firm is large, ($\mathbb{I}[Large_{i,t}]$), which takes a value of 1 if the firm's total assets are in the top quintile of the sample. I fail to reject the null that the earnings response differs for larger firms. In the second, I run the same IV regression as in my main setup on a restricted sample of firms in the top quintile of the total asset distribution. I fail to reject the null that the estimated coefficient is different from 1.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}(Large_{i,t})$	$\Delta EPS_{i,t}$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta EPS_{i,t}$
IV stages	First		Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\partial AFE_{i,t}$	-1.802***	-0.0280		-2.058***	
	(0.4765)	(0.0383)		(0.6002)	
$\partial AFE_{i,t} \times$ I(Large$_{i,t}$)	-0.3227	-2.452***			
	(0.7574)	(0.6237)			
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			1.208***		0.6531**
			(0.3942)		(0.3191)
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}(Large_{i,t})$			-0.2143		
			(0.4522)		
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	77,216	77,216	77,216	21,634	21,634
R^2	0.25719	0.11227	0.11046	0.26308	0.34664
F-test (1st stage)	21.175	41.870		18.069	
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			21.175		18.069
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}(Large_{i,t})$			41.870		
Wu-Hausman, p-value			0.00678		0.59980

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G Robustness Tests of Differential Stock Market Response

To ensure that the differential stock market response I document in Section 3.2.3 is not driven by the specific approach of restricting the sample to firms in the top quintile I conduct a series of additional exercises with different assumptions. In the first, I use raw excess returns as the dependent variable. In the second, I use quartiles to separate the samples instead of quintiles. In the third, I use the median split. In the fourth, I do not perform subsampling, but directly estimate a differential response using the entire sample. To do this, I estimate the following expression:

$$r_{i,m} = \phi_i + \tau_{j,m} + \beta_0 \Delta \mathbb{F}_{t-1}[EPS_{i,t}] + \beta_1 \Delta \mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}[Large_{i,t}] + \Gamma X_{i,m} + \epsilon_{i,m} \tag{G1}$$

The only difference in the specification to that in Equation 18 is the inclusion of $\Delta \mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}[Large_{i,t}]$, where $\mathbb{I}[Large_{i,t}]$ is an indicator taking a value of one if the firm is in the top quintile of the total asset distribution in year t. All other variables are defined identically to those in Equation 18.

In the fifth specification, I use the number of analysts covering the firm instead of total asset size to differentiate between firms. The intuition here is that the number of assets is another proxy for market attention, and hence the market's ability to identify arbitrariness in forecast shocks. As in the main specification, 'large' denotes firms in the top quintile of the analyst coverage distribution.

Finally, I construct two measures of cumulative abnormal returns (CAR) generated in the year of the shock, rather than looking only at monthly returns. I define these two measures in the following way:

$$CAR^1_{i,t} = \sum_{m=1}^{12} AR_{i,m} \tag{G2}$$

$$CAR^2_{i,t} = 1 - \prod_{m=1}^{12} (1 + AR_{i,m}) \tag{G3}$$

I then estimate the following expression, where :

$$CAR^k_{i,t} = \phi_i + \tau_t + \beta_0 \Delta \mathbb{F}_{t-1}[EPS_{i,t}] + \beta_1 \Delta \mathbb{F}_{t-1}[EPS_{i,t}] \times \mathbb{I}[Large_{i,t}] + \Gamma X_{i,m} + \epsilon_{i,m} \tag{G4}$$

where, as before, $\mathbb{I}[Large_{i,t}]$ is an indicator taking a value of one if the firm is in the top quintile of the total asset distribution in year t, and k is either 1 or 2 depending on the measure of CAR being used.

Results for these six specifications can be found in Tables G1, G2, G3, G4, G5, and G6 respectively. In all six cases, we arrive at coefficients consistent with larger firms facing more negative returns than smaller firms.

Table G1: Robustness —Differential Stock Market Response using Raw Excess Returns

In this table I report the first and second stage results from the IV estimation of Equation 17, where I restrict the sample to firms in the bottom four quintiles of the total assets distribution (Columns (1) and (2)), and to firms in the top quintiles (Columns (3) and (4)). Unlike in my main analysis, the dependent variable is raw excess stock market returns. I find a negative and statistically significant coefficient in my restricted sample of firms in the top quintile of assets.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Raw Returns	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	Raw Returns
IV stages	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
$\partial AFE_{i,t}$	-0.7740***		-2.327***	
	(0.2015)		(0.2486)	
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		0.0588		-0.0310***
		(0.0389)		(0.0118)
Fixed-effects				
Industry-Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	335,372	335,372	104,634	104,634
R^2	0.27413	0.14868	0.36016	0.38675
F-test (1st stage)	13.100		139.41	
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$		13.100		139.41
Wu-Hausman, p-value		0.15472		0.00011

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table G2: Robustness —Differential Stock Market Response using Quartiles

In this table I report the second stage results from the IV estimation of Equation 17, where I restrict the sample to firms in the bottom three quartiles of the total assets distribution (Columns (1) and (2)), and to firms in the top quartile (Columns (3) and (4)). I report results for both abnormal stock market returns and raw excess returns as the dependent variable. I find a negative and statistically significant coefficient in my restricted sample of firms in the top quartile of assets for raw excess returns, and a negative though statistically insignificant coefficient for abnormal returns.

Dependent Variables:	Raw Returns		Abnormal Returns	
Model:	(1)	(2)	(3)	(4)
Size:	Small	Large	Small	Large
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	0.0352	-0.0263*	0.0384	-0.0166
	(0.0278)	(0.0143)	(0.0258)	(0.0137)
Fixed-effects				
Industry-Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	310,131	129,875	310,131	129,875
R^2	0.23281	0.38024	0.06992	0.24169
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	27.238	109.70	26.674	110.12
Wu-Hausman, p-value	0.27015	0.00321	0.17309	0.03730

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table G3: Robustness —Differential Stock Market Response using Median Split

In this table I report the second stage results from the IV estimation of Equation 17, where I restrict the sample to firms in the bottom half of the total assets distribution (Columns (1) and (2)), and to firms in the top half (Columns (3) and (4)). I report results for both abnormal stock market returns and raw excess returns as the dependent variable. I find a negative and statistically significant coefficient in my restricted sample of firms in the top half of assets for raw excess returns, and a negative though statistically insignificant coefficient for abnormal returns.

Dependent Variables:	Raw Returns		Abnormal Returns	
Model:	(1)	(2)	(3)	(4)
Size:	Below	Above	Below	Above
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	0.0765**	-0.0278*	0.0729**	-0.0158
	(0.0335)	(0.0163)	(0.0314)	(0.0150)
Fixed-effects				
Industry-Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	188,613	251,393	188,613	251,393
R^2	0.07603	0.30460	-0.08639	0.16927
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	24.404	88.243	24.188	88.702
Wu-Hausman, p-value	0.01548	0.00564	0.01277	0.06889

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table G4: Robustness —Differential Stock Market Response using Indicator

In this table I report the second stage results from the IV estimation of Equation G4, where I include an additional interaction term between the consensus forecast shock and an indicator that takes a value of one if the firm is in the top quintile of the total asset distribution. I find a positive and statistically significant coefficient on the consensus forecast shock, and a negative and statistically significant coefficient on the interaction term.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$	Raw Returns	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$	Abnormal Returns
IV stages	First		Second	First		Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\partial AFE_{i,t}$	-1.062***	-0.2839***		-1.052***	-0.2820***	
	(0.1990)	(0.0477)		(0.1994)	(0.0477)	
$\partial AFE_{i,t} \times$ Large$_{i,t}$	-0.3316	-1.375***		-0.3366	-1.374***	
	(0.2791)	(0.1970)		(0.2801)	(0.1973)	
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			0.0713*			0.0700**
			(0.0367)			(0.0349)
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$			-0.1069***			-0.0918***
			(0.0354)			(0.0334)
Fixed-effects						
Industry-Month	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	440,006	440,006	440,006	440,006	440,006	440,006
R^2	0.25371	0.18501	0.09118	0.25345	0.18488	-0.10272
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			34.038			33.651
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$			136.45			135.89
Wu-Hausman, p-value			0.00213			0.01196

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table G5: Robustness —Differential Stock Market Response using Number of Analysts

In this table I report the second stage results from the IV estimation of Equation 17, where I restrict the sample to firms in the bottom four quintiles of the analyst coverage distribution (Columns (1) and (2)), and to firms in the top quintile (Columns (3) and (4)). I report results for both abnormal stock market returns and raw excess returns as the dependent variable. I find a negative though statistically insignificant coefficient in my restricted sample of firms in the top quintile of analyst coverage for both raw and abnormal returns.

Dependent Variables:	Raw Returns		Abnormal Returns	
Model:	(1)	(2)	(3)	(4)
Size:	Small	Large	Small	Large
Variables				
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	-0.0008	-0.0214	0.0075	-0.0118
	(0.0356)	(0.0218)	(0.0342)	(0.0210)
Fixed-effects				
Industry-Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	341,855	98,233	341,855	98,233
R^2	0.25804	0.42882	0.12691	0.29235
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	14.113	58.049	13.899	57.109
Wu-Hausman, p-value	0.82797	0.10427	0.94445	0.29723

Clustered (Industry-Month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table G6: Robustness —Differential Stock Market Response using Indicator

In this table I report the second stage results from the IV estimation of Equation G1, where I first construct annualized values of cumulative abnormal returns (CAR), and estimate an interaction term between the consensus forecast shock and an indicator that takes a value of one if the firm is in the top quintile of the total asset distribution. I find a positive and statistically significant coefficient on the consensus forecast shock, and a negative and statistically significant coefficient on the interaction term.

Dependent Variables:	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$	CAR^1	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$	$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$	CAR^2
IV stages	First		Second	First		Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\partial AFE_{i,t}$	-1.839***	-0.0229		-1.839***	-0.0229	
	(0.6246)	(0.0502)		(0.6246)	(0.0502)	
$\partial AFE_{i,t} \times$ Large$_{i,t}$	-0.5839	-2.495***		-0.5839	-2.495***	
	(0.8547)	(0.5799)		(0.8547)	(0.5799)	
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			0.3584**			0.3291**
			(0.1481)			(0.1395)
$\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$			-0.5257***			-0.4805***
			(0.1673)			(0.1600)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	51,493	51,493	51,493	51,493	51,493	51,493
R^2	0.17818	0.09415	-0.31456	0.17818	0.09415	-0.18298
F-test (1st stage)	16.580	46.404		16.580	46.404	
F-test (1st stage),$\Delta\mathbb{F}_{t-1}[EPS_{i,t}]$			16.580			16.580
F-test (1st stage), $\Delta\mathbb{F}_{t-1}[EPS_{i,t}] \times Large_{i,t}$			46.404			46.404
Wu-Hausman, p-value			0.00011			0.00122

Clustered (permno) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H Proof of Theorem 1

Note that:

$$P_t = \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t[h(\alpha_{t+j})] + \text{ borrowing conjecture} \tag{H1}$$

Up to a first-order approximation,

$$\mathbb{E}_t[h(\alpha_{t+j})] = h(\mathbb{E}_t[\alpha_{t+j}])$$

We know that $\mathbb{E}_t[\alpha_{t+j}] = \mathbb{E}_t[\alpha_t], \forall j$ by Equation 28. Therefore:

$$P_t = \frac{1}{r}h(\mathbb{E}_t[\alpha_t]) + \text{borrowing conjecture}$$

$$\begin{aligned}\implies \frac{\partial P_t}{\partial b_t} &= \frac{1}{r}\frac{\partial h(\mathbb{E}_t[\alpha_t])}{\partial b_t} \\ &= \frac{1}{r}h'(\mathbb{E}_t[\alpha_t])\frac{\partial \mathbb{E}_t[\alpha_t]}{\partial b_t}\end{aligned}$$

Application of the Extended Kalman Filter shows that:

$$\mathbb{E}_t[\alpha_t] = \mathbb{E}_{t-1}[\alpha_t] + K_t\left(\begin{bmatrix} e_t^n \\ \phi_t^n \end{bmatrix} - \mathbf{h}(\mathbb{E}_{t-1}[\alpha_t])\right)$$

where, in general:

$$\begin{aligned}\underbrace{K_t}_{1\times 2} &= P_{t|t-1}H_t^T S_t^{-1} \\ \underbrace{S_t}_{2\times 2} &= H_t P_{t|t-1} H_t^T + R \\ \underbrace{H_t}_{2\times 1} &= \left.\frac{\partial \mathbf{h}}{\partial \alpha}\right|_{\mathbb{E}_{t-1}[\alpha_t]} \\ \underbrace{R}_{2\times 2} &= \begin{bmatrix} \sigma_\epsilon^2 & 0 \\ 0 & \sigma_\xi^2 \end{bmatrix} \\ \underbrace{P_{t|t-1}}_{1\times 1} &= P_{t-1|t-1} + \sigma_\eta^2 \\ \underbrace{P_{t|t}}_{1\times 1} &= (1 - K_t H_t)P_{t|t-1}\end{aligned}$$

Note that K_t becomes a constant only if H_t is constant. This occurs only when $h(.)$ is a linear function. It follows from the above that:

$$\frac{\partial \mathbb{E}_t[\alpha_t]}{\partial b_t} = K_{1,t} + K_{2,t}$$

So it follows that:

$$\begin{aligned}\frac{\partial P_t}{\partial b_t} &= \frac{1}{r} h'(\mathbb{E}_t[\alpha_t])\,(K_{1,t} + K_{2,t}) \\ &= \frac{1}{r} K_t \mathbf{h}'(\mathbb{E}_t[\alpha_t])\end{aligned}$$

By the FOC of the manager's problem:

$$\begin{aligned}c'(b^*) &= \frac{1+r}{1-\pi}\left(1 + \pi \frac{\partial P_t}{\partial b_t}\right) \\ &= \frac{1+r}{1-\pi}\left(1 + \frac{\pi}{r} K_t \mathbf{h}'(\mathbb{E}_t[\alpha_t])\right)\end{aligned}$$