The Role of Accounting Quality during Mutual Fund Fire Sales[☆]

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Abstract

We study the *ex ante* role of accounting quality in mitigating the undervaluation generated by mutual fund fire sales. Asymmetric information between distressed mutual funds and potential buyers of the securities being fire sold leads to an adverse selection problem resulting in an equilibrium in which buyers only trade at prices below intrinsic value. Sellers accept these lower prices only because they have severe liquidity needs. To the extent that accounting quality helps market participants better estimate the intrinsic value of securities being fire sold, we expect the adverse selection problem to be less severe for firms with better accounting quality. Consistently, we find that high accounting quality is associated with smaller fire sale discounts. This result is explained by two complementary mechanisms. Analysts are more likely to provide price-correcting recommendations and arbitrageurs trade more heavily on high accounting quality firms during mutual fund fire sales. Overall, our results show that accounting quality mitigate stock underpricing caused by non-fundamental reasons.

Keywords: Accounting quality, mispricing, fire sales, analysts, institutional investors

JEL: G14, M41

[☆]We appreciate comments from Ted Christensen, Mark Clatworthy, Christina Dargenidou, Miguel Duro, Juan Manuel García Lara, Beatriz García-Osma, Jo Horton, Akram Khalilov, David Martinez-Miera, Gaizka Ormazábal, Joaquín Pirez Pirez, Cathy Shakespeare, Ian Tonks, Ann Vanstraelen, Pablo Ruiz Verdú, Lorien Stice-Lawrence, and Steven Young and seminar participants at University of Exeter, Lancaster University, Universidad de San Andrés, Warwick Business School, XIII Workshop on Empirical Research in Financial Accounting, and the 2019 AAA Annual Meeting. Mariano Scapin appreciates funding from the Bristol Benjamin Meaker Distinguished Visiting Professor scheme, University of Bristol.

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1. Introduction

Does accounting quality (AQ) matter for stock valuation? The role of AQ in capital markets is a fundamental issue that has been widely studied in the accounting literature (Kothari 2001, Dechow et al. 2010, Richardson et al. 2010).[1] Theoretically, stock prices change because of fundamental news or non-fundamental reasons. Fundamental news includes firm-specific accounting information (e.g., earnings), non-accounting information (e.g., new product announcements), and market-wide news (e.g., changes in the inflation rate). On the other hand, non-fundamental reasons include, for example, noise trading or investor sentiment (Baker and Wurgler 2006). Seminal accounting research shows that accounting information explains stock prices (Ball and Brown 1968, Beaver 1968, Dechow 1994) but also that the quality of accounting information varies across firms and that high AQ is associated with lower mispricing of accruals (Sloan 1996, Collins and Hribar 2000, Xie 2001, Dechow and Dichev 2002, Richardson et al. 2005, Chan et al. 2006, Allen et al. 2013).[2] A question that has attracted less attention in the accounting literature is whether AQ mitigates stock mispricing arising due to non-fundamental reasons. In our paper, we aim to address this research question.

Different from the arrival of fundamental information, which is typically characterized by an announcement (e.g., earnings announcements), a key aspect of non-fundamental shocks is the lack of announcement and public information regarding their nature. Prior literature shows that information processing in financial markets depends on whether there is an announcement (and further, whether the timing of news release is known in advance) (Chae 2005, Graham et al. 2006, Honkanen and Schmidt 2022). Therefore, it is not obvious that because AQ mitigates mispricing arising from fundamental news, it should necessarily mitigate non-fundamental mispricing.

Answering our research question is crucial because non-fundamental factors have important effects on the cross-section of stock returns (Shleifer and Summers 1990, De Long et al. 1990, Lee

[1] We understand AQ as the extent to which accruals convey precise information to investors about a firm's expected cash flows.

[2] Prior research also shows that the quality of voluntary disclosure affects stock prices (Botosan 2006, Hirst et al. 2008) and mitigates the mispricing of accounting information (Drake et al. 2009).

et al. 1991, Barberis et al. 1998, Daniel et al. 1998, Neal and Wheatley 1998, Baker and Wurgler 2006, 2007, Subrahmanyam 2008), and mispricing due to non-fundamental reasons is costly for firms (Baker et al. 2003, Khan et al. 2012, Edmans et al. 2012, Campello and Graham 2013, Dong et al. 2021). Therefore, better AQ could potentially counterbalance the negative effects of mispricing caused by non-fundamental factors.

To answer our research question, we focus on a specific setting where mispricing is driven by widespread mutual fund fire sales. Prior literature shows that this non-fundamental shock is economically large, long lived, and hard for market participants to identify (Coval and Stafford 2007, Sulaeman and Wei 2019, Honkanen and Schmidt 2022). Coval and Stafford (2007) show that mutual funds facing significant outflows are forced to fire sell part of their holdings to cover redemptions. When several distressed funds are forced to sell the same stocks at the same time (i.e., there is a supply shock), theory predicts that stock prices will fall below their equilibrium price because liquidity providers will demand a premium to absorb the supply shock (Kurlat 2016, Dow and Han 2018).

The economic intuition is as follows. Managers of distressed mutual funds have better information about the intrinsic value of stocks than potential buyers, and at the same time, different buyers have different information to assess the quality of the stocks being fire sold. This generates an adverse selection problem. When mutual funds are forced to liquidate their positions, it is reasonable to expect that they will get rid of the 'bad' stocks in their portfolio; however, because of the severity of the liquidity needs, they end up liquidating a significant proportion of their portfolio, which includes both 'bad' and 'good' stocks (Huang et al. 2022). More fire sales means more stocks are supplied to the market; once the 'better-informed' investors (i.e., those that can potentially distinguish 'bad' from 'good' stocks) exhaust their wealth, liquidity should be provided by the 'worse-informed' investors (i.e., those that cannot distinguish 'bad' from 'good' stocks). The 'worse-informed' investors, knowing they are not so good at telling apart the bad stocks, will only trade at lower prices. Akin to the 'lemons' problem (Akerlof 1970), prices of fire-sold stocks must fall for markets to clear. In other words, information asymmetries between mutual fund managers and market participants drive fire sale discounts.

To the extent that high AQ is useful for investors in estimating firm value (Dechow 1994, Barth et al. 2001, Dechow and Dichev 2002, Dechow and Schrand 2004, Francis et al. 2005, Dichev et al. 2013, McNichols and Stubben 2015) and mitigates adverse selection by reducing the degree of information asymmetry between managers of distressed mutual funds and other capital market participants (Bushman and Smith 2001, Healy and Palepu 2001, Easley et al. 2002, Easley and O'Hara 2004, Francis et al. 2004, Lambert et al. 2007), we predict that firms with better AQ will suffer smaller fire sale discounts. However, several papers cast doubt on the usefulness of accounting earnings for valuation purposes (Srivastava 2014, Bushman et al. 2016, Lev and Gu 2016, Lev 2018). If earnings poorly summarize firms' economic performance, then investors may rely on alternative sources of information (Stickel 1995, Jegadeesh et al. 2004, Graham et al. 2005, Ball and Shivakumar 2008, Beyer et al. 2010, Shao et al. 2021). As a result, earnings may not be informative enough among other sources of fundamental information for AQ to have a first-order effect on stock prices (Zimmerman 2013).

To better understand the mechanisms through which AQ mitigates fire sale discounts, we study the behavior of sell-side analysts and institutional investors during mutual fund fire sales. First, when distressed mutual funds liquidate their positions, investors may want to revise their forecasts of firm value, as they may be uncertain about whether the fire sale is about fundamentals or not. For example, the mutual fund decision to liquidate a position and the subsequent stock price decline could itself be the result of unknown bad news about the firm that was just revealed to the market (Kothari et al. 2009), and revising forecasts inferred from poor-quality financial reports is unlikely to reduce the uncertainty of stock price estimates (Callen et al. 2013). Since analysts rely on accounting information to produce their recommendations (Brown et al. 2015, Cascino et al. 2021) and changes in analysts' recommendations facilitate the process by which information is incorporated into stock prices (Womack 1996, Jegadeesh et al. 2004), if better financial reporting helps analysts uncover non-fundamental mispricing, then we expect analysts to issue more price-correcting recommendations for high-AQ firms.

Second, we explore the role of arbitrageurs. Bushee et al. (2019) show that sophisticated short-term investors are less likely to pursue arbitrage strategies on stocks with poor AQ because of higher perceived holding costs. Short-term pressures and the long holding periods required to realize profits impose high costs on investors, reducing the profitability of the trade in the first place. Therefore, in the event of mispricing, arbitrageurs will acquire differentially more stocks with high AQ (i.e., lower holding costs), thereby providing liquidity and reducing the price impact of fire sales. To test this mechanism, we examine changes in the holdings of transient institutional investors, as they engage in strategies focusing on financial statement variables and have short-term investing horizons (Bushee and Noe 2000, Collins et al. 2003). We expect transient institutional investors to increase their holdings in firms with better AQ.

Using a sample of 6,711 firm-quarter observations of U.S. publicly traded firms subject to mutual fund fire sales during the period 2004-2017, we first replicate the main result in Coval and Stafford (2007). Our results indicate that firms affected by mutual fund fire sales experience an abnormal return of -1.39% on average during the quarter of the shock. Consistent with Coval and Stafford (2007), we find that mispricing reverts after approximately 20 months (see Figure 1). We then examine whether fire sale discounts (i.e., non-fundamental mispricing) are lower for firms with better AQ. Measuring AQ as the extent to which accruals map into firms' expected cash flows following Dechow and Dichev (2002) and McNichols (2002), we find evidence of a smaller mispricing for firms with better AQ around the fire-sale quarter. Specifically, after controlling for other determinants of firms information environment and firm characteristics, abnormal stock returns (i.e., evidence of fire sale discounts) are 2.27% lower for firms in the bottom decile relative to firms in the top decile of AQ.[3]

Regarding our proposed mechanisms, we find that both sell-side analysts and transient institutional investors act to mitigate the effects of mutual fund fire sales. In particular, sell-side analysts provide, on average, more favorable recommendations for high-AQ firms and transient institutional

[3]Our results are robust to using alternative measures of abnormal returns and AQ (see Section 4.3). In additional analyses (see Section 5), we also show that our results are not explained by firm's idiosyncratic shocks, firm complexity, managerial ability, corporate governance, or other market factors not included in our main specification.

investors increase their holdings of these firms around the quarter of the fire sales. Interestingly, we do not find any effect for non-transient investors, which are typically long-term oriented and less likely to exploit mispricing opportunities. Taken together, our results suggest that better AQ mitigates fire sale discounts by reducing information asymmetries between market participants.

Our paper makes several contributions to the literature. First, we document a negative relation between AQ and fire sale discounts. This is a novel result that provides empirical support for the theoretical arguments in Kurlat (2016) and Dow and Han (2018). Our results complement the findings in Huang et al. (2022) that information asymmetries are related to fire sale discounts by showing that one potential source of information asymmetries is the quality of accounting information. Second, we add to the empirical literature on the mispricing caused by mutual fund fire sales. Several papers look at *ex-post* market participants' responses to mutual fund fire sales such as insider trading (Ali et al. 2011), sell-side analysts' recommendations (Sulaeman and Wei 2019), and management forecasts (Kadach 2017, Jiang et al. 2021) and find that these help revert mispricing in the quarters following mutual fund fire sales.[4] Our paper, in contrast, focuses on the *ex-ante* effect of AQ on fire sale discounts rather than the subsequent price reversals. Third, our study also contributes to the literature that studies the effect of financial reporting quality on stock prices during extreme market events (Mitton 2002, Barton and Waymire 2004, Hilary 2008). Our setting differs from financial crisis shocks because mutual funds' extreme flow-driven mispricing occurs every other quarter and the source of the noise in prices is unknown to investors. Moreover, the staggered nature of the shock reduces concerns regarding confounding effects that might arise during market crashes, such as changes in risk aversion or aggregate market conditions.

Finally, our paper contributes to the broad literature that focuses on the capital market benefits of high AQ (Francis et al. 2004, 2005, Aboody et al. 2005, Ecker et al. 2006, Biddle and Hilary 2006, Biddle et al. 2009, Kim and Qi 2010, Ogneva 2012, Bhattacharya et al. 2012, 2013, Barth et al. 2013). Different from prior research, we examine the relation between AQ and mispric-

[4]Jiang et al. (2021) also consider 'earnings management' as a potential managerial response following mutual fund fire sales for firms that do not issue guidance, but they do not directly test whether 'earnings management' lowers fire sale discount in the quarter of the shock.

ing from an alternative perspective using a specific setting where mispricing is caused by non-fundamental reasons (Coval and Stafford 2007) and explore the mechanisms of the relation. We show that AQ is useful for valuation when there is mispricing driven by non-fundamental reasons. More price-correcting recommendations and increased trading of transient institutional investors of firms with better AQ are potential mechanisms underlying the relation between AQ and fire sale discounts.

2. Hypothesis development

A 'fire sale is a situation where sellers' liquidity needs force them to sell assets at market prices below their intrinsic value (Shleifer and Vishny 2011). In Akerlof (1970) seminal paper, adverse selection problems between (informed) sellers and (uninformed) investors lead markets to collapse. Financial fire sales are paradoxical, as traditional models assume that declines in asset prices are driven by asset specialization or market frictions that limit arbitrage, which are uncommon among financial assets (Huang et al. 2022). Therefore, traditional models cannot explain the strong price impact or its persistence. Kurlat (2016) and Dow and Han (2018) extend Akerlof (1970) work to explain fire sales in financial assets. Despite their different approaches, both models arrive at the same conclusion. Information asymmetries between informed sellers and less-informed buyers lead to fire sale discounts.[5]

The economic intuition behind these models applied to our setting (i.e., mutual funds fire sales) is as follows. Distressed mutual funds experiencing large outflows need to sell their holdings to cover redemptions. Because of the severity of their liquidity needs, they liquidate a significant proportion of their portfolio, including 'bad' and 'good' stocks. Mutual fund managers are better informed about the intrinsic value of the stocks they are selling relative to potential buyers, leading to an adverse selection problem.

[5]Kurlat (2016) considers a Walrasian competitive equilibrium with information asymmetries, whereas Dow and Han (2018) develop a model combining limits to arbitrage (Grossman and Stiglitz 1980) and adverse selection (Akerlof 1970) in a rational expectations equilibrium framework. We refer readers to Kurlat (2016) and Dow and Han (2018) for details on their respective models.

When several mutual funds are forced to sell the same securities at the same time there is an excess of supply in the market for stocks being sold. Those investors that are better informed and can potentially distinguish 'good' from 'bad' stocks will provide liquidity until they exhaust their wealth. It then follows that the remaining liquidity should be provided by investors that are worse informed and are less likely to distinguish 'good' from 'bad' stocks. Less informed investors anticipate this and will only trade at lower prices. The prices of fire-sold stocks must fall for markets to clear. Mutual fund managers sell their holdings at a price below their intrinsic value only because they are forced to do so (i.e., they are distressed) and not for informational reasons. In other words, information asymmetries between mutual fund managers and market participants drive fire sale discounts.

The Financial Accounting Standard Board (FASB) and the International Accounting Standard Board (IASB) state that the objective of financial reporting is to provide useful information to current and potential investors for decision-making. Consistently, prior literature shows that analysts and investors care about the quality of earnings and that better AQ is associated with more precise estimates of firm value (Dechow 1994, Barth et al. 2001, Dechow and Dichev 2002, Dechow and Schrand 2004, Francis et al. 2005, Dechow et al. 2010, Richardson et al. 2010, Dichev et al. 2013, McNichols and Stubben 2015). If information asymmetries between mutual fund managers and market participants drive fire sale discounts, then to the extent that high AQ helps potential buyers better estimate the intrinsic value of the securities being fire sold, we expect high AQ to alleviate the adverse selection problem between sellers and buyers. Therefore, we predict that firms with better AQ will suffer smaller fire sale discounts. This leads to our hypothesis:

Hypothesis 1. *Fire sale discounts are smaller for firms with high AQ relative to firms with low AQ.*

On the other hand, recent papers suggest that earnings have become a noisier measure of firm economic performance over time (Lev and Zarowin 1999, Francis and Schipper 1999, Srivastava 2014, Bushman et al. 2016, Lev and Gu 2016, Lev 2018), casting doubt on their usefulness for firm valuation. If earnings are a poor summary measure of firms' fundamental news, investors may rely on other sources of information for valuation purposes (e.g., industry reports, analysts' forecasts and recommendations, or management forecasts) (Stickel 1995, Jegadeesh et al. 2004, Graham et al. 2005, Ball and Shivakumar 2008, Beyer et al. 2010, Basu et al. 2013, Amiram et al. 2016). Recently, Shao et al. (2021) provide evidence suggesting that, despite earnings explaining less of the variation in firms' annual returns over time, fundamental information has become more relevant for capital markets in explaining stock prices. In this case, AQ would have no impact on stock prices (Zimmerman 2013).

3. Methodology

*3.1. **Research design***

To provide evidence on the relationship between AQ and non-fundamental mispricing, we focus on a sample of firms suffering price pressures due to mutual fund fire sales and estimate the following pooled cross-sectional regression:

$$CAR_i = \beta \times AQ_i + \gamma \times Controls_i + \varepsilon_i \tag{1}$$

where AQ_i denotes firm i AQ as of the most recent fiscal year prior to the shock quarter, and it captures the extent to which accruals convey information to investors about firm's expected cash flows (we provide further details in Section 3.4). Our dependent variable, CAR_i, is firm i abnormal return around the quarter of the shock. CAR_i captures the magnitude of the non-fundamental mispricing and is defined in Section 3.3. A key aspect of our research design is the fact that we focus on a relatively homogeneous group of firms that are all affected by mutual fund fire sales. In Section 3.2, we provide details on the identification of the firm-quarters subject to non-fundamental mispricing.

The main coefficient of interest in model (1) is β, which captures the effect of AQ on non-fundamental mispricing. If AQ mitigates mispricing due to mutual fund fire sales (i.e., reduces fire sale discounts), we expect β to be positive and statistically significant. We estimate model (1) for alternative windows around the shock quarter. The rationale for this is provided in Section 3.2.

$Controls_i$ include a set of control variables. We control for the magnitude of fire sales price pressures (*Pressure*) because mispricing may be related to the intensity of fire sales (Coval and Stafford 2007). We control quarterly earnings surprises (*EPS_Surprise*) to account for the market reaction to accounting information revealed in the shock quarter. We control for analyst coverage (*LnNumEst*) and the frequency of management earnings forecasts (*NForecasts*) to capture the potential effect of differences in a firm's information environment (Beyer et al. 2010). We also include controls for good news EPS forecast (*GN_Forecast*) and bad news EPS forecast (*BN_Forecast*) issued in the quarter of the shock to capture potential managerial responses to mispricing (Kadach 2017, Jiang et al. 2021). We control for institutional ownership (*InstHold*) since more sophisticated investors might see through mispricing and better understand the long-term value implications of earnings manipulations and act as external monitors (Bushee 1998, Bushee et al. 2019). We control for the level of short interest (*SIR*(%)) to capture potential hoarding of bad news that may result in higher price crash risk (Hutton et al. 2009, Kothari et al. 2009). We include further controls that are typically used in prior literature to account for firm fundamentals (Francis et al. 2005, Ben-Rephael et al. 2017). These controls include: firm size (*MktCap*), growth opportunities (*Mkt_to_Book*), operating cycle (*Op_cycle*), volatility of cash flows (*S_CFO*), volatility of returns (*S_Sales*), and the incidence of losses (*Loss*).[6]

Finally, we also include quarter-year and industry (defined by the Fama and French 48 industry groups) fixed effects to control for time- and industry-specific factors that might be correlated with returns. Standard errors are clustered at the firm level. Appendix 1 provides definitions of all variables.

3.2. ***Shock to non-fundamentals***

Coval and Stafford (2007) show that when mutual funds facing liquidity needs (i.e., investors' redemptions exceed cash available) are forced to fire sale stocks commonly held among them, this results in severe stock mispricing for the securities being fire-sold. This mispricing reverts over the

[6] All control variables are calculated at the end of the fiscal year prior to the shock quarter.

next 24 months following the fire sales. Importantly, this reversal is not observed among mutual funds' widespread selling not driven by liquidity needs, which are more likely to be opportunistic voluntary transactions based on information (Coval and Stafford 2007). The reversal in the initial negative abnormal returns observed during mutual fund fire sales suggests that the shift in prices is not driven by fundamental information. We follow the same approach to identify which firms are subject to mutual fund fire sales.[7]

First, we identify distressed mutual funds as those having extreme flows in a given quarter. Mutual fund flows (MFF_{jt}) are calculated as follows:

$$MFF_{jt} = \frac{TNA_{j,t} - TNA_{j,t-1}(1+R_{j,t})}{TNA_{j,t-1}} \tag{2}$$

where total net assets, $TNA_{j,t}$, are fund j's TNA in quarter t and $R_{j,t}$ is fund j's return during quarter t.[8] We drop highly concentrated funds (fewer than 10 stock holdings) and those with extreme changes in TNA (Coval and Stafford 2007, Ali et al. 2011, Sulaeman and Wei 2019).[9] Distressed mutual funds are those in the top and bottom deciles of MFF's distribution in a given quarter.

Second, for each stock, we obtain a proxy for price pressure, $Pressure_{it}$, as the difference between outflow-induced sales and inflow-induced purchases, and we normalize it by the average trading volume:

$$Pressure_{i,t} = \frac{\Sigma_j(max(0,-\Delta H)|MFF_{j,t} < P(10th)) - \Sigma_j(max(0,\Delta H)|MFF_{j,t} > P(90th))}{Vol_{i,t-1}} \tag{3}$$

where ΔH is the change in holdings from quarter $t-1$ to quarter t and $Vol_{i,t-1}$ is the trading

[7] Several previous papers exploit this 'non-fundamental shock' to stock prices and replicate the patterns observed by Coval and Stafford (2007) (i.e., significant price drop followed by a significant price reversal) (Ali et al. 2011, Khan et al. 2012, Sulaeman and Wei 2019). We observe the same patterns in abnormal returns documented in prior papers (see Figure 1).

[8] The CRSP Mutual Fund database provides monthly data for returns and TNA, but stock holdings are only available on a quarterly basis. Therefore, to merge the two databases, we convert all the variables to a quarterly frequency.

[9] Following Coval and Stafford (2007), we drop extreme changes in TNA and retain those with $-50\% < \Delta TNA < 200\%$.

volume in the previous quarter.

As documented by Coval and Stafford (2007), funds with large inflows (outflows) tend to increase (decrease) their existing positions, creating significant upward (downward) price pressure in the stocks held in their portfolios. Importantly, equation (3) nets out sales by funds with extreme outflows with purchases by funds with extreme inflows and considers only the fire sales that are not absorbed by extreme purchases. Finally, following previous literature, we define a firm to be suffering from a fire sale if it is in the top decile of the distribution of *Pressure*.

Because it is difficult to pinpoint the beginning and end of the fire sale period we consider three alternative windows for our tests. The main event window, q=(0) is the quarter in which we observe a firm in the top decile of the distribution of *Pressure*. Then, we consider the quarter of the shock and the previous quarter, q=(-1,0), and one quarter before and one quarter after the shock, q=(-1,1).

One concern with the price pressure proxy developed by Coval and Stafford (2007) is that it is based on actual trades, which might contain information about managers' views of future stock performance (Berger 2021, Huang et al. 2022). This is particularly relevant when comparing firms with and without mutual fund fire sales, as there may be 'selection into treatment' (i.e., exposure to the shock may be driven by firm characteristics).[10] This is less of a concern in our research design since we condition our tests on a sample of firms subject to mutual fund fire sales and exploit the cross-sectional variation in AQ. In other words, we look *only* at firms that experience mutual funds fire sales, which constitute a relatively homogeneous group.

3.3. ***Abnormal returns measure***

We use abnormal returns calculated with the four-factor model (Carhart 1997) as our main proxy for non-fundamental mispricing. For each firm i and month t, we model expected returns

[10]However, Huang et al. (2022) show that price pressure from fire sales cannot be explained by pure selection because managers are forced to sell both 'good' and 'bad' quality assets, making it difficult for the arbitrageurs to distinguish the underlying quality of the securities being sold.

(estimated using 60 months of prior data) as follows:

$$R_{i,t} - r_f = \alpha_{i,t} + \beta_{MKT} \times RMRF_t + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \beta_{WML} \times WML_t + \varepsilon_{i,t} \quad (4)$$

where the dependent variable is firm's i month t excess return (i.e., firms' monthly returns ($R_{i,t}$) minus the risk free rate (r_f)); *RMRF* is the excess return on a value-weighted aggregate market portfolio; and *SMB* (small minus big size) , *HML* (high minus low book-to-market), and *WML* (winners minus losers) are returns on value-weighted, zero-investment, factor-mimicking portfolios. Abnormal returns, *AR*, are obtained as the difference between the actual return and the expected return predicted by model (4).

We then aggregate returns quarterly to obtain the compound return around the quarter of the shock, CAR_q, where q are quarters relative to the event quarter and can take values $q = 0, (-1,0), (-1,1)$ to estimate abnormal returns in alternative windows.[11]

3.4. *Accounting quality measure*

We follow prior literature and use the Dechow and Dichev (2002) approach to proxy for AQ. The rationale for this proxy is that, the larger the residuals from model (5), the greater the uncertainty associated with the mapping of accruals into cash flows, which could also be interpreted as the uncertainty perceived by investors when using accounting information to assess the value of a firm. This measure has been widely used in the literature, which increases the comparability of our study with prior work.[12]

The Dechow and Dichev (2002) model captures the extent to which cash flows from operations map into accruals and reflects the ability of accruals to predict firms' future cash flows. As advised by McNichols (2002), we augment the Dechow and Dichev (2002) model with changes in revenue and property, plant and equipment. Then, we estimate the following model for each year-industry

[11] For robustness we also calculate abnormal returns considering two alternative models of expected returns: the CAPM and the 3-factor model (Fama and French 1993).

[12] For example, prior papers following the same approach include Francis et al. (2005), Hilary (2008), Core et al. (2008), Biddle et al. (2009), Rajgopal and Venkatachalam (2011), Ogneva (2012), McNichols and Stubben (2015), Bushee et al. (2019), Christensen et al. (2022).

(defined by the Fama and French 48 industry groups) with at least 20 observations:

$$\Delta WC_t = \phi_0 + \phi_1 \times CFO_{t-1} + \phi_2 \times CFO_t + \phi_3 \times CFO_{t+1} + \phi_4 \times \Delta Sales_t + \phi_5 \times PPE_t + \varepsilon_t \quad (5)$$

where ΔWC is changes in working capital accruals, CFO is cash flows from operations, $\Delta Sales$ is changes in revenues, and PPE is gross property, plant, and equipment. All variables are deflated by lagged total assets.

The residuals from model (5) reflect accruals that do not map into cash flow realizations and the volatility of these residuals is an inverse measure of AQ. Following Francis et al. (2005), we measure AQ as the standard deviation of firm-specific residuals from model (5) over the last five years, multiplied by minus one, so higher values reflect better AQ. To control for the effect of outliers and potential non-linearities, and facilitate the economic interpretation of the results we calculate the deciles of this measure. Then, our main proxy for AQ is *Decile_AQ*. Those firms in the top (bottom) decile, $Decile\_AQ = 10$, ($Decile\_AQ = 1$), are the ones with the highest (lowest) AQ.

4. Sample and results

Our sample consists of US publicly listed firms subject to mutual fund fire sales in at least one quarter during the 2004-2017 period. Our sample period starts in 2004 because before that mutual funds were not obliged to disclose their holdings on a quarterly basis. Using mutual fund holdings quarterly data allows us to have a more precise measure of fire sale pressures. We exclude firms in financial and regulated industries (SIC codes 49 and 60-69) since the accruals process in these industries might not be comparable with the remaining firms. We obtain stock price data from CRSP and retain all ordinary shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3). The risk-free rate and factor data used to estimate abnormal returns are collected from the Kenneth R. French Data Library.[13] We obtain financial and seg-

[13] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ data_library.html.

ment information data from Compustat, analyst coverage and management forecasts from I/B/E/S and institutional ownership information from Thomson Reuters 13F. To calculate mutual funds' outflows, we gather data on returns and total net assets from the CRSP Mutual Fund database. Following Shive and Yun (2013), we use quarterly holding data from Thomson Reuters between 2004 and June 2008 and CRSP Mutual Fund database thereafter. In line with previous papers, we drop bond, money market, and international mutual funds as well as those that do not primarily invest in US common equity (Coval and Stafford 2007, Ali et al. 2011, Khan et al. 2012).[14]

After imposing all data requirements for the estimation of model (1), our final sample consists of 6,711 firm-event observations. All continuous variables are winsorized at 1% and 99% to mitigate concerns regarding outliers.

4.1. ***Descriptive statistics***

Table 1, columns 1 to 6, presents summary statistics on our full sample. Similar to prior studies, data requirements to calculate our proxies of AQ and abnormal returns bias our sample toward larger and better performing firms than the average firm in Compustat (Francis et al. 2005).

Firms in our sample experience an average abnormal return of between -1.39% and -2.12% around the quarter of the shock. The magnitude of these results is smaller than the mispricing documented in prior studies (Coval and Stafford 2007, Sulaeman and Wei 2019) but still economically meaningful. The smaller absolute value of abnormal returns in the quarter of the shock in our paper is most likely explained by the fact that academic research tends to eliminate stock return predictability (Johnson and Schwartz 2001, McLean and Pontiff 2016) and our sample focuses on more recent years compared to Coval and Stafford (2007) and Sulaeman and Wei (2019).

In Figure 1, we plot cumulative average abnormal returns around the quarter of the shock for firms experiencing mutual fund fire sales, from 3 months before the shock until 21 months after. Importantly, Figure 1 shows that the significant negative abnormal returns during mutual fund fire

[14] In particular, we retain funds with investment objective codes 2, 3, 4 and 7 from the Thomson Reuters holdings. For the CRSP holdings, we retain funds with the following Lipper objective codes: G, SG, MC, SP, I, B, GI, FX, EI, TK, H, MSI, NR, FS, EMN, S, CS, UT, TL, CA, DSB, ID, BM, and CG (Shive and Yun 2013).

sales are subsequently reversed after 20 months. These patterns shown in Figure 1 –suggesting that the shift in prices is not driven by fundamental information– replicate the same abnormal returns patterns in prior papers (Coval and Stafford 2007) validating the shock to non-fundamentals in our particular sample and period.

Table 1, columns 6 and 7, presents summary statistics by subsamples of high vs. low AQ firms (i.e., above/below the median *AQ* of the average firm in Compustat). Our final sample includes relatively more high *AQ* firms. There are 4,088 (2,623) firm-quarter observations for high *AQ* firms compared to 2,623 firm-quarter observations for low *AQ* firms. This does not necessarily mean that mutual funds are more likely to sell high-AQ firms during mutual fund fire sales; rather, mutual fund ownership increases with AQ (DeFond et al. 2011), and the portfolio of funds in our sample is tilted towards firms with better AQ. The univariate results already indicate that firms with better AQ suffer lower fire sale discounts. The rest of the summary statistics presented in Table 1 are generally consistent with recent studies exploiting this type of mispricing (Sulaeman and Wei 2019, Jiang et al. 2021).

Table 2 presents summary statistics of fund characteristics and their trading in response to price pressures, sorted into deciles, according to actual quarterly flows. Panel A shows that mutual funds experience a wide range of flows: funds in the lowest decile lose -17.45% of their quarterly TNA, while funds in the top decile increase their flows by 57.91%. Funds in the lowest decile are smaller in terms of TNA and are somewhat less diversified. The typical mutual fund holds less than 3% of TNA in the form of cash, which is not enough to cover extreme redemptions.

Panel B displays the fraction of positions that are initiated, expanded, maintained, reduced and eliminated by mutual funds sorted by flow decile. We find that mutual funds experiencing extreme outflows reduce or eliminate 66% of their positions, while funds in the top decile increase 61% of their positions. These results suggest that funds maintain their investment strategy and that they are unlikely to cherry pick the stocks they sell to mitigate the costs of their liquidity needs. All these figures are consistent with prior studies using the mutual fund fire sales setting (see Table 2, p.487 in Coval and Stafford (2007)).

It could still be argued that managers can pick some of the shares they sell and that those shares might be of lower AQ. In Panel C, we provide summary statistics of the average *Decile_AQ*, considering the full Compustat sample, for the stocks that mutual funds initiate, expand, maintain, reduce and eliminate sorted by flow decile. The results indicate that funds tend to invest in firms that have relatively high AQ and, importantly, that there are no systematic differences between the average *Decile_AQ* for the positions increased or reduced by funds for the different flow deciles. This suggests that funds experiencing extreme flows do not mitigate the costs of their liquidity demands by transacting selectively in stocks with high or low AQ, consistent with previous evidence by Coval and Stafford (2007) that stressed funds do not trade selectively their holdings.

4.2. Main results

Table 3 presents our main results considering three alternative windows around the quarter of the shock: column 1 includes the quarter of the shock and the previous quarter (-1,0), column 2 includes only the quarter of the shock (0), and column 3 considers the window (-1,1) including the quarters prior to and following the shock. In line with our prediction, we find β to be positive and statistically significant in all three windows.[15] These results indicate that firms with better AQ experience smaller fire sale discounts. Regarding the economic magnitude of our findings, moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 2.01% to 5.89%.

We find that the significance of the control variables is, in general, weaker than that for AQ, consistent with Hilary (2008). Analysts are considered informed stakeholders, and having more analysts following the firm would be expected to reduce mispricing through faster incorporation of news into prices, competing with our main hypothesis. However, we find that the coefficient on *LnNumEst* is negative and statistically significant, suggesting that analysts would rather exacerbate the shock. This result is not surprising since analysts seem not to recognize this type of mispricing. In particular, Sulaeman and Wei (2019) document that only 11% to 13% of analysts

[15] We find similar results using the raw values of our AQ proxy instead of the deciles (untabulated).

can identify mispricings caused by mutual fund fire sales. Regarding the other determinants of firms' information environment, we find that voluntary disclosure, *NForecasts*, has a positive and statistically significant association with stock returns around the quarter of the shock.

A potential concern is that AQ might be capturing the effect of corporate governance mechanisms, especially in the presence of institutional investors (Bushee 1998, Chung et al. 2002). Interestingly, the coefficient on the fraction of institutional investor ownership is negative and statistically insignificant in most specifications. This result might seem surprising because institutional investors are considered sophisticated shareholders and are therefore are expected to mitigate the effect of exogenous mispricing. Our results suggest that the level of institutional ownership does not affect the extent of mispricing, consistent with Hilary (2008).

The coefficient on *EPS_Surprise* is positive and highly significant, as expected. The inclusion of this variable increases the explanatory power of the specification. Moreover, consistent with the shock being unrelated to firm fundamentals, we find that the coefficient on *Decile_AQ* is quantitatively similar when we exclude this variable (untabulated). Similarly, we find that good new (*GN_Forecast*) and bad new forecasts (*BN_Forecast*) have high explanatory power over abnormal returns during the quarter of the shock, but they do not affect the size of the main coefficient of interest, *Decile_AQ*. In other words, our main variable of interest is orthogonal to the information contained in earnings surprises and management forecasts. These results are important in light of recent papers showing that managers issue earnings forecast in response to market disruptions (Jiang et al. 2021, Kadach 2017) and suggest that AQ at the time of the shock plays an important role above and beyond other information voluntarily disclosed by managers.

Finally, the rest of the control variables are, in general, statistically insignificant and relatively unstable, similar to Hilary (2008). Interestingly, *Pressure*, the fraction of the average trading volume that is fire sold in the quarter of the shock, is generally insignificant. By construction, firms in our sample have higher *Pressure* than firms that are not being fire sold. However, conditional on facing price pressures, this variable cannot further explain returns. This can be explained by the fact that this proxy does not account for the trading of undistressed investors, which will absorb the shares that distressed funds liquidate. Moreover, by considering only 10% of the distribution of *Pressure*, we are significantly reducing the variation in this variable.

Overall, these findings show that better AQ is associated with lower mispricing during mutual fund fire sales. The mispricing observed during the quarter of the shock is driven by non-fundamental reasons (i.e., distressed mutual funds liquidity needs). Thus, our results shed new light on the usefulness of AQ for firm valuation in this particular setting. We find that better AQ mitigates fire sale discounts, supporting theoretical models predictions that information asymmetries between mutual fund managers and market participants drive the fire sale discounts (Kurlat 2016, Dow and Han 2018). These results suggest that better AQ not only reduces the mispricing of fundamental information (as documented by prior literature) but also mitigates the mispricing caused by non-fundamental shocks.

4.3. ***Robustness checks***

Alternative abnormal returns models

We test the robustness of our results by using the market model and the 3-factor model (Fama and French 1993) as alternatives to measure abnormal returns. Table 4, panel A, presents the results of these robustness checks. Using the market model (columns 1 to 3), we find that our results are stronger both in magnitude and significance and for the 3-factor model (columns 4 to 6), we find very similar results to our main specification. Overall, our main result is robust to using both alternative measures of abnormal returns.

Alternative AQ measures

We test the robustness of our results using two alternative measures of AQ. First, we consider the financial statement divergence (FSD) score proposed by Amiram et al. (2015).[16] Amiram et al. (2015) show that, in the absence of errors and manipulation, accounting numbers should follow Benford's Law (BL) theoretical distribution. Therefore, larger deviations of financial statement numbers from the BL distribution are associated with lower AQ. Amiram et al. (2015)'s FSD score

[16] We thank Zahn Bozanic for making these data available for public use.

captures financial statement deviations from BL's distribution. The authors find that higher FSD scores predict future material misstatements. An appealing feature of this measure is that the conformity of financial statement numbers with BL distribution is exogenous to firm characteristics. We create a dummy variable, $Top\_Quintile\_FSD$, to indicate whether the firm is in the top quintile of the FSD score (i.e., lower AQ).

Second, following Loughran and McDonald (2014), we consider the length of the 10-K.[17] The authors find that the length of the 10-K, captures readability better than other measures (i.e., Fog index). Moreover, they document that stock price volatility and analysts forecast errors are lower in the period immediately following the filing of shorter 10-Ks relative to longer 10-Ks, suggesting that readability is associated with less ambiguity in valuation. We create a dummy variable, $Top\_Quintile\_file\_size$, to indicate whether the firm is in the top quintile of the 10-K filing size in that fiscal year (i.e., lower AQ). Under both alternative AQ proxies, we expect β to be negative, indicating that firms with low AQ suffer larger fire sale discounts relative to firms with high AQ.

The results in Table 4, panel B, indicate that our main findings are robust to using these alternative measures of AQ.[18]

*4.4. **Mechanisms***

In this section, we examine the mechanisms through which AQ potentially leads to lower fire sale discounts. In particular, we study the decisions made by two types of market participants during the fire sales quarter, sell-side analysts and transient institutional investors. These mechanisms are not mutually exclusive, and may complement each other in explaining why high-AQ firms experience lower fire sale discounts.

[17] We collect these data directly from the Software Repository for Accounting and Finance at University of Notre Dame, Available at: https://sraf.nd.edu/data/augmented-10-x-header-data/.

[18] In untabulated results, we find that the relationship between accounting quality as proxied by FSD score or file size and abnormal returns is not linear. One potential explanation is that small increments in these variables might not be indicative of lower accounting quality for investors; rather, financial statements might appear more unreliable and less useful when the deviations are large enough, or when financial statements are excessively long.

Changes in analysts' recommendations

Prior research shows that changes in analysts recommendations facilitate the process by which information is incorporated into stock prices (Womack 1996, Jegadeesh et al. 2004). Moreover, survey evidence indicates that analysts rely on accounting information to produce their recommendations (Brown et al. 2015, Cascino et al. 2021). In a recent paper, Gibbons et al. (2021) show that analysts' use of the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system is correlated with longer and more informative recommendations. In the context of mutual fund fire sales, Sulaeman and Wei (2019) show that skilled analysts issue price-correcting recommendations in response to price pressures induced by mutual fund fire sales. Therefore, if high AQ-helps analysts identify mispriced stock, we expect better AQ to be associated with positive changes in analysts' recommendations.

To test this mechanism, we estimate the following pooled cross-sectional regression model around the fire sales quarter:

$$Y_i = \beta \times AQ_i + \gamma \times Controls_i + \varepsilon_i \tag{6}$$

where our dependent variable is either $DRec_i$ or $DBuy_i$. $DRec_i$ is the change in median consensus recommendation around the quarter of the shock. Analysts' recommendations range from 1 to 5, where 1 is strong buy, and 5 is strong sell. We multiply changes in analysts' recommendation by -1, so positive changes indicate a more favorable recommendation. Prior literature documents that changes in consensus recommendation contain information above and beyond other predictive variables (Jegadeesh et al. 2004). $DBuy_i$ is the change in the percentage of buy recommendations. As in our main specification, we estimate model (6) using three alternative windows: the quarter of the shock, the quarter before, and the quarter after the shock. We measure AQ_i as explained in Section 3.4., and $Controls_i$ includes the same set of control variables as in model (1). We expect β to be positive.

Table 5, columns 1 to 3 (4 to 6), shows our findings using *DRec* (*DBuy*) as the dependent variable. Overall, we find that firms with better AQ receive more favorable recommendations in the quarter of the shock and a higher change in the proportion of buy recommendations, both, in the quarter of the shock and in the following quarter. These results provide support for the argument that better AQ helps market participants price securities at the arrival of non-fundamental information, as captured by analysts' recommendations. Moreover, our results complement Sulaeman and Wei (2019). These authors find that analysts play a key role in incorporating information into prices during fire sales, and we document that AQ is an important factor driving this. Therefore, when accounting information does not provide adequate information to assess firm valuation, analysts might wait to see larger deviations from fundamental prices before changing to a more favorable recommendation, prolonging the mispricing.

Importantly, analyzing analysts' recommendations might also proxy other market participants' assessments of firm value, for which we do not have information due to data limitations, or because financial constraints would not allow them to trade on mispricing. Analysts' recommendations are observable and given that no trading is involved, are not affected by financial constraints. Therefore, to the extent that other market participants might use financial reports to price securities, they might find it easier to recognize mispricing for firms with higher AQ.

Changes in institutional investors holdings

Our second mechanism explores the role of different types of institutional investors during mutual fund fire sales. The cost of arbitrage strategies depends on both the idiosyncratic risk of the assets and how long it takes for the mispricing to be resolved. Therefore, even if investors identify mispriced securities, they may decide not to pursue arbitrage strategies when they expect the mispricing not to be resolved in the short term. Moreover, the cost of arbitrage strategies is exacerbated when arbitrageurs trade on others people's money, as fund providers might decide to withdraw their funds before the mispricing has been corrected (Shleifer and Vishny 1997). Therefore, it is logical to think arbitrageurs will tilt their portfolios toward assets they expect to revert faster to fundamental value. Consistent with this idea, Bushee et al. (2019) show that transient investors are reluctant to engage in arbitrage trading of low-AQ firms suggesting that investors perceive that these firms have higher holding costs. If AQ helps arbitrageurs identify mispriced stocks and better AQ is associated with lower holding costs of arbitrage strategies, we expect transient institutional investors to increase their holdings of firms with better AQ during mutual fund fire sales.

Transient institutional investors are the ideal candidates to test our prediction because they are considered sophisticated investors that will likely see through mispricing, and because of their short-term orientation, they are also likely to act as arbitrageurs(Bushee 1998, Bushee and Noe 2000, Bushee 2001, Collins et al. 2003, Ke and Ramalingegowda 2005). Not all institutional investors have the same investment focus. Non-transient investors (i.e., dedicated and quasi-indexers) are less likely to implement short-term arbitrage strategies (Bushee and Noe 2000, Bushee 2001); therefore, we should not observe any association between AQ and non-transient investor holdings during mutual fund fire sales.

To test this mechanism, we estimate the following pooled cross-sectional regression model around the fire sales quarter:

$$Y_i = \beta \times AQ_i + \gamma \times Controls_i + \varepsilon_i \tag{7}$$

where Y_i is either $DTra_i$, the change in holdings by transient institutional investors around the quarter of the shock, or $DNTra_i$, the change in holdings by non-transient institutional investors (i.e., dedicated and quasi-indexer investors) around the quarter of the shock.[19] As in our main specification, we estimate model (7) using three alternative windows: the quarter of the shock, the quarter before, and the quarter after the shock. We measure AQ_i as explained in Section 3.4., and $Controls_i$ includes the same set of control variables as in model (1).

The main coefficient of interest, β, captures the effect of AQ on institutional investor holdings around the quarter of the shock. For transient institutional investors, we expect β to be positive

[19]We obtain data on institutional investors holdings from Thomson Reuters Institutional (13F) Holdings database and use Bushee (1998) institutional ownership classification available from Bushee's personal website (here).

and statistically significant. On the other hand, studying the behavior of non-transient investors serves as a placebo test, and we expect β to be not statistically different from zero, as they have a longer-term horizon and are not expected to change their portfolio holdings to exploit mispricing.

Table 6, columns 1 to 3 (4 to 6), shows our findings using $DTra_i$ ($DNTra_i$) as the dependent variable. The results in columns 1 to 3 show that transient investors buy relatively more stocks of firms with better AQ in the quarter of the shock and in the following quarter, consistent with the idea that arbitrageurs prefer to exploit arbitrage strategies with lower holding costs (Bushee et al. 2019). As expected, we do not observe the same effect for non-transient institutional investors (columns 4 to 6). These results lend confidence to our proposed mechanism since non-transient investors are unlikely to act as arbitrageurs.

5. Additional analyses

5.1. *Accounting quality and other sources of information*

In a competitive information market, where investors can use multiple sources of information for valuation purposes, the usefulness of financial reporting may depend on how much fundamental information is available through other more timely sources (Graham et al. 2005, Ball and Shivakumar 2008, Beyer et al. 2010, Basu et al. 2013). If earnings are a good (poor) summary measure of firms' fundamental news, other sources of information may become less (more) relevant to produce superior estimates of firm value. Alternatively, better financial reporting quality could play a 'confirmatory role' leading to a complementary relation between higher AQ and other sources of information (Ball 2001, Ball et al. 2012).

We test these predictions using two alternative sources of information, changes in analysts' recommendations and management earnings forecasts. First, we augment model (1) with an interaction between $Decile\_AQ$ and $DRec$. Second, we augment model (1) to include an interaction between $Decile\_AQ$ and management forecasts, both, $GN\_Forecast$ (good news) and $BN\_Forecast$ (bad news).

Table 7 presents the results of these cross-sectional tests. In columns 1 to 3, we find that the estimated coefficient on the interaction term $Decile\_AQ \times DRec$ is negative and statistically significant, except from column 2, where the result is marginally insignificant. In columns 4 to 6, we also find a negative and significant coefficient on $Decile\_AQ \times GN\_Forecast$. Taken together, the results in Table 7 suggest that both AQ and other sources of information (i.e., analysts recommendations and management earnings forecasts) mitigate mispricing, and –consistent with the usefulness of AQ for firm valuation– the effect of other sources of information is weaker for firms with better financial reporting quality.

5.2. ***Alternative explanations***

Despite prior research considering mutual fund fire sales as a plausible exogenous shock (Coval and Stafford 2007, Sulaeman and Wei 2019, Jiang et al. 2021), there may still be the concern that managers of distressed mutual funds select to liquidate firms with certain specific characteristics and that this could explain both firms' AQ and mutual fund fire sale discounts, leading to an omitted variable problem (Berger 2021). This is less of a concern in our setting since we focus only on firms that are subject to mutual fund fire sales, and prior literature shows that while there may be some discretion as to which securities distressed mutual funds sell, on average, mutual funds liquidate both firms with 'good' and 'bad' fundamentals (Huang et al. 2022). Nonetheless, we try to alleviate these and other concerns by ruling out potential alternative explanations of our results.

Placebo test

First, we run a placebo test. We estimate our main model for quarters in which the firms in our sample are not subject to mutual fund fire sales. In particular, we focus on the same fiscal quarter in which the firm is suffering fire sales one year and two years before the shock. By analyzing the same fiscal quarter for the placebo periods, we account for potential seasonal effects in stock returns (Heston and Sadka 2008). If our results are driven by other observables that are correlated with our proxy for AQ, we should also find a positive and significant coefficient for $Decile\_AQ$ for the placebo periods in which there are no mutual fund fire sales.

Table 8 presents the placebo test results for our main proxy of AQ (columns 1 and 2) and for the two alternative proxies of AQ considered in our robustness checks (columns 3 to 6). Overall, we find that for both placebo quarters and all the proxies of AQ, the estimated coefficient of *Decile_AQ* is either not significantly different from zero or marginally negative. The economic magnitude of these coefficients is also negligible (i.e., around 1% of the effect in our main tests). These results suggest that our results are unlikely to capture other firm fundamentals correlated with financial reporting quality and abnormal returns. Moreover, the marginally negative coefficients would suggest that, if any, the effect of a potential omitted variable would go against finding a result.

Idiosyncratic shocks

One potential alternative explanation for our results is that of measurement error in our AQ proxy. Concerns regarding accrual model misspecification in prior literature suggest that residuals from our model (5) may be systematically related to firm fundamentals (Kothari et al. 2005, Dechow et al. 2010, Collins et al. 2017, Owens et al. 2017), which could explain our results. To alleviate these concerns, we follow Owens et al. (2017) suggestion and control for firm idiosyncratic shocks to firms' underlying economics in our main model. Idiosyncratic shocks are proxied by the firm-specific stock-return variation of each firm over the same five-year period that we use to estimate *AQ*; then we take the decile of this measure (*Decile_IdioShock*). The results in Table 9, panel A, columns 1 to 3, indicate that our main findings are robust to this specification.[20]

Firm complexity

Another potential alternative story could be that poor AQ actually captures firm complexity, which prior literature shows impedes the incorporation of firm information into prices (Cohen and Lou 2012, Barinov et al. 2022). Then, it could be argued that complex firms experience higher mispricing due to the difficulty market participants face in distinguishing the source of the noise and therefore impeding them from trading on the mispriced stocks. To rule out this explanation, we include *Complexity* as an additional control variable in our main regression model. Following Barinov et al. (2022), we measure firm complexity as one minus the Herfindahl-Hirschman index

[20]The smaller sample size for this specification marginally reduces the statistical significance of the results.

calculated using firms' segment sales. The results in Table 9, panel A, columns 4 to 6, indicate that our main findings are robust to this specification.[21]

Market-level factors

We further address concerns that our results might be driven by market-level factors that are not accounted for in the main specification. Following Ben-Rephael et al. (2017), we include as additional controls abnormal trading volume (*AVol*), quarterly stock return (*Ret*), stock turnover (*Turnover*), and volatility (*SDRet*).[22] The results in Table 9, panel A, columns 7 to 9, indicate that our main findings are robust to this specification.

Managerial ability

Another potential, competing argument, is that our results are explained by managerial ability. Prior evidence shows that managerial ability is associated with both AQ and stock price reactions (Demerjian et al. 2012, 2013). If market participants perceive that high-ability managers are better able to adjust their firms' policies in response to the shock, and AQ is associated with managerial ability, our results may be biased. To test whether this omitted variable may be driving our results, we control for managerial ability in our main model using the decile rank of MA-score (Demerjian et al. 2012).[23] The results in Table 9, panel B, columns 1 to 3, indicate that our main findings are robust to this specification.

Corporate governance

Finally, we consider the role of corporate governance. Previous studies show that corporate governance is related to both AQ (Klein 2002, Farber 2005, Bowen et al. 2008, Dechow et al. 2010)

[21] In untabulated results, we also find that our main findings are robust to alternative definitions of firm complexity, such as the number of segments or a dummy equal to one if the firm is a conglomerate.

[22] Because we cannot precisely identify the quarter of the shock, and it has been shown that price pressures may start before the quarter of the shock (Coval and Stafford 2007, Sulaeman and Wei 2019), we include these additional controls with 2 lags to avoid having a *bad-controls* problem (Angrist and Pischke 2008). Nevertheless, some concerns might remain that these explanatory variables are affected by the shock, and therefore we do not include them in our main specifications.

[23] Data on the managerial ability variable are available from Peter Demerjian website at: https://peterdemerjian.weebly.com/managerialability.html.

and firm fundamentals (Jensen and Meckling 1976, La Porta et al. 2002, Gompers et al. 2003, Larcker et al. 2007). If firms with better corporate governance are likely to exhibit higher financial reporting quality and the market perceives that these firms are likely to have better prospects, our results might be biased. We consider different proxies of internal governance. First, following Coles et al. (2014), we consider co-option, measured as the fraction of independent directors appointed after the CEO took office. Higher co-option is typically associated with poorer governance, as co-opted directors are less likely to monitor a firm's management (Khanna et al. 2015). We collect data on co-opted directors from Lilitha Naveen's website.[24] Second, following Hasan et al. (2021), we use CEO tenure and CEO share ownership as proxies for internal governance. Firms that have low CEO share ownership and high CEO tenure generally have more severe managerial agency problems, and therefore weaker internal governance. The results in Table 9, panel B, columns 4 to 9, indicate that our main findings are robust to controlling for corporate governance.[25]

6. Conclusion

We study whether AQ mitigates mispricing due to non-fundamental reasons. We exploit a shock to firms' stock prices due to price pressures induced by mutual fund fire sales to identify mispriced firms. We find evidence of AQ reducing fire sale discounts. We study two potential mechanisms. We find that sell-side analysts are more likely to provide price-correcting recommendations and that transient institutional investors are more likely to increase their holdings for firms with better AQ during mutual fund fire sales. In cross-sectional analyses, we find that for high-AQ firms other sources of fundamental information are less important in reducing mispricing. Our results are not explained by firm idiosyncratic shocks, firm complexity, internal governance, managerial ability, or management forecasts. Thus, we interpret our results as AQ lessening adverse selection problems by reducing the degree of information asymmetry between distressed mutual fund managers and capital market participants. Our findings provide empirical support for

[24] Available at: https://sites.temple.edu/lnaveen/data/.

[25] Note that including controls for internal governance severely reduces our sample size, as these variables are mostly available for larger firms. For that reason, we do not include them in the main specification.

theoretical models showing that fire sale discounts are explained by information asymmetries between distressed sellers and potential buyers of the assets being fire sold (Kurlat 2016, Dow and Han 2018), and provide novel evidence on the usefulness of AQ in valuation when securities are mispriced for non-fundamental reasons.

APPENDIX 1

Variable definitions

Name	Definition
Dependent Variables	
$CAR(t)$	Cumulative abnormal return over quarters t (for $t = 0, (-1,0), (-1,1)$) estimated using the 4-factor model (CRSP item retx; Fama-French factors items rf, mktrf, smb, hml, and umd).
$DRec(t)$	Quarterly change in median consensus recommendation in t (for $t = -1,0,1$) (I/B/E/S item MEDREC).
$DBuy(t)$	Quarterly change in percentage of buy recommendations in t (for $t = -1,0,1$) (I/B/E/S item BUYPCT).
$DTra(t)$	Change in transient investors' holdings (Thomson Reuters items shares and shrout1) over quarters t (for $t = -1,0,1$). Investor classification from Bushee's website.
$DNTra(t)$	Change in non-transient (dedicated and quasi-indexer) investors' holdings (Thomson Reuters items shares and shrout1) over quarters t (for $t = -1,0,1$). Investor classification from Bushee's website.
Accounting Quality	
AQ	Standard deviation of the residuals from Eq (5) over the past 5 years multiplied by (-1) (Compustat items act, at, che, dlc, lct, oancf, ppegt, rev).
Decile_AQ	Annual decile ranking of AQ.
Main Controls	
LnNumEst	Natural logarithm of one plus the number of analysts following the company in quarter t (I/B/E/S Summary file item numest).
NForecasts	Categorical variable ranging from 0 to 4 indicating the number of quarters in which the firm issues at least one EPS management forecast over the last four quarters (I/B/E/E/S Guidance items val_1 and val_2).
MktCap	Natural logarithm of market value as of the previous fiscal year (Compustat items csho and prcc_f)
Mkt_to_Book	Market value to book value of assets as of the previous fiscal year (Compustat items at, csho, prcc_f, ceq, txdb).
InstHold	Fraction of shares outstanding owned by institutional investors during quarter t (Thomson Reuters 13F item instown_perc).
Pressure	Difference between outflow-induced sales and inflow-induced purchases normalized by the average trading volume: where ΔH is the change in holding from quarter $t-1$ to quarter t, and $Vol_{i,t-1}$ is the trading volume in the previous quarter (CRSP, CRSP Mutual Fund, Thomson Reuters).

(Continues on next page)

Name	Definition
Main Controls (cont.)	
EPS_Surprise	Difference between actual EPS and the median estimate before the quarter end (I/B/E/S Detail Adjusted file items actual and value).
Op_cycle	Sum of days accounts receivable and days inventory (Compustat items rect, sale, invt, cogs).
S_CFO	Standard deviation of the cash flows from operations (Compustat items oancf and at) over the last 10 years (we require a minimum of 5 years of data).
S_Sales	Standard deviation of sales (Compustat items sale and at) over the last 10 years (we require a minimum of 5 years of data).
Loss	Indicator variable that takes value 1 if the firm suffer a loss (Compustat item ib$<$0) in quarter t and zero otherwise.
SIR (%)	Mean value of short interest (Compustat item shortintadj) relative to shares outstanding (CRSP item shrout) in the quarter before the shock.
GN_Forecast	Dummy equal to 1 if the manager issues an earnings forecast in the quarter that exceeds the prevailing mean (I/B/E/E/S Guidance items val_1 and val_2; I/B/E/S Detail Unadjusted file item value).
BN_Forecast	Dummy equal to 1 if the manager issues an earnings forecast in the quarter that is below the prevailing mean (I/B/E/E/S Guidance items val_1 and val_2; I/B/E/S Detail Unadjusted file item value).
Additional Controls	
Spread	Absolute value of (ask-bid)/(midpoint) using monthly prices (CRSP items askhi and bidlo).
AVol	Monthly volume in CRSP divided by the previous 12-month average total trading volume (CRSP item vol), quarterly average.
HLtoH	Ratio between the stock's monthly high and low price difference and the monthly high price (CRSP items askhi and bidlo), quarterly average.
Ret	Quarterly stock return (CRSP item retx).
Turnover	Quarterly average stock turnover (CRSP items vol and shrout).
SDRet	Standard deviation of stock returns over a 6-month window (CRSP item retx).
IdioShock	Firm-specific stock return variation for firm i between years t and t-5 (CRSP items ret, vwretd, siccd).
Decile_IdioShock	Annual decile ranking of IdioShock.
Complexity	HHI concentration of sales among the firm segments (Compustat, Historical segments, sics1 and sales)

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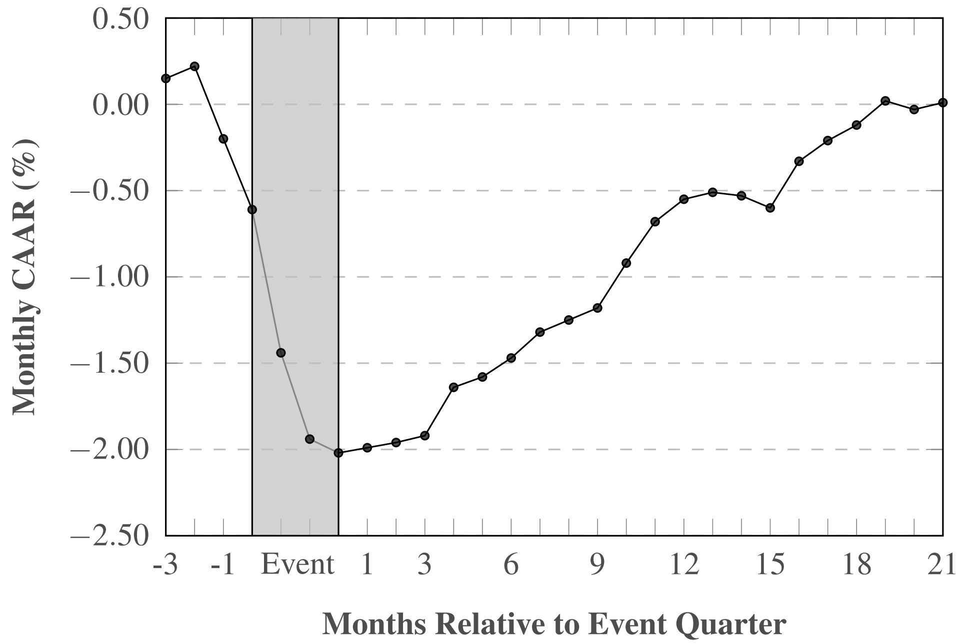

Figure 1 Cumulative average abnormal returns (CAAR) around the mutual fund fire sales quarter.

	Full sample (N=6,711)					High AQ	Low AQ	High - Low
	Mean	SD	Q1	Median	Q3	Mean	Mean	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQ	-0.06	0.05	-0.07	-0.05	-0.03	-0.04	-0.10	0.07***
CAR(0)	-1.39	16.51	-11.25	-1.74	7.86	-1.05	-1.92	0.87**
CAR(-1,0)	-2.12	22.42	-16.35	-3.47	9.81	-1.40	-3.24	1.83***
CAR(-1,1)	-2.02	27.59	-18.88	-4.16	11.39	-1.04	-3.55	2.51***
DRec(0)	-0.03	0.42	0.00	0.00	0.00	-0.02	-0.05	0.03***
DBuy(0)	-1.07	14.98	-5.49	0.00	3.64	-0.61	-1.79	1.18***
DTra(0)	0.17	2.93	-1.37	0.06	1.64	0.22	0.08	0.14*
DNTra(0)	0.13	6.52	-3.11	0.07	3.38	0.18	0.06	0.11
LnNumEst	2.01	0.67	1.61	1.95	2.48	2.05	1.96	0.09***
NForecasts	1.02	1.67	0.00	0.00	2.00	1.11	0.89	0.22***
MktCap	7.05	1.34	6.11	6.90	7.89	7.25	6.74	0.51***
Size	6.81	1.38	5.85	6.68	7.66	7.03	6.45	0.58***
Mkt_to_Book	2.13	1.44	1.27	1.69	2.47	2.04	2.26	-0.22***
InstHold	0.80	0.19	0.70	0.85	0.93	0.81	0.79	0.03***
Pressure	1.90	1.42	0.88	1.51	2.54	1.86	1.97	-0.11***
EPS_Surprise	1.04	13.74	-1.50	1.29	4.70	1.05	1.03	0.01
Op_cycle	127	121	71	110	161	123	134	-10.93***
S_CFO	0.07	0.10	0.03	0.05	0.08	0.05	0.10	-0.05***
S_Sales	0.22	0.19	0.11	0.17	0.27	0.19	0.28	-0.09***
Loss	0.20	0.26	0.00	0.10	0.30	0.16	0.27	-0.11***
SIR (%)	0.06	0.06	0.02	0.04	0.08	0.06	0.07	-0.01***
GN_Forecast	0.08	0.28	0.00	0.00	0.00	0.09	0.07	0.02***
BN_Forecast	0.20	0.40	0.00	0.00	0.00	0.22	0.18	0.03***

Table 1 Firm summary statistics. This table presents summary statistics of the main variables used in this paper. Columns 1 to 5 present summary statistics for the full sample. Columns 6 and 7 show mean value for the subsamples of high (firms above the median of AQ) and low AQ (firms below the median of AQ), respectively. High (low) AQ subsample is composed of 4,088 (2,623) firm-quarter observations. Column 8 shows the t-test of the difference in mean between firms with high and low AQ. All variables are defined in Appendix 1.

Panel A: Fund characteristics by decile of flows					
Decile	Flow (%)	TNA	# Holding	% Cash	% Stock
1	-17.45%	690	105	1.99	95.05
2	-7.45%	1315	115	1.86	94.86
3	-4.94%	1321	124	2.00	94.68
4	-3.42%	1950	137	2.09	94.57
5	-2.23%	2464	159	2.03	94.66
6	-1.01%	3425	180	2.16	94.55
7	0.45%	3834	230	2.26	94.52
8	2.78%	4581	242	2.21	94.90
9	7.72%	2922	216	2.44	95.08
10	57.91%	1105	161	2.54	95.42
Panel B: Fund trading behavior					
Decile	Initiate	Expand	Maintain	Reduce	Eliminate
1	0.13	0.12	0.10	0.53	0.13
2	0.12	0.15	0.17	0.43	0.12
3	0.11	0.17	0.23	0.38	0.11
4	0.11	0.18	0.26	0.34	0.11
5	0.10	0.20	0.30	0.30	0.10
6	0.10	0.23	0.31	0.27	0.09
7	0.10	0.30	0.30	0.21	0.09
8	0.10	0.40	0.24	0.17	0.09
9	0.10	0.52	0.16	0.14	0.09
10	0.12	0.61	0.08	0.09	0.10
Panel C: Mean Decile_AQ of positions					
Decile	Initiate	Expand	Maintain	Reduce	Eliminate
1	6.55	6.59	6.58	6.76	6.50
2	6.59	6.71	6.76	6.85	6.61
3	6.63	6.77	6.82	6.91	6.70
4	6.68	6.81	6.94	6.96	6.71
5	6.65	6.85	6.92	6.97	6.74
6	6.63	6.85	6.91	6.96	6.71
7	6.62	6.84	6.89	6.91	6.67
8	6.56	6.85	6.80	6.82	6.61
9	6.60	6.88	6.80	6.80	6.66
10	6.56	6.88	6.77	6.75	6.58

Table 2 Mutual fund holdings and trading. This table presents summary statistics of mutual funds' holdings and trading behavior conditional on actual flows. Mutual fund flows are estimated as in equation (2). We assign these deciles to each mutual fund by calendar quarter. Panel A reports fund flows, TNA, number of holdings, cash holdings and stock holdings averaged across all funds in the decile. Panel B shows the fraction of positions initiated, expanded, maintained, reduced and eliminated. Panel C displays the average *Decile_AQ* of initiated, expanded, maintained, reduced and eliminated positions by mutual fund flow deciles.

	CAR(-1,0) (1)	CAR(0) (2)	CAR(-1,1) (3)
Decile_AQ	0.362***	0.201**	0.589***
	(2.581)	(2.021)	(3.329)
LnNumEst	-2.448***	-1.368***	-2.688***
	(-3.524)	(-2.840)	(-2.989)
NForecasts	0.999**	0.767**	1.258**
	(2.090)	(2.227)	(2.085)
MktCap	0.491	0.372	0.299
	(1.308)	(1.442)	(0.618)
Mkt_to_Book	0.235	-0.247	0.395
	(0.790)	(-1.242)	(0.930)
InstHold	-2.064	-0.252	-5.747**
	(-1.109)	(-0.193)	(-2.403)
EPS_Surprise	0.171***	0.109***	0.344***
	(6.157)	(5.533)	(7.736)
Pressure	-0.606**	-0.237	-0.323
	(-2.233)	(-1.146)	(-1.025)
Op_cycle	-0.002	0.002	-0.001
	(-0.419)	(0.698)	(-0.201)
S_CFO	-5.025	0.054	-11.723**
	(-1.179)	(0.017)	(-2.110)
S_Sales	-1.456	-0.922	-1.664
	(-0.787)	(-0.698)	(-0.703)
Loss	-3.073*	-1.551	-3.505
	(-1.863)	(-1.338)	(-1.623)
SIR (%)	5.408	6.191	14.860*
	(0.974)	(1.556)	(1.930)
GN_Forecast	4.828**	1.651	4.379*
	(2.453)	(1.180)	(1.787)
BN_Forecast	-7.655***	-5.873***	-8.662***
	(-4.367)	(-4.537)	(-3.904)
Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	6,711	6,711	6,711
Adj R2	0.049	0.036	0.063

Table 3 Baseline results. This table reports the results of the effect of AQ on stock mispricing. In columns 1 to 3, the explanatory variable is the deciles of the augmented McNichols (2002) model. All variables are defined in Appendix 1. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Robustness to benchmark to estimate abnormal returns						
	CAR^{m}(-1,0)	CAR^{m}(0)	CAR^{m}(-1,1)	CAR^{3f}(-1,0)	CAR^{3f}(0)	CAR^{3f}(-1,1)
	(1)	(2)	(3)	(4)	(5)	(6)
Decile_AQ	0.413***	0.277***	0.621***	0.362**	0.209**	0.544***
	(2.903)	(2.694)	(3.476)	(2.538)	(2.097)	(3.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,711	6,711	6,711	6,711	6,711	6,711
Adj R2	0.076	0.062	0.090	0.051	0.038	0.069
Panel B: Robustness to proxy for AQ						
	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)
	(1)	(2)	(3)	(4)	(5)	(6)
Top_Quintile_FSD	-3.947**	-3.667***	-4.363**			
	(-2.219)	(-2.684)	(-2.020)			
Top_Quintile_file_size				-1.951***	-1.276***	-1.812**
				(-2.847)	(-2.675)	(-2.099)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,177	6,177	6,177	6,667	6,667	6,667
Adj R2	0.049	0.038	0.063	0.048	0.035	0.062

Table 4 Robustness to abnormal returns and AQ proxies. This table reports robustness tests for the proxies for abnormal returns (columns 1 to 3) and AQ (columns 4 to 9). In columns 1 to 3, abnormal returns are estimated using the market model. In columns 4 to 6, the proxy for AQ is the FSD score (Amiram et al. 2016). In columns 7 to 9, the proxy for AQ is the 10-K length (Loughran and McDonald 2014). The rest of the variables are defined in Appendix 1. All regressions include the main controls included in the main specification (model (1)), industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	DRec(-1)	DRec(0)	DRec(+1)	DBuy(-1)	DBuy(0)	DBuy(+1)
	(1)	(2)	(3)	(4)	(5)	(6)
Decile_AQ	-0.003	0.005**	0.002	-0.086	0.143*	0.164**
	(-1.318)	(2.180)	(1.099)	(-1.175)	(1.795)	(2.041)
LnNumEst	-0.021**	-0.008	-0.003	-0.858**	-0.154	-0.008
	(-1.976)	(-0.768)	(-0.259)	(-2.239)	(-0.375)	(-0.020)
NForecasts	0.008	0.001	0.011	-0.030	0.326	0.616*
	(0.842)	(0.131)	(1.180)	(-0.095)	(0.915)	(1.848)
MktCap	0.014***	0.008	0.003	0.431**	0.077	0.157
	(2.616)	(1.338)	(0.504)	(2.161)	(0.361)	(0.781)
Mkt_to_Book	-0.004	-0.007*	-0.004	-0.210*	-0.351**	-0.037
	(-1.019)	(-1.673)	(-1.015)	(-1.708)	(-1.973)	(-0.213)
InstHold	-0.027	-0.060**	-0.047*	-1.425	-1.546	-1.658
	(-0.946)	(-1.991)	(-1.668)	(-1.401)	(-1.361)	(-1.460)
EPS_Surprise	-0.001	0.001***	0.001*	-0.005	0.031**	0.034**
	(-1.431)	(2.697)	(1.851)	(-0.351)	(2.146)	(1.998)
Pressure	0.002	0.004	-0.003	0.098	0.123	0.099
	(0.546)	(0.902)	(-0.585)	(0.625)	(0.686)	(0.554)
Op_cycle	0.000	-0.000	0.000	0.001	-0.002	0.001
	(1.024)	(-1.321)	(1.286)	(0.854)	(-1.493)	(0.752)
S_CFO	-0.003	0.023	-0.205***	-1.600	0.582	-7.656***
	(-0.043)	(0.316)	(-2.698)	(-0.795)	(0.215)	(-2.790)
S_Sales	0.031	-0.005	0.061**	0.047	-0.827	3.195***
	(1.094)	(-0.182)	(2.109)	(0.049)	(-0.767)	(3.478)
Loss	0.015	-0.056**	0.026	1.257	-2.337**	1.230
	(0.685)	(-2.251)	(1.140)	(1.572)	(-2.535)	(1.464)
SIR (%)	0.177**	0.002	0.022	-0.583	-0.869	-2.356
	(2.078)	(0.020)	(0.246)	(-0.192)	(-0.269)	(-0.769)
GN_Forecast	-0.021	0.036	-0.037	1.241	0.718	-2.032
	(-0.563)	(0.923)	(-0.966)	(1.015)	(0.507)	(-1.493)
BN_Forecast	-0.017	-0.036	-0.037	0.072	-2.684*	-2.370*
	(-0.483)	(-0.953)	(-1.105)	(0.062)	(-1.952)	(-1.909)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,711	6,711	6,711	6,711	6,711	6,711
Adj R2	0.008	0.015	0.007	0.018	0.021	0.011

Table 5 Changes in analysts' recommendations. This table reports how AQ can mitigate stock mispricing. In columns 1 to 3, we report the results of estimating model (6) using quarterly change in analysts recommendation as the dependent variable, while columns in 4 to 5 we look at the quarterly change in buy recommendations. All variables are defined in Appendix 1. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	DTra(-1)	DTra(0)	DTra(+1)	DNTra(-1)	DNTra(0)	DNTra(+1)
	(1)	(2)	(3)	(4)	(5)	(6)
Decile_AQ	0.000	0.047***	0.030**	0.004	-0.038	0.014
	(0.024)	(3.036)	(2.008)	(0.134)	(-1.089)	(0.367)
LnNumEst	-0.036	0.093	0.151*	-0.196	-0.347**	-0.400**
	(-0.527)	(1.235)	(1.891)	(-1.273)	(-2.079)	(-2.459)
NForecasts	0.089	0.099	0.117*	-0.262*	-0.011	0.170
	(1.397)	(1.570)	(1.813)	(-1.863)	(-0.072)	(1.094)
MktCap	0.008	-0.077*	-0.129***	0.561***	0.475***	0.655***
	(0.206)	(-1.868)	(-3.053)	(5.412)	(4.497)	(6.308)
Mkt_to_Book	-0.045	-0.064**	-0.044	0.164***	0.191***	0.166**
	(-1.379)	(-2.095)	(-1.533)	(2.598)	(2.638)	(2.470)
InstHold	-0.349**	-0.200	-0.474***	-0.710*	-1.337***	-1.850***
	(-2.054)	(-1.115)	(-2.597)	(-1.691)	(-3.426)	(-4.664)
EPS_Surprise	0.005**	0.016***	0.024***	0.001	0.007	0.024***
	(2.190)	(5.579)	(7.140)	(0.229)	(1.089)	(4.186)
Pressure	-0.019	0.126***	0.022	-0.149***	-0.233***	-0.090
	(-0.801)	(4.545)	(0.860)	(-2.788)	(-3.998)	(-1.612)
Op_cycle	-0.000	0.001*	-0.000	-0.000	0.000	0.000
	(-0.109)	(1.867)	(-0.753)	(-0.285)	(0.050)	(0.600)
S_CFO	0.378	0.043	-0.398	-1.255*	-0.581	-1.141
	(0.905)	(0.113)	(-0.938)	(-1.657)	(-0.891)	(-1.493)
S_Sales	-0.278	-0.247	-0.046	1.212***	-0.310	0.393
	(-1.335)	(-1.343)	(-0.245)	(3.004)	(-0.732)	(0.913)
Loss	0.065	-0.114	-0.096	-0.176	-0.101	-0.315
	(0.401)	(-0.731)	(-0.598)	(-0.576)	(-0.308)	(-0.913)
SIR (%)	-0.962	-0.792	-0.286	0.988	-5.857***	-4.834***
	(-1.398)	(-1.228)	(-0.450)	(0.606)	(-3.326)	(-2.781)
GN_Forecast	0.042	0.374	-0.564**	1.158**	0.649	0.101
	(0.167)	(1.456)	(-2.018)	(2.076)	(1.026)	(0.166)
BN_Forecast	-0.369	-0.870***	-0.543**	0.667	-0.267	-0.544
	(-1.561)	(-3.697)	(-2.245)	(1.280)	(-0.450)	(-0.927)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,711	6,711	6,704	6,711	6,711	6,704
Adj R2	0.107	0.109	0.149	0.181	0.126	0.132

Table 6 Investors' trades. This table reports one mechanism via which AQ can mitigate stock mispricing. In columns 1 to 3, we report the results of estimating model (6) using quarterly change in transient investors holdings as the dependent variable, while columns in 4 to 6 we look at the quarterly change in non-transient investors holdings. All variables are defined in Appendix 1. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)
	(1)	(2)	(3)	(4)	(5)	(6)
Decile_AQ	0.329**	0.173*	0.553***	0.353**	0.208*	0.590***
	(2.349)	(1.746)	(3.135)	(2.152)	(1.828)	(2.890)
DRec x Decile_AQ	-0.643**	-0.351	-0.770**			
	(-2.158)	(-1.570)	(-2.062)			
GN_Forecast x Decile_AQ				-1.123**	-0.827***	-1.145*
				(-2.467)	(-2.735)	(-1.788)
BN_Forecast x Decile_AQ				0.461	0.270	0.413
				(1.619)	(1.303)	(1.114)
DRec	7.620***	6.172***	8.305***			
	(3.737)	(4.070)	(3.320)			
GN_Forecast	4.702**	1.509	4.257*	12.117***	7.003***	11.796**
	(2.377)	(1.069)	(1.738)	(3.254)	(2.848)	(2.358)
BN_Forecast	-7.475***	-5.703***	-8.476***	-10.500***	-7.543***	-11.219***
	(-4.243)	(-4.384)	(-3.828)	(-4.094)	(-4.039)	(-3.444)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,711	6,711	6,711	6,711	6,711	6,711
Adj R2	0.054	0.047	0.067	0.050	0.037	0.064

Table 7 Cross sectional analyses. This table analysis whether changes in analysts recommendation and manager forecasts released at the time of the shock have a differential effect for firm with high or low AQ. Columns 1 to 3 consider the interaction between reporting quality and analysts recommendations. Columns 5 to 6 reports the interaction between managerial earnings forecasts and AQ. All regressions include industry and quarter-year fixed effects, and the controls included in our main specification, defined in Appendix 1. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	CAR(-4)	CAR(-8)	CAR(-4)	CAR(-8)	CAR(-4)	CAR(-8)
	(1)	(2)	(3)	(4)	(5)	(6)
Decile_AQ	-0.002*	-0.000				
	(-1.961)	(-0.197)				
Top_Quintile_FSD			-0.018	-0.031**		
			(-1.609)	(-2.268)		
Top_Quintile_file_size					0.002	-0.014***
					(0.431)	(-2.679)
LnNumEst	-0.026***	-0.013***	-0.027***	-0.014***	-0.026***	-0.014***
	(-5.907)	(-2.724)	(-5.771)	(-2.721)	(-5.842)	(-2.841)
NForecasts	-0.005	0.004	-0.006*	0.004	-0.005	0.004
	(-1.286)	(1.015)	(-1.671)	(0.820)	(-1.492)	(1.017)
MktCap	0.008***	0.001	0.007***	-0.000	0.007***	0.002
	(3.248)	(0.266)	(2.899)	(-0.094)	(2.868)	(0.905)
Mkt_to_Book	0.013***	0.014***	0.015***	0.014***	0.013***	0.013***
	(5.946)	(6.051)	(6.356)	(5.870)	(5.973)	(5.680)
InstHold	-0.018	0.004	-0.022	-0.004	-0.019	0.004
	(-1.235)	(0.266)	(-1.486)	(-0.244)	(-1.352)	(0.274)
EPS_Surprise	0.000	0.000	0.000	0.000	0.000*	0.000
	(1.546)	(0.502)	(1.344)	(0.888)	(1.646)	(0.499)
Pressure	-0.005***	-0.004*	-0.004**	-0.005**	-0.005***	-0.003*
	(-3.019)	(-1.858)	(-2.532)	(-2.228)	(-3.076)	(-1.757)
Op_cycle	-0.000*	0.000	-0.000	0.000	-0.000*	0.000
	(-1.945)	(0.961)	(-1.199)	(1.620)	(-1.740)	(0.917)
S_CFO	-0.034	-0.022	-0.027	-0.016	-0.025	-0.024
	(-1.103)	(-0.519)	(-0.852)	(-0.371)	(-0.810)	(-0.559)
S_Sales	-0.011	0.016	-0.004	0.013	-0.007	0.017
	(-0.783)	(1.077)	(-0.251)	(0.824)	(-0.505)	(1.170)
Loss	0.007	-0.005	0.009	-0.004	0.009	-0.002
	(0.690)	(-0.373)	(0.756)	(-0.330)	(0.797)	(-0.138)
SIR (%)	-0.032	0.019	-0.026	0.029	-0.026	0.017
	(-0.691)	(0.453)	(-0.531)	(0.686)	(-0.571)	(0.406)
GN_Forecast	0.019	-0.027*	0.023	-0.025	0.021	-0.029*
	(1.286)	(-1.721)	(1.548)	(-1.503)	(1.439)	(-1.849)
BN_Forecast	0.022	-0.009	0.026*	-0.007	0.025*	-0.010
	(1.641)	(-0.609)	(1.837)	(-0.432)	(1.834)	(-0.663)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,604	6,355	6,078	5,860	6,561	6,316
Adj R2	0.044	0.023	0.046	0.024	0.044	0.024

Table 8 Placebo test. This table reports the results of the placebo test performed a year before (-4) and two years before (-8) the shock. In columns 1 and 2, the explanatory variable is the deciles of the augmented (McNichols 2002) model, in columns 3 and 4 is the top quintile of the FSD score (Amiram et al. 2016), and in columns 5 and 6 is the top quintile of the length of the 10-K (Loughran and McDonald 2014). All variables are defined in Appendix 1. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Idiosyncratic shocks, firm complexity and market level controls

	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decile_AQ	0.392***	0.171	0.662***	0.365***	0.204**	0.595***	0.307**	0.169*	0.531***
	(2.592)	(1.592)	(3.461)	(2.597)	(2.053)	(3.364)	(2.145)	(1.676)	(2.950)
Decile_IdioShock	-0.088	-0.123	0.124						
	(-0.415)	(-0.846)	(0.478)						
Complexity				-0.098	-0.387	-1.243			
				(-0.056)	(-0.326)	(-0.557)			
Spread							-0.423	-10.108	-9.011
							(-0.051)	(-1.591)	(-0.868)
AVol							-1.062	-1.423**	-1.635
							(-1.169)	(-2.138)	(-1.471)
Ret							-0.181***	-0.033	-0.151**
							(-2.790)	(-0.692)	(-2.006)
Turnover							-0.695	-0.230	-0.704
							(-1.521)	(-0.695)	(-1.205)
SDRet							-22.519**	-9.187	-15.461
							(-2.237)	(-1.301)	(-1.284)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,657	5,657	5,657	6,708	6,708	6,708	6,710	6,710	6,710
Adj R2	0.044	0.034	0.059	0.049	0.036	0.063	0.053	0.040	0.066

Panel B: Managerial ability and internal governance

	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)	CAR(-1,0)	CAR(0)	CAR(-1,1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decile_AQ	0.381***	0.200**	0.625***	0.491***	0.315***	0.579***	0.398**	0.194*	0.566***
	(2.722)	(2.037)	(3.554)	(2.895)	(2.640)	(2.775)	(2.481)	(1.714)	(2.813)
MA-Score	0.953	0.157	0.847						
	(0.860)	(0.200)	(0.607)						
Co-opted Indep				1.374	0.922	2.068			
				(1.073)	(1.034)	(1.256)			
CEO_Own							-0.055	0.001	-0.064
							(-0.687)	(0.016)	(-0.616)
Ln_Tenure							0.345	0.271	0.671
							(0.833)	(0.920)	(1.216)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,642	6,642	6,642	3,806	3,806	3,806	4,749	4,749	4,749
Adj R2	0.052	0.038	0.068	0.050	0.038	0.077	0.055	0.040	0.071

Table 9 Alternative explanations. This table explores whether potentially omitted variables might explain our results. In Panel A we consider the role of idiosyncratic shocks (columns 1 to 3) (Owens et al. 2017), firm complexity (columns 4 to 6) (Cohen and Lou 2012, Barinov et al. 2022), and market level factors (columns 7 to 9). In Panel B we analyze the role of managerial ability (columns 1 to 3) (Demerjian et al. 2013), and internal governance proxies by co-opted board (columns 4 to 6) (Coles et al. 2014) and CEO ownership and tenure (columns 7 to 9) (Hasan et al. 2021). The number of observations vary in every specification depending on data availability. All regressions include industry and quarter-year fixed effects, and the controls included in our main specification, defined in Appendix 1. Standard errors are clustered at the firm level. Robust t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.