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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 the potential buyers of the securities being fire sold leads to an adverse selection problem resulting in an equilibrium in which buyers trade only at prices below the 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 the 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 mitigates stock undervaluation caused by nonfundamental factors.

Keywords: Accounting quality; Mispricing; Fire sales; Analysts; Institutional investors

JEL codes: G14; M41

1. Introduction

In this study, we examine the role of accounting quality (AQ) when a firm's stock faces significant selling pressure due to mutual fund fire sales.[1] The literature shows that stock price undervaluation due to mutual fund fire sales is economically large, long lived, and difficult for market participants to identify (Coval & Stafford, 2007; Honkanen & Schmidt, 2022; Sulaeman & Wei, 2019). By focusing on undervaluation during mutual fund fire sales, our paper is the first to study the role of AQ in mispricing arising from selling pressure that is unrelated to a firm's fundamentals.

Our study is motivated by fire-sale theories that predict that information asymmetries between informed sellers and less informed buyers lead to fire-sale discounts (Dow & Han, 2018; Kurlat, 2016). The economic intuition is as follows. Managers of distressed mutual funds have better information about the intrinsic value of stocks than do potential buyers, and at the same

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

time, different buyers have different information with which to assess the quality of the stocks being fire sold. This situation 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, these mutual funds end up liquidating a significant proportion of their portfolio, which includes both 'bad' and 'good' stocks (Huang et al., 2022). A higher number of fire sales means that a larger number of stocks are supplied to the market; once the 'better-informed' investors exhaust their wealth, liquidity should be provided by the 'worse-informed' investors, who, knowing they are not so good at telling bad stocks from good stocks, will trade only 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.

If high AQ helps investors estimate firm value and reduce information asymmetry between distressed mutual fund managers and other market participants, then we expect that firms with better AQ will experience smaller fire-sale discounts. In terms of the empirical identification of the effect of AQ, one advantage of our study is that mutual fund fire sales might be viewed as an exogenous shock that makes investors pay attention to the firm's accounting information.

To understand how AQ reduces fire-sale discounts, we examine the behavior of sell-side analysts and institutional investors during mutual fund liquidations. When funds liquidate their positions, investors may revise their firm value forecasts due to uncertainty about the nature of the fire sale. Analysts rely on accounting information for recommendations (Brown et al., 2015; Cascino et al., 2021), and changes in their recommendations aid the incorporation of information into stock prices (Jegadeesh et al., 2004; Womack, 1996). If better financial reporting helps analysts uncover nonfundamental mispricing, then we expect analysts to issue more price-correcting recommendations for high-AQ firms. We further study the role of arbitrageurs. According to Bushee et al. (2019), sophisticated short-term investors are less likely to arbitrage stocks with poor AQ due to higher holding costs and reduced profitability. In the presence of mispricing, arbitrageurs will acquire more stocks with high AQ (i.e., lower holding costs), providing liquidity and mitigating the price impact of fire sales. We expect arbitrageurs to increase their holdings in firms with better AQ.

Using a sample of 6711 firm-quarter observations of U.S. publicly traded firms from 2004 to 2017, we first replicate the main finding of Coval and Stafford (2007). Our results show that firms affected by mutual fund fire sales experience an average abnormal return of -1.39% during the quarter of the shock. Consistent with Coval and Stafford (2007), we observe a reversion of mispricing after approximately 20 months (see Figure 1). We then examine whether fire-sale discounts are lower for firms with better AQ than for those with worse AQ. By measuring AQ as the extent to which accruals map into firms' expected cash flows (Dechow & Dichev, 2002; McNichols, 2002) and fire-sale discounts as the abnormal returns around the quarter of the shock, we find evidence of reduced mispricing for firms with higher AQ.

We show that abnormal stock returns are 2.01% lower for firms in the bottom decile relative to those in the top decile of AQ in the quarter of the shock, after controlling for firm characteristics and other factors influencing firms' information environment. In line with our proposed mechanisms, we find that sell-side analysts and transient institutional investors contribute to mitigating the impact of mutual fund fire sales. Sell-side analysts offer more favorable recommendations, on average, for high-AQ firms than for low-AQ firms. We also find that transient institutional investors, who typically engage in strategies focusing on financial statement variables and have short-term investing horizons (Bushee & Noe, 2000; Collins et al., 2003), increase their holdings of high-AQ firms during the quarter in which the fire sale occurs. Notably, we do not observe any effect for nontransient investors, who are typically focused on the long term and less inclined to exploit mispricing opportunities.

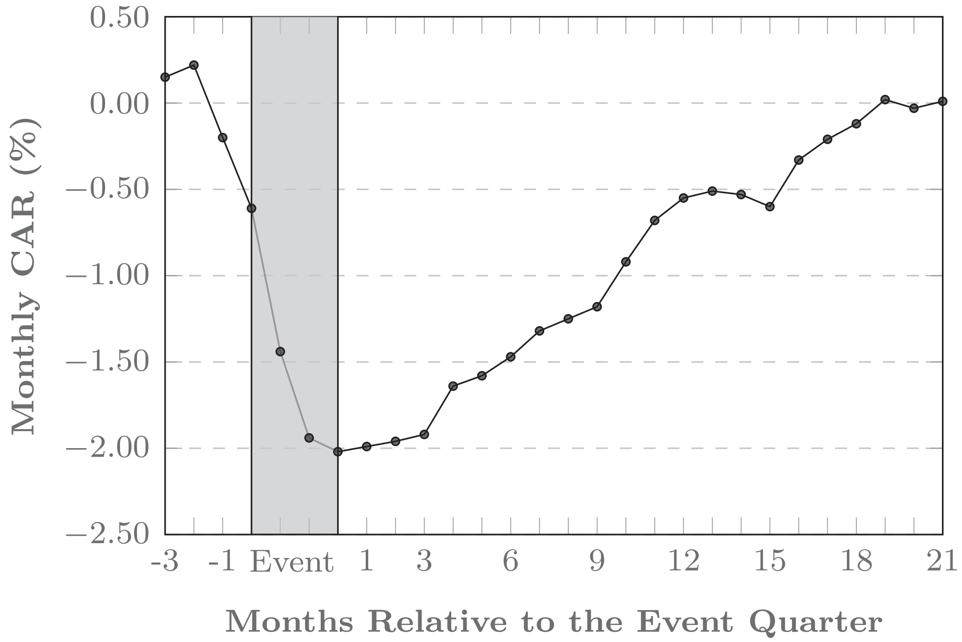

Figure 1. Cumulative abnormal returns around the mutual fund fire sales quarter.

Our paper makes several contributions to the literature. First, we document a negative relationship between AQ and fire-sale discounts, supporting the theoretical arguments in Kurlat (2016) and Dow and Han (2018). This novel finding complements (Huang et al., 2022)'s identification of information asymmetries as a factor in fire-sale discounts by highlighting accounting information quality as a potential source of such asymmetries.

Second, we contribute to the literature on mispricing resulting from mutual fund fire sales. While previous studies have examined *ex post* responses such as insider trading (Ali et al., 2011), sell-side analysts' recommendations (Sulaeman & Wei, 2019), and management forecasts (Jiang et al., 2021; Kadach, 2017), our focus lies on the *ex ante* effect of AQ on fire-sale discounts rather than on subsequent price reversals.

Third, our study adds to the literature investigating the impact of financial reporting quality on stock prices during extreme market events (Barton & Waymire, 2004; Hilary, 2008; Mitton, 2002). Our unique setting differs from that of financial crisis shocks, as mutual funds' flow-driven mispricing occurs regularly, and the source of price noise remains unknown to investors. Additionally, the staggered nature of the shock helps alleviate concerns about confounding effects, such as changes in risk aversion or overall market conditions, that may arise during market crashes.

Finally, our paper contributes to the literature on the capital market benefits of high AQ.[2] We take a distinct approach by examining the relationship between AQ and mispricing within a specific context in which mispricing arises from nonfundamental factors (Coval & Stafford, 2007). Furthermore, we explore the mechanisms that drive this relationship. Our findings demonstrate the usefulness of AQ for valuation when nonfundamental mispricing occurs. The presence of more price-correcting recommendations and increased trading by transient institutional investors

[2] See, e.g., Francis et al. (2004), Bhattacharya et al. (2013), Barth et al. (2013), and Ng (2011).

in firms with higher AQ are potential mechanisms underlying the connection between AQ and fire-sale discounts.

2. Literature Review and Hypothesis Development

The role of AQ in capital markets is a fundamental issue that has been widely studied in the accounting literature (Dechow et al., 2010; Kothari, 2001; Richardson et al., 2010). Theoretically, stock prices change due to either fundamental news or nonfundamental reasons. Fundamental news includes firm-specific accounting information (e.g., earnings), nonaccounting information (e.g., new product announcements), and marketwide news (e.g., changes in the inflation rate). In contrast, nonfundamental reasons include, for example, noise trading or investor sentiment (Baker & Wurgler, 2006). Seminal accounting research shows that accounting information explains stock prices (Ball & Brown, 1968; Dechow, 1994), but also that the quality of accounting information varies across firms and that high AQ is associated with the lower mispricing of accruals (Allen et al., 2013; Dechow & Dichev, 2002; Richardson et al., 2005; Sloan, 1996).

A question that has attracted less attention in the accounting literature is whether AQ mitigates stock mispricing arising due to nonfundamental reasons. In this paper, we focus on the specific setting in which mispricing is driven by widespread mutual fund fire sales. A 'fire sale' is a situation in which sellers' liquidity needs force them to sell assets at market prices below their intrinsic value (Shleifer & Vishny, 2011). Two alternative theoretical models predict that information asymmetries lead to fire-sale discounts.

First, Kurlat (2016) develops a model of competitive equilibrium with heterogeneous assets and information. In their model, sellers and buyers exchange assets of different qualities (good and bad) in many nonexclusive markets simultaneously. Agents have heterogeneous information about the quality of such assets. Sellers know which asset they own, while buyers observe only an imperfect signal about the quality of the asset. Buyers are of different types, where the type can be interpreted according to how informed the buyer is regarding the intrinsic value of a particular asset. Sellers, some of whom are distressed, will sell if prices are above their reservation price. The buyer chooses the number of units to demand of each asset in each market and an acceptance rule (i.e., which assets to trade in each market) consistent with their own information. In equilibrium, all trades take place in a single market at the same price. Distressed sellers supply their entire endowment of assets, and nondistressed sellers bring only bad-quality assets to the market. Buyers never trade after a better-informed buyer because this changes the relative proportion of good-quality assets supplied to the market. In other words, buyers will suffer the worst adverse selection problem if more informed buyers clear their trades in advance of them. Buyers buy only if the terms of trade are favorable to them. Better-informed buyers have more favorable terms of trade and buy because they can tell a higher proportion of the bad-quality assets apart from that of good-quality assets. Less informed buyers obtain worse terms of trade and do not buy any assets. In equilibrium, the worst assets are rejected by all buyers, all good-quality assets are sold, and a fraction of those bad assets that fool some buyers are sold. In Kurlat (2016), fire sales could be explained by an increase in the fraction of distressed sellers. An increase in this fraction improves the pool of assets being sold in the market because only distressed sellers supply good-quality assets, which could result in higher prices on average. In contrast, this situation also leads to a higher supply of assets to the market, which results in less informed buyers absorbing excess supply to clear the markets. Due to adverse selection problems, less informed buyers will enter the market only at lower prices. Furthermore, fire sales happen only when the latter effect dominates.

Second, Dow and Han (2018) develop a model that combines limits to arbitrage (Grossman & Stiglitz, 1980) with adverse selection (Akerlof, 1970) in a noisy rational-expectations equilibrium framework. In their model, sellers and arbitrageurs are informed about the quality of the assets being sold but are capital constrained. Hedgers and investors are unconstrained but also uninformed. Because sellers are informed, they normally sell overvalued assets. If they sell undervalued assets, then they do so because they need liquidity and not for informational reasons. In equilibrium, good assets are never overvalued, and bad assets are never undervalued; then, arbitrageurs are always willing to buy (sell) good (bad) assets. Hedgers and investors attempt to infer the quality of the asset from the market clearing price and face an adverse selection problem. When there is a reduction in arbitrageurs' amount of capital, both the demand and supply of assets are affected. Prices become less informative, and investors' posterior belief becomes less accurate at revealing the fundamental value of the marketable asset. Then, because prices are noisier, sellers essentially supply bad-quality assets to the market, thus declining the average quality of the traded assets and exacerbating the adverse selection problem in the market. Investors withdraw from the market even if they are not capital constrained. High-quality assets are traded only by those sellers facing severe liquidity needs who are forced to sell at a discount.

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. In our setting of mutual fund fire sales, the economic intuition is as follows. 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. Mutual fund managers experiencing fire sales have better information about the intrinsic value of the stocks than do potential buyers, and at the same time, different buyers have different information with which to assess the quality of the stocks being fire sold. This situation 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; however, because of the severity of the liquidity needs, these mutual funds end up liquidating a significant proportion of their portfolio, which includes both 'bad' and 'good' stocks (Huang et al., 2022). Once 'better-informed' investors (i.e., those that can potentially distinguish 'bad' from 'good' stocks) exhaust their wealth, liquidity should be provided by the less informed investors, who, knowing that they are not so good at telling the bad stocks apart from the good stocks, will trade only at lower prices. Akin to the 'lemons' problem (Akerlof, 1970), 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.[3] 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, thus leading to our hypothesis:

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

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[3]See, e.g., Dechow and Dichev (2002), Dechow and Schrand (2004), Francis et al. (2005), Richardson et al. (2010), Dichev et al. (2013), and McNichols and Stubben (2015).

In contrast, recent papers suggest that earnings have become a noisier measure of firm economic performance over time (Bushman et al., 2016; Francis & Schipper, 1999; Lev, 2018; Lev & Gu, 2016; Lev & Zarowin, 1999; Srivastava, 2014), casting doubt on their usefulness for firm valuation. If earnings are a poor summary measure of firms' fundamental news, then investors may rely on other sources of information for valuation purposes (e.g., industry reports, analysts' forecasts and recommendations, or management forecasts) (Amiram et al., 2016; Ball & Shivakumar, 2008; Basu et al., 2013; Beyer et al., 2010; Graham et al., 2005). 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 should have no impact on stock prices (Zimmerman, 2013).

3. Methodology

3.1. Research Design

To provide evidence of the relationship between AQ and nonfundamental 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:

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

where AQ_i denotes firm i AQ as of the most recent fiscal year prior to the quarter of the shock, capturing the extent to which accruals convey information to investors about the firm's expected cash flows (we provide further details in Section 3.4). Our dependent variable, CAR_i, is firm i's abnormal return around the quarter of the shock. CAR_i captures the magnitude of the nonfundamental 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-quarter subject to nonfundamental mispricing.

The main coefficient of interest in model (1) is β, which captures the effect of AQ on nonfundamental mispricing. If AQ mitigates mispricing due to mutual fund fire sales (i.e., reduces fire-sale discounts), then we expect β to be positive and significant. We estimate model (1) for alternative windows around the quarter of the shock. The rationale for this approach 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 & Stafford, 2007). We control for quarterly earnings surprises (*EPS_Surprise*) to account for the market reaction to accounting information revealed in the quarter of the shock. We control for analyst coverage (*LnNumEst*) and the frequency of management earnings forecasts (*NForecasts*) to capture the potential effect of differences in firms' information environment (Beyer et al., 2010). We also include controls for a good news earnings per share (EPS) forecast (*GN_Forecast*) and a bad news EPS forecast (*BN_Forecast*) issued in the quarter of the shock to capture potential managerial responses to mispricing (Jiang et al., 2021; Kadach, 2017). 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 any 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 (Ben-Rephael et al., 2017; Francis et al., 2005). 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*).[4]

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 provides the definitions of all variables.

3.2. Nonfundamental Shocks

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 next 24 months following fire sales. Importantly, this reversal is not observed among mutual funds' widespread selling not being driven by liquidity needs, which are more likely to be opportunistic voluntary transactions based on information (Coval & 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.[5]

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

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

where total net assets (TNA), $TNA_{j,t}$, is fund j's TNA in quarter t and $R_{j,t}$ is fund j's return during quarter t.[6] We drop highly concentrated funds (fewer than 10 stock holdings) and those with extreme changes in *TNA* (Ali et al., 2011; Coval & Stafford, 2007; Sulaeman & Wei, 2019).[7] Distressed mutual funds are those in the top and bottom deciles of *MFF*'s distribution in a given quarter.[8]

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 normalize it by the average trading volume as follows:

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

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

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

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

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

[8] Because of regulatory limitations, mutual funds are restricted from holding concentrated stakes. Therefore, a single mutual fund is unlikely to create excess supply for a stock.

where ΔH_{ijt} is the change in holdings from quarter $t-1$ to quarter t and $Vol_{i,t-1}$ is the trading 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 those fire sales that are not absorbed by extreme purchases. Finally, following the previous literature, we define a firm as 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, 2023; Huang et al., 2022). This is particularly relevant when comparing firms with and without mutual fund fire sales, as 'selection into treatment' (i.e., exposure to the shock driven by firm characteristics) may exist.[9] This situation 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 nonfundamental mispricing. For each firm i and month t, we model expected returns (estimated using 60 months of prior data) as follows:

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

where the dependent variable is firm's i month t excess returns (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 large), *HML* (high minus low book-to-market ratio), and *WML* (winners minus losers) are returns on value-weighted, zero-investment, and factor-mimicking portfolios. Abnormal returns *AR* are obtained as the difference between actual returns and those expected returns predicted by model (4).

We then aggregate returns quarterly to obtain the compound return around the quarter of the shock, CAR_q, where q denotes quarters relative to the event quarter and can take values $q=0, (-1,0), (-1,1)$ to estimate abnormal returns in alternative windows.[10]

3.4. AQ Measure

We follow prior literature and use Dechow and Dichev (2002)'s approach to proxy for AQ. The rationale behind the use of this proxy is that the larger the residuals from model (5) are, the

[9] 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 arbitrageurs to distinguish the underlying quality of the securities being sold.

[10] For robustness, we also calculate abnormal returns considering two alternative models of expected returns: the capital asset pricing model (CAPM) and the 3-factor model (Fama & French, 1993). See Online Appendix Section OA.1.

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.[11]

Dechow and Dichev (2002)'s 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 (Dechow & Dichev, 2002)'s model with changes in revenue and property, plant and equipment. Then, we estimate the following model for each year-industry (defined by the Fama and French 48 industry groups) with at least 20 observations:

$$\Delta WC_{i,t} = \phi_0 + \phi_1 \times CFO_{i,t-1} + \phi_2 \times CFO_{i.t} + \phi_3 \times CFO_{i,t+1} + \phi_4 \times \Delta Sales_{i,t} + \phi_5 \times PPE_{i,t} + \epsilon_{i,t} \tag{5}$$

where ΔWC denotes changes in working capital accruals, *CFO* denotes cash flows from operations, $\Delta Sales$ denotes changes in revenue, and *PPE* denotes 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 negative one; thus, higher values reflect better AQ. To control for the effect of outliers and potential nonlinearities 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 those 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 year, mutual funds were not obliged to disclose their holdings on a quarterly basis. The use of quarterly data on mutual fund holdings 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 to those of the remaining firms. We obtain stock price data from the CRSP and retain all ordinary shares (share codes 10 and 11) traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automatic Quotation System (NASDAQ) (exchange codes 1, 2, and 3, respectively). The risk-free rate and factor data used to estimate abnormal returns are collected from the Kenneth R. French Data Library.[12] We obtain financial and segment information data from Compustat, analyst coverage and management forecasts from the Institutional Brokers' Estimate System (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 holdings data from Thomson Reuters between 2004 and June 2008 and the CRSP Mutual Fund database thereafter. In line with previous papers, we drop bond, money market, and international mutual

[11]Some prior papers following the same approach include Francis et al. (2005), Core et al. (2008), Biddle et al. (2009), McNichols and Stubben (2015), Bushee et al. (2019), and Christensen et al. (2022).

[12]This library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1. Firm summary statistics.

	Full sample ($N = 6711$)					High AQ	Low AQ	High – Low
	Mean (1)	SD (2)	Q1 (3)	Median (4)	Q3 (5)	Mean (6)	Mean (7)	*t*-test (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***

Note: This table presents the summary statistics of the main variables used in this paper. Columns 1 to 5 present the summary statistics for the full sample. Columns 6 and 7 show the mean value for the subsamples of high- (firms above the median of AQ) and low-AQ (firms below the median of AQ) firms, respectively. The high-AQ (low-AQ) subsample is composed of 4088 (2623) firm-quarter observations. Column 8 shows the *t*-test of the difference in means between firms with high AQ and those with low AQ. All variables are defined in Appendix.

funds as well as those that do not invest primarily in US common equity (Ali et al., 2011; Coval & Stafford, 2007; Khan et al., 2012).[13]

After imposing all data requirements for the estimation of model (1), our final sample consists of 6711 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 5, presents the summary statistics of 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 compared to 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 & Stafford, 2007; Sulaeman & Wei, 2019) but still economically meaningful. The smaller absolute value of abnormal returns in the quarter of the shock in

[13] 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 & Yun, 2013).

our paper is most likely explained by the fact that academic research tends to eliminate stock-return predictability (McLean & Pontiff, 2016) and that our sample focuses on more recent years compared to the samples of Coval and Stafford (2007) and Sulaeman and Wei (2019).

In Figure 1, we plot cumulative average abnormal returns (CAAR) 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 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 return patterns as those in prior papers (Coval & Stafford, 2007), validating the nonfundamental shock in our particular sample and period.

Table 1, columns 6 and 7, presents the 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 than low-*AQ* firms. There are 4088 (2623) firm-quarter observations for high-*AQ* firms compared to 2623 firm-quarter observations for low-*AQ* firms. This finding 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 increasing AQ (DeFond et al., 2011), and the portfolio of funds in our sample is tilted toward firms with better AQ. We find that in the event quarter (CAR(0)), high-AQ (low-AQ) firms experience a median four-factor abnormal return of -1.05% (-1.92%), -1.40% (-3.24%) if we include the quarter previous to the event (CAR(-1,0)) or -1.04% (-3.55%) if we include one quarter before and after the event (CAR(-1,1)). The differences in means reported in column 8 are statistically significant in all three event windows. These initial univariate results provide the first indication that firms with better AQ suffer lower fire-sale discounts. The remaining summary statistics presented in Table 1 are generally consistent with recent studies exploiting this type of mispricing (Jiang et al., 2021; Sulaeman & Wei, 2019).

Table 2 presents the 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 those 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. This finding suggests that when facing extreme outflows (inflows), mutual funds mostly reduce (increase) the level of their existing positions rather than selling (buying) a small fraction of these positions. Suggesting mutual funds attempt to maintain their investment strategy and, therefore, that trades are less likely to contain information. This is an important assumption used in the construction of the fire sale variable. As discussed in Section 3.2., all these figures are consistent with prior studies using the mutual fund fire sale setting (see Table 2, p.487, in Coval & 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 the 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 finding suggests that funds experiencing extreme flows do not

Table 2. Mutual fund holdings and trading.

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

Note: This table presents the 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.

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 selectively trade 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

Table 3. Baseline results and placebo test.

	CAR(− 1,0) (1)	CAR(0) (2)	CAR(− 1,1) (3)	CAR(− 4) (4)	CAR(− 8) (5)
Decile_AQ	0.362***	0.201**	0.589***	− 0.002*	− 0.000
	(2.581)	(2.021)	(3.329)	(− 1.961)	(− 0.197)
LnNumEst	− 2.448***	− 1.368***	− 2.688***	− 0.026***	− 0.013***
	(− 3.524)	(− 2.840)	(− 2.989)	(− 5.907)	(− 2.724)
NForecasts	0.999**	0.767**	1.258**	− 0.005	0.004
	(2.090)	(2.227)	(2.085)	(− 1.286)	(1.015)
MktCap	0.491	0.372	0.299	0.008***	0.001
	(1.308)	(1.442)	(0.618)	(3.248)	(0.266)
Mkt_to_Book	0.235	− 0.247	0.395	0.013***	0.014***
	(0.790)	(− 1.242)	(0.930)	(5.946)	(6.051)
InstHold	− 2.064	− 0.252	− 5.747**	− 0.018	0.004
	(− 1.109)	(− 0.193)	(− 2.403)	(− 1.235)	(0.266)
EPS_Surprise	0.171***	0.109***	0.344***	0.000	0.000
	(6.157)	(5.533)	(7.736)	(1.546)	(0.502)
Pressure	− 0.606**	− 0.237	− 0.323	− 0.005***	− 0.004*
	(− 2.233)	(− 1.146)	(− 1.025)	(− 3.019)	(− 1.858)
Op_cycle	− 0.002	0.002	− 0.001	− 0.000*	0.000
	(− 0.419)	(0.698)	(− 0.201)	(− 1.945)	(0.961)
S_CFO	− 5.025	0.054	− 11.723**	− 0.034	− 0.022
	(− 1.179)	(0.017)	(− 2.110)	(− 1.103)	(− 0.519)
S_Sales	− 1.456	− 0.922	− 1.664	− 0.011	0.016
	(− 0.787)	(− 0.698)	(− 0.703)	(− 0.783)	(1.077)
Loss	− 3.073*	− 1.551	− 3.505	0.007	− 0.005
	(− 1.863)	(− 1.338)	(− 1.623)	(0.690)	(− 0.373)
SIR (%)	5.408	6.191	14.860*	− 0.032	0.019
	(0.974)	(1.556)	(1.930)	(− 0.691)	(0.453)
GN_Forecast	4.828**	1.651	4.379*	0.019	− 0.027*
	(2.453)	(1.180)	(1.787)	(1.286)	(− 1.721)
BN_Forecast	− 7.655***	− 5.873***	− 8.662***	0.022	− 0.009
	(− 4.367)	(− 4.537)	(− 3.904)	(1.641)	(− 0.609)
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	6711	6711	6711	6604	6355
Adj R2	0.049	0.036	0.063	0.044	0.023

Note: 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. Columns 4 and 5 present the results of a placebo test where the shock window is one and two years before the fire-sale quarter, respectively. All variables are defined in Appendix. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

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. 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% and 5.89%.[14]

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 the faster incorporation of news into prices, competing with our main hypothesis. However, we find that the

[14]To ease the interpretation of the results, we use *Decile_AQ*, but we obtain similar results using the raw values of our AQ proxy instead of the deciles. See Table OA.2 in the Online Appendix.

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 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 nonsignificant in most specifications. This result might seem surprising because institutional investors are considered sophisticated shareholders and are therefore 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).[15]

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 news (*GN_Forecast*) and bad news forecasts (*BN_Forecast*) have high explanatory power over abnormal returns during the quarter of the shock but 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 forecasts 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 that played by other information voluntarily disclosed by managers.

Finally, the remaining control variables are, in general, nonsignificant, 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 nonsignificant. By construction, firms in our sample are shown to have higher *Pressure* than that of firms that are not being fire sold. However, conditional on facing price pressures, this variable cannot further explain returns, which can be explained by the fact that this proxy does not account for the trading of undistressed investors, which will absorb the shares liquidated by 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 nonfundamental 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 the theoretical model predictions that information asymmetries between mutual fund managers and market participants drive fire-sale discounts (Dow & Han, 2018; Kurlat, 2016). 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 nonfundamental shocks.[16]

[15] In Section 4.5 we consider additional proxies of corporate governance.

[16] Our results are robust to using the market model and 3-factor model to estimate abnormal returns (see Online Appendix Section OA.1.). We also test the robustness of our results to using alternative measures of AQ. We find that higher earnings persistence (Dechow et al., 2010; Francis et al., 2004), conservatism (Chen et al., 2007; Gao, 2013; LaFond

To alleviate concerns regarding our research design, we run a placebo test. We estimate our main model for those 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 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 & Sadka, 2008). If our results are driven by other unobservables that are correlated with our proxy for AQ, then 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 3 presents the placebo test results for our main proxy of AQ using one year (column 4) and two years before the shock (column 5) as the placebo quarters. Overall, we find that for both placebo quarters, 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., approximately 1% of the effect in our main tests). These results suggest that our findings 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 bias against our results.

4.3. 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 than do low-AQ firms.

4.3.1. Changes in analysts' recommendations

Prior research shows that changes in analysts' recommendations facilitate the process by which information is incorporated into stock prices (Jegadeesh et al., 2004; Womack, 1996). 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 the price pressures induced by mutual fund fire sales. Therefore, if high AQ helps analysts identify mispriced stocks, then 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 quarter of the fire sale:

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

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' recommendations

& Watts, 2008), and unexpected audit fees (Ball et al., 2012; Lobo & Zhao, 2013) are associated with smaller fire-sale discounts. In contrast, higher earnings predictability, earnings smoothing (Dechow et al., 2010; Francis et al., 2004), and larger deviations from Benford's Law (Amiram et al., 2015) are associated with larger fire-sale discounts. Overall, these results are consistent with our main prediction that better AQ decrease fire-sale discounts (see Online Appendix Section OA.2.2.).

by negative one, and thus, positive changes indicate a more favorable recommendation. Prior literature documents that changes in consensus recommendation contain information above and beyond that of 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 the shock, 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 that in model (1). We expect β to be positive.

Table 4, 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

Table 4. Changes in analysts' recommendations.

	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	6711	6711	6711	6711	6711	6711
Adj R2	0.008	0.015	0.007	0.018	0.021	0.011

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

that better AQ helps market participants price securities at the arrival of nonfundamental information, as captured by analysts' recommendations. Moreover, our results complement those of Sulaeman and Wei (2019), who find that analysts play a key role in incorporating information into prices during fire sales. We document that AQ is an important factor driving this relationship. Therefore, when accounting information does not provide adequate information with which to assess firm valuation, analysts might wait to see larger deviations from fundamental prices before changing to a more favorable recommendation, prolonging the mispricing duration.

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 than for those with lower AQ.

4.3.2. 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 other people's money, as fund providers might decide to withdraw their funds before the mispricing has been corrected (Shleifer & Vishny, 1997). Therefore, it is logical to assume that arbitrageurs will tilt their portfolios toward those assets that they expect to revert faster to the 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 these firms to have higher holding costs. If AQ helps arbitrageurs identify mispriced stocks and better AQ is associated with lower holding costs of arbitrage strategies, then 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 with which 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, 2001; Bushee & Noe, 2000; Collins et al., 2003; Ke & Ramalingegowda, 2005). Not all institutional investors have the same investment focus. Nontransient investors (i.e., dedicated and quasi-indexers) are less likely to implement short-term arbitrage strategies (Bushee, 2001; Bushee & Noe, 2000) than are transient investors; therefore, we should not observe any association between AQ and nontransient investor holdings during mutual fund fire sales.

To test this mechanism, we estimate the following pooled cross-sectional regression model around the quarter in which the fire sale occurs:

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

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 nontransient institutional investors (i.e., dedicated and quasi-indexer investors) around the quarter of the shock.[17] As in our main

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

specification, we estimate model (6) using three alternative windows: the quarter of the shock, the quarter before the shock, 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 those used 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 and statistically significant. In contrast, studying the behavior of nontransient investors serves as a placebo test, and we expect β to be not significantly different from zero, as nontransient investors have a longer-term horizon and are not expected to change their portfolio holdings to exploit mispricing compared to transient investors.

Table 5, 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

Table 5. Investors' trades.

	DTra(− 1) (1)	DTra(0) (2)	DTra(+ 1) (3)	DNTra(− 1) (4)	DNTra(0) (5)	DNTra(+ 1) (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	6711	6711	6704	6711	6711	6704
Adj R2	0.107	0.109	0.149	0.181	0.126	0.132

Note: This table reports one mechanism through 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 in columns in 4 to 6, we look at the quarterly change in nontransient investors' holdings. All variables are defined in Appendix. All regressions include industry and quarter-year fixed effects. Standard errors are clustered at the firm level. Robust t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

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 nontransient institutional investors (columns 4 to 6). These results lend confidence to our proposed mechanism since nontransient investors are unlikely to act as arbitrageurs.

4.4. AQ and Information From Other Sources

Next, we turn to the interaction between AQ and information from other sources. 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 timelier sources (Ball & Shivakumar, 2008; Basu et al., 2013; Beyer et al., 2010; Graham et al., 2005). If earnings are a good (poor) summary measure of firms' fundamental news, then other sources of information may become less (more) relevant for producing 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 examine whether AQ plays a more important role when other sources of information are available.

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). The coefficient on the interaction term assesses whether having better AQ is incrementally beneficial for firms with alternative sources of information available.

Table 6. AQ and information from other sources.

	CAR(− 1,0) (1)	CAR(0) (2)	CAR(− 1,1) (3)	CAR(− 1,0) (4)	CAR(0) (5)	CAR(− 1,1) (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	6711	6711	6711	6711	6711	6711
Adj R2	0.054	0.047	0.067	0.050	0.037	0.064

Note: This table analyzes whether changes in analysts' recommendation and manager forecasts released at the time of the shock have different effects for firms with high or low AQ. Columns 1 to 3 consider the interaction between reporting quality and analysts' recommendations. Columns 4 to 6 report 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, as defined in Appendix. Standard errors are clustered at the firm level. Robust t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6 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* × *DRec* is negative and statistically significant, except for in column 2, where the result is marginally nonsignificant. In columns 4 to 6, we also find a negative and significant coefficient on *Decile_AQ* × *GN_Forecast*. Taken together, the results in Table 6 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 AQ is stronger when other timelier sources of information are not available.

4.5. Additional Tests

Our main findings indicate that AQ mitigates fire-sale discounts. Despite prior research considering mutual fund fire sales as a plausible exogenous shock (Coval & Stafford, 2007; Jiang et al., 2021; Sulaeman & Wei, 2019), there may still be the concern that managers of distressed mutual funds select to liquidate firms with certain specific characteristics and that this situation could explain both firms' AQ and mutual fund fire-sale discounts, leading to an omitted variable problem (Berger, 2023). Therefore, to eliminate potential alternative interpretations of our results, we conduct several additional analyzes. For the sake of brevity, we report these tests in Table OA.5 in the Online Appendix.

First, one potential alternative explanation of 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 (Collins et al., 2017; Dechow et al., 2010; Kothari et al., 2005; Owens et al., 2017), which could explain our results. To alleviate these concerns, we follow Owens et al. (2017)'s suggestion and control for firm idiosyncratic shocks to firms' underlying economics in our main model.[18] Our main results hold, and thus, moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 1.71% to 6.62%.

Second, we include additional controls for potential omitted variables: firm complexity, managerial ability, corporate governance, and market-level factors. Prior literature shows that firm complexity impedes the incorporation of firm information into prices (Barinov et al., 2022; Cohen & Lou, 2012). As such, it could be argued that complex firms experience higher degrees of mispricing due to the difficulty faced by market participants in distinguishing the source of the noise, therefore impeding them from trading on the mispriced stocks. If more complex firms are also of lower AQ, then this could confound our results. 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 (HHI) calculated using firms' segment sales. The estimated coefficient for *Complexity* is negative but statistically nonsignificant, and our main results hold. After including this additional control, we still observe that moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 2.04% and 5.95%.

Previous evidence shows that managerial ability is associated with both AQ and stock price reactions (Demerjian et al., 2013, 2012). If market participants perceive that high-ability managers are better able to adjust their firms' policies in response to the shock and that AQ is associated with managerial ability, then 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

[18] 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*. We include the decile of this measure (*Decile_IdioShock*) as an additional control.

using the decile rank of the MA score (Demerjian et al., 2012).[19] We find that the MA score does not affect abnormal returns, and our main findings are robust to this specification. Under this specification, moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 2.00% and 6.25%.

We also consider the role of corporate governance. Previous studies show that corporate governance is related to both AQ (Bowen et al., 2008; Dechow et al., 2010; Farber, 2005; Klein, 2002) and firm fundamentals (Gompers et al., 2003; Jensen & Meckling, 1976; La Porta et al., 2002; 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, then our results may 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 chief executive officer (CEO) takes office. Higher degrees of co-option are typically associated with poorer governance, as co-opted directors are less likely to monitor a firm's management than are non-co-opted directors (Khanna et al., 2015).[20] Second, following Hasan et al. (2021), we use CEO share ownership and CEO tenure 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. Our results are robust to including these additional corporate governance controls. We find that after controlling for corporate governance effects, moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 1.94% and 5.79%. The inclusion of controls for firm complexity, managerial ability, and internal governance severely reduces our sample size significantly. For this reason, we do not include them in the main specification.

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 (*AV ol*), quarterly stock return (*Ret*), stock turnover (*Turnover*), and volatility (*SDRet*). 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 & Stafford, 2007; Sulaeman & Wei, 2019), we include these additional controls with 2 lags to avoid having a *bad controls* problem (Angrist & 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. Our main results hold after including these additional controls, and thus, moving from the bottom to the top decile in *Decile_AQ* is associated with higher cumulative abnormal returns of between 1.69% and 5.31%.

5. Conclusions

We study whether AQ mitigates mispricing due to nonfundamental 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 increase their holdings for firms with better AQ during mutual fund fire sales. In cross-sectional analyzes, we find that the effect of AQ in reducing mispricing is more important when other sources of fundamental information are not available. 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

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

[20]We collect data on co-opted directors from Lilitha Naveen's website, available at https://sites.temple.edu/lnaveen/data/.

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

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Appendix. Variable definitions

Name	Definition
Dependent Variables	
$CAR(t)$	Cumulative abnormal returns 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 nontransient (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.
Independent Variable	
AQ	Standard deviation of the residuals from Equation (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 in value 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	Ratio of 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, and Thomson Reuters).
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 cash flows from operations (Compustat items oancf and at) over the last 10 years (we require a minimum of 5 years of data).

(*Continued*).

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 a value of 1 if the firm suffers 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 the CRSP divided by the previous 12-month average total trading volume (CRSP item vol), quarterly average.
HLtoH	Ratio of the stock's monthly high and low price difference to 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)