Actively Managed Funds and Earnings News: Evidence from Trade-Level Data

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ABSTRACT

We use trade-level data to examine the role of actively managed funds (AMFs) in earnings news dissemination. AMFs trade (172 percent) more on earnings announcement (EA) days than on non-EA days. The EA buys made by AMFs are reliably more profitable than their non-EA buys. At the fund level, AMFs with higher trading intensity during EAs are also more profitable than AMFs with lower trading intensity during EAs. Furthermore, we find that increased AMF trading during EAs reduces post earnings announcement drift (PEAD) and leads to faster price adjustment, measured in various ways. Moreover, the directional trades of AMFs generally shift returns from the post-EA period to the EA period. Collectively, our evidence suggests that AMFs are relatively sophisticated processors of earnings news and that their trading during EAs improves the price discovery process.

Keywords: actively managed funds, earnings announcements, information processing, price efficiency, post earnings announcement drift, trading volume

JEL Classifications: G12, G14, G23, M41

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1 INTRODUCTION

In this study, we examine the response of active fund managers to earnings news. An estimated $58.4 trillion was run by active fund managers in 2015 and this number is estimated to grow to $74 trillion by 2020 (PricewaterhouseCoopers 2017). However, surprisingly little is known about how actively managed funds (AMFs) respond to the release of corporate earnings.[1] Prior studies find that an investor holding a passive market portfolio earns higher after-cost returns, on average, than the typical active fund manager (French 2008; Fama and French 2010). We argue that these results do not necessarily imply a lack of skill in AMF managers. AMFs trade for many reasons, and investor flows and the size of funds could drive the underperformance of actively managed portfolios (Berk and Green 2004; Coval and Stafford 2007; Frazzini and Lamont 2008; Song 2017). To shed light on the information processing capabilities of AMFs, we utilize trade-level data and focus our analyses on trades around earnings announcements (EAs). Our goal in focusing on EAs is to isolate AMF trades that are more likely to be information-driven. Our results provide evidence of AMF skill in responding to this important class of information events.

We have two motives for studying the AMF reaction to earnings news. First, we are interested in evaluating the extent to which AMF trades reflect sophisticated processing of earnings news. Prior research has documented multiple behavioral biases of individual investors, which lead to economically significant losses (Barber and Odean 2000; Barber, Lee, Liu, and Odean 2009a; Barber, Odean, and Zhu 2009b).[2] AMFs are managed by investment professionals, who

[1] Our AMF sample includes both mutual funds (MFs) that cater to retail investors and other active fund managers that cater to institutional clients. These AMFs typically hold long-only portfolios and do not engage in short-selling. A relatively small portion of the trades in our sample are by known hedge funds (HFs). We remove these HF trades when conducting our main analyses and separately analyze them in a later test.

[2] For example, individual investors are known to trade too much. They also tend to overreact to salient news events, leading to short term price reactions that reverse over subsequent months (e.g., Barber and Odean 2008; Da, Engelberg, and Gao 2011). Individual investors also underreact to earnings, contributing to the post earnings announcement drift (PEAD) (Bhattacharya 2001; Battalio and Mendenhall 2005).

charge active fees and are presumably more sophisticated information processors. Yet prior studies on AMFs' ability to add investment value have yielded surprisingly mixed results.[3] In this study, we examine whether the AMF response to earnings news reflects a higher level of sophistication. To the extent that AMFs have an information advantage over retail investors, we are interested in documenting the nature and extent of that advantage.

We address this question by combining an event study setting with the use of granular trade-level data. One reason for the mixed results in prior AMF studies could be the low power of portfolio-based performance measures. Kothari and Warner (2001) find that performance measures used in mutual fund studies have little ability to detect abnormal fund performance. Their results suggest that an event study would be a much more powerful setting in which to evaluate the performance of asset managers. We combine this insight with detailed data on AMF trades, which allow us to pin down precisely the profitability of each AMF transaction.

The event study setting also helps to mitigate concerns about the effect of "flow-induced trading." Prior studies show that the performance of AMFs is negatively affected by so-called "dumb money flows," whereby AMF managers are forced to unwind their positions due to retail investor redemptions (Coval and Stafford 2007; Frazzini and Lamont 2008; Lou 2012). By focusing on the AMF trades around EAs, our research design reduces the likelihood that these trades are undertaken for liquidity-related reasons. Furthermore, by comparing EA trades to non-EA trades for each individual fund, we are able to isolate AMF performance in response to earnings news releases while controlling for a host of non-EA related factors, including flow-induced trading.

[3] The evidence on mutual fund (MF) performance is particularly damning, with some studies finding that even their gross returns underperform those of passive benchmarks (Jensen 1968; Malkiel 1995; French 2008; Fama and French 2010). However, these results seem quite sensitive to the choice of benchmark (Lehman and Modest 1987; Carhart 1997; Daniel, Grinblatt, Titman, and Wermers 1997; Kothari and Warner 2001).

A second reason to study AMF reaction to earnings news stems from the broader issue of market efficiency. The issue of whether institutional investors help correct market mispricing has been widely debated. Some evidence suggests that institutional investors fail to take advantage of various pricing anomalies, and in some cases may even exacerbate them (Lewellen 2011; Edelen et al. 2016). Other studies find that higher institutional trading or ownership, and greater institutional attention to news, can improve price discovery. For example, Henry and Koski (2017) find that institutions earn higher profits around ex-dividend event days. Cheng, Hameed, Subrahmanyam, and Titman (2017) find that the magnitudes of short-term return reversals are higher following declines in the number of active institutional investors. Similarly, Bartov, Radhakrishnan, and Krinsky (2000) report that the level of institutional ownership is negatively correlated with the size of the post-earnings announcement drift (PEAD). Stocks with increases in mutual fund holdings have higher subsequent EA returns (Baker et al. 2010). In addition, greater institutional attention, as measured by Bloomberg terminal searches and the number of news reads, has also been associated with improved price discovery (Ben-Rephael, Da, and Israelsen 2017). However, none of these studies investigate the role of AMF trading in response to earnings news.

We contribute to this literature by using detailed trade-level data to evaluate the role of AMFs in the price discovery process associated with earnings news. Specifically, we examine three related hypotheses. First, if AMF participation improves overall price discovery, then, ceteris paribus, we expect the EAs with greater abnormal AMF participation to exhibit faster and more complete price adjustments than EAs with little or no abnormal AMF participation. Specifically, we hypothesize that increased AMF trading during EAs leads to faster price convergence and reduced post-EA price drift. Second, we hypothesize that the *directional* (buy minus sell) trades of AMFs will generally ameliorate price drifts – that is, we expect net directional trading by AMFs to shift returns from the post-EA period to the EA period. Finally, we conduct a detailed comparison of EA vs non-EA trades, controlling for the specific AMF in question. To the extent that AMFs have an informational advantage in processing the value implications of earnings news, we expect their EA period trades to be more profitable than their non-EA trades.

Our analysis is aided by a unique dataset from Abel Noser Solutions (formerly Ancerno Limited), a widely recognized consulting firm that provides transaction cost monitoring services to a large set of institutional clients. The Ancerno dataset consists of all trades made by Abel Noser's sizeable client base from January 2003 to December 2010.[4] Prior research (e.g., Puckett and Yan 2011) shows that the characteristics of stocks held and traded by Ancerno's institutional clients are not significantly different from the characteristics of stocks held and traded by the average 13F-filing institution. The trades in Ancerno account for around 12 percent of CRSP volume (Hu et al. 2017). For our main analyses, we define AMF trades as those conducted by Ancerno's non-pension fund clients (clienttype=2), after removing a set of known hedge funds (Jame 2018). Based on conversations with Ancerno, most of the clienttype=2 trades are made by mutual funds (MFs), but this category may also include some funds that manage money for institutions (other than pension funds). To be safe, we therefore refer to this group of traders as AMFs rather than MFs.[5] In supplemental tests (see Section 3.6), we also separately analyze the trades carried out by those clients known to be hedge funds.[6]

Prior studies have identified a number of agency issues that may affect the trading decisions

[4] During this sample period, Ancerno data featured individual client identifiers. While actual client names have been redacted, these identifier codes allow us to track the trades made by each unique client identification code over time. After 2010, Ancerno data did not contain individual client identification codes.

[5] In fact, there is little conceptual distinction between MFs and other AMFs. Prior literature on AMF performance likely focused on MFs because these funds are easier to identify through their 13F filings.

[6] We separately analyze hedge fund trades because: (a) these funds are widely viewed as the most sophisticated active asset managers (Agarwal, Jiang, Tang, and Yang 2013; Jame 2018), and (b) prior evidence on AMF underperformance have generally focused on long-only funds, in particular MFs. We exclude clienttype=1 (pension plan sponsor) trades because many of these plan sponsors employ hedge funds to run their portfolios.

of active managers.[7] By focusing on a short event window around an earnings release, our research design reduces the likelihood that agency conflicts are the reason for AMF trading decisions (i.e., these pressures are less likely to vary for a given AMF manager in that short window). While general non-EA period trades by AMFs may be impacted by the preferences of their clients, their decision to trade at the EA, and the exact timing of those trades in relation to the release of earnings news, are more likely to reflect AMF manager discretion in maximizing returns.

Our analysis reveals several key findings. First, we document a significant AMF reaction to earnings news. We find positive abnormal trading volume from AMFs starting the day before the EA, up to a few days after the EA, with the highest abnormal volume occurring on Day 0. On average, AMFs place 172 percent more trades on the EA day (Day 0) than on an adjacent non-EA day, where adjacent non-EA days are defined as days (-25, -2) and (+5, +25) relative to the EA. The average Day 1 AMF volume is 55 percent higher than the average non-EA period AMF volume. We also find some evidence that AMFs anticipate earnings news, as the average AMF volume on the day prior to the EA is 14 percent higher than the average non-EA period AMF volume. As a proportion of total trading volume, AMFs do not place significantly more trades in the EA period than in the non-EA period, indicating that AMFs are not more focused on EAs than other market participants.

Next, we examine the implications of AMF trading for the post-earnings announcement drift (PEAD) anomaly. Bernard and Thomas (1990) show that the market price response to earnings behaves as if some investors are using a simple seasonal random walk model. As a result,

[7] For example, MF managers are compensated relative to their peers, so there has been evidence that mid-year "losers" increase fund volatility in the second half of an annual assessment period relative to mid-year "winners" (Brown, Harlow, and Starks 1996; Chevalier and Ellison 1997). MF managers are also compensated based on whether or not they beat their benchmarks, as well as their assets under management (AUM), so they have an incentive to make trading decisions to increase their fund size (Khorana 1996; Farnsworth and Taylor 2006). Berk and Van Binsbergen (2015) find that investors reward MF managers' skill by investing more capital with better funds, and therefore the cross-sectional distribution of skill is reflected in fund size.

prices seem to adjust sluggishly to the serial correlation in standardized unexpected earnings (SUE). To the extent that AMFs are more sophisticated in their understanding of these earnings patterns, AMF trading around EAs may on average mitigate the PEAD effect.

Consistent with prior studies, we show that the PEAD effect has declined over time, and that in recent years, it is only significant among small firms (Dechow, Sloan, and Zha 2014). More importantly, we find that the amount of abnormal AMF trading during an EA is associated with the size of the subsequent PEAD among small stocks. Specifically, an increase in EA AMF volume from the bottom to top decile is associated with a 1.4 percent decrease in the returns to a PEAD strategy. We also find that the return observed in the EA period, (0, +4), captures more of the total (0, +60) return, when there is high AMF trading as a fraction of total volume in the EA period. Taken together, these findings suggest that elevated AMF trading during earnings news releases is associated with an increase in the speed of price adjustment to earnings news.

After showing that non-directional AMF trading reduces PEAD, we focus more sharply on the effect of *directional* AMF trades. This test is important because it provides a more direct link between the information that AMFs trade on and the PEAD effect. First, we find that AMFs generally trade in the same direction as SUE, suggesting their trading activities are not merely supplying liquidity. Next, focusing on the sample of small stocks where a significant PEAD effect still exists, we find that *directional* AMF trades do improve price discovery. Specifically, our results show that when AMFs trade in the same direction as the SUE strategy ("concordant" trading), a much higher fraction of the total difference in returns occurs in the 5-day EA period, as compared to when AMFs trade in the opposite direction to SUE ("discordant" trading).[8] This

[8] We define "discordant" observations as those with the lowest quintile net AMF trading when SUE is high and "concordant" observations as those with the highest quintile net AMF trading when SUE is low. We then examine the difference between average SUE3 and SUE1 EA period size-adjusted (0, +4) returns as a proportion of the

evidence shows that the *direction* of AMF trading significantly impacts the timely incorporation of earnings news into stock price.

Finally, we evaluate the profitability of AMF trades during both EA and non-EA periods. To conduct these tests, we mimic each AMF trade (i.e., we buy or sell a given stock at the same price as was obtained by the AMF). We then compute the return on the trade assuming it is unwound at the closing price on day +60 after the date of the initial trade. In other words, we compute the 60-day mimicking return an AMF would have earned as a result of each trade, after controlling for market and size-related price movements. These results show the gain or loss from each AMF trade.

Our first finding is that AMF trades earn negative size-adjusted returns when they are not conditioned on EA periods. This result is consistent with recent work by Chakrabarty, Moulton, and Trzcinka (2017), who also find that shorter-horizon round-trip trades made by AMFs are, on average, unprofitable. Our methods differ somewhat, but the general tenor of the results is the same: unconditional AMF trades earn negative average returns.[9] As noted earlier, these results could be due to non-informational trading that AMFs have been forced to make as a result of capital flows into or out of their funds.

Next, we focus on the short window around each EA day. Our premise is that AMF buys initiated on the day of the earnings release are likely to be triggered by information released on that day. Our results show that EA buys are more profitable than non-EA buys, which suggests that AMFs process earnings news efficiently. We do not find the symmetric difference in profitability for AMF sells on the EA day versus non-EA days, likely due to selling reflecting

difference between average SUE3 and SUE1 total size-adjusted (0, +63) returns, where SUE3 (SUE1) refers to SUE in the top (bottom) tercile of the sample.

[9] Chakrabarty et al. (2017) use only actual round-trip trades by the same AMF, while we focus on 60-day mimicking returns and apply them to all AMF trades.

opportunity costs (i.e., the opportunity cost of not holding another stock) rather than negative signals released at the EA.

Finally, we provide some evidence on the relative performance of two sub-populations within active asset managers. First, we examine the AMFs that concentrate a greater proportion of their trading activities around earnings announcements (i.e., the "EA-focused managers"). To construct this test, we first sort AMFs based on how much of their annual trading takes place in the EA period. Our cross-sectional results show that AMFs who focus their trades in the EA period make more profitable trades both in the EA and non-EA periods. In general, it appears that the subset of EA-focused managers has an informational advantage over the other AMFs.

Second, we focus on a population of known hedge funds (HFs). These asset managers differ from other AMFs in that they typically hold both long and short positions. Most HFs will also use some leverage when constructing their portfolios. The combination of short-selling and leverage allows HFs to be, on average, nimbler traders who can exploit a wider set of mispricings more quickly. In our final set of tests, we focus on the EA trades of a set of Ancerno clients known to be HFs.[10]

The results of our HF tests generally reinforce our prior findings on the broader set of AMFs. As with other AMFs, we find that HFs increase their trading around earnings news releases. However, unlike the trades of other AMFs, HF trades are profitable even when they are not executed around EA periods. HF trades are more profitable than AMF trades, in both the EA and non-EA periods. However, we do not find any evidence that HF trades at the EA differ in profitability from those in non-EA periods. Taken as a whole, our evidence suggests HFs are particularly sophisticated processors of information, both during and outside of the EA period. The

[10] Specifically, we use the sample of HFs identified by Jame (2018). These HFs were expressly removed from the sample in our earlier analyses of AMFs.

finding that HFs trade profitably outside EA periods also provides some validation for our procedure of removing HFs from the AMF sample in our other tests.

Our study contributes to the longstanding literature on AMF performance. Most prior studies on AMF, and particularly MF, performance conclude that they underperform. However, these results in prior research are inconsistent with costly information acquisition (Ippolito 1989; Berk and Green 2004). One possible reason for these results is that investor flows are driving AMF underperformance, making it difficult to test whether AMFs are sophisticated processors of information (Edelen 1999). Another potential reason is the low power of typical performance measures used in prior studies (Kothari and Warner 2001). We address these problems using an event study approach and highly granular trade-level data. Other papers have used trade-level data to infer the skill of institutional investors, but they either focus on hedge funds (e.g., von Beschwitz, Lunghi, and Schmidt 2017), non-EA news (Huang et al. 2016), or the profitability of institutional trades without conditioning on information events (e.g., Di Mascio, Lines, and Naik 2016).[11] In addition, we address the need for research using trade-level data in accounting and around corporate events, as described in Hu et al. (2017).

Our results provide relatively unambiguous evidence of AMF skill in processing earnings news. Consistent with prior studies, we find that AMFs in our sample underperform a size-matched portfolio by 0.04 percent over 60 days when we do not condition on any information events. However, we also find that their trades on the announcement day are *profitable*. AMFs, especially those with significant dollar volume during firms' EA periods, generally make value-

[11] Gallagher, Looi, and Pinnuck (2010) study Australian fund managers' trades around EAs. Consistent with our results, they find that EA directional trades are related to the sign of the news at the EA. However, they do not study the improvement in price discovery, which is the focus of this paper. von Beschwitz et al. (2017) focus on the profitability of hedge fund trades and find that hedge funds earn significant abnormal returns at the trade-level. The authors use a 60-day window, because mispricings that hedge funds can exploit will decay over time. We adopt a 60-day window as well.

enhancing trades on the day of the earnings release. Specifically, AMF trades on the EA day outperform a size-matched portfolio by 0.14 percent over 60 days. Our focus on AMFs, excluding hedge funds, is important because prior studies have distinguished the two groups from each other in skill level, attributing hedge funds to "smart money" and AMFs to "dumb money" (Ha and Hu 2017).[12] In this study, we provide evidence that this important set of institutional investors possesses an informational advantage in the processing of earnings news.

Our results also speak to the broader issue of market efficiency. Specifically, we find that AMFs play a significant role in facilitating the integration of earnings information into price. Using multiple tests, we show that increased AMF trading leads to a faster and more complete price discovery process in relation to earnings news. These findings extend the literature on PEAD by directly linking the magnitude of the price drift to the amount of EA intervention by AMFs. In addition, our results on the effect of directional AMF trading among small firms suggest that the persistence of the PEAD effect could be due to elevated arbitrage costs, which limit AMF involvement among these stocks.

The paper proceeds as follows. Section 2 outlines hypotheses and reviews related literature. Section 3 details our research design and provides results. Section 4 concludes.

2 HYPOTHESIS DEVELOPMENT

In this section, we detail what we expect to find in our analyses. Our hypotheses, stated in alternative form, are:

H1: AMFs trade in response to EAs.

EAs contain useful firm fundamental information. Earlier studies document a price

[12] Another study that finds skill in hedge funds is Agarwal et al. (2013). The authors find that the confidential filings of hedge funds exhibit superior performance and are consistent with private information. Our analyses in Section 3.6 address hedge funds in addition to AMFs.

reaction to earnings news (Ball and Brown 1968; Beaver 1968). While these studies do not distinguish between retail and institutional investors, subsequent studies have found that institutions in particular influence a firm's information environment and price formation process (e.g., Utama and Cready 1997; El-Gazzar 1998; Jiambalvo, Rajgopal, and Venkatachalam 2002; Collins, Gong, and Hribar 2003). As new information about firm fundamentals is made available at the EA, AMFs might be significant players in impounding that information into price. Thus, we expect AMFs to have abnormal trading volume in the EA period.

Prior research has also claimed that institutional investors are sophisticated processors of information. As the EA contains such a significant information signal regarding value of a firm, we might expect AMFs to comprise a greater proportion of total EA volume, meaning they trade on earnings news more so than the average market participant. Cready, Kumas, and Subasi (2014) find that institutions increase their trade sizes at earnings announcements, consistent with a response to earnings news. Hu, Ke, and Yu (2018) find that transient institutions sell in response to small negative earnings surprises. Engelberg, McLean, and Pontiff (2017) hypothesize that, if anomaly returns are due to expectation errors, anomaly portfolios should perform better on days when new information is released, because new information leads investors to update their expectations.

H2: AMF trading helps correct the PEAD anomaly.

Over a short horizon of less than a year, stock prices exhibit patterns suggestive of investor underreaction to recent news, leading to a price drift in the direction of the news event (Cutler, Poterba, and Summers 1991; Bernard and Thomas 1989; Jegadeesh and Titman 1993; Chan, Jegadeesh, and Lakonishok 1997). Over longer horizons of 3 to 5 years, stock prices overreact to a series of good or bad news, so stocks with consistently good news are overpriced and stocks with consistently bad news are underpriced (Cutler et al. 1991; De Bondt and Thaler 1985; Chopra, Lakonishok, and Ritter 1992; Lakonishok, Shleifer, and Vishny 1994; La Porta 1996). PEAD is an indication of underreaction to earnings news (Bernard and Thomas 1990). In particular, earnings exhibit a quarterly autocorrelation structure (+, +, +, –), whereby SUEs are negatively correlated with one-year-prior SUEs and positively correlated with SUEs of other quarters. Investors fail to recognize this autocorrelation, resulting in the returns of high SUE firms drifting upward and returns of low SUE firms drifting downward. However, Dechow et al. (2014) find that, in recent years, PEAD has essentially disappeared.

Prior studies have linked the activities of small retail traders to PEAD (Bhattacharya 2001; Bartov et al. 2000; Battalio and Mendenhall 2005). Cohen, Gompers, and Vuolteenaho (2002), Campbell, Ramadorai, and Schwartz (2009), and Hendershott, Livdan, and Schürhoff (2015) show that institutions exploit PEAD and anticipate earnings surprises. Short sellers in particular have been shown to process news (Engelberg, Reed, and Ringgenberg 2012) and mitigate PEAD (Boehmer and Wu 2013). Given their size, we expect the AMFs in our sample to have a much more significant impact on price formation than retail investors. Thus, we expect that their trading will reduce the magnitude of the PEAD. In particular, given that in recent years PEAD is only significant among small stocks, we expect the marginal effect of AMF trading to be most evident for these small stocks.

While we expect AMF trading to mitigate PEAD, it is possible that in equilibrium AMF activities will not be able to fully eliminate this anomaly. Arbitrageurs that bet against mispricing face the risk of unpredictable movements in investor sentiment, and they can lose money in the short run (De Long, Shleifer, Summers, and Waldmann 1990; Shleifer and Vishny 1997). For these reasons, arbitrage costs might prevent AMF trades around the EA from fully correcting the

PEAD anomaly.

H3: AMF trading increases the speed of price adjustment.

The magnitude of PEAD is related to the speed of price adjustment. If investors fully incorporate all information in earnings into price in the first few days after the EA, the fraction of longer horizon returns captured in the first few days will be high. Given the potential market price impact of AMFs, we expect their trading will more quickly incorporate earnings information into price. Therefore, the fraction of long run returns captured in the EA period will be higher when AMF trading volume as a fraction of total trading volume is high. Furthermore, when AMFs trade in the same direction as SUE, we expect these trades to facilitate price adjustment.

Prior research has documented that EAs are significant information events during which prices correct to fundamental value. Between 25 and 30 percent of the returns to value strategies in Lakonishok et al. (1994) and 40 percent of the returns to accrual strategies are concentrated in the three days around EAs (La Porta, Lakonishok, Shleifer, and Vishny 1997; Sloan 1996). In addition, around 25 percent of momentum profits are clustered in the three days around EAs (Jegadeesh and Titman 1993). Prices adjust toward fundamental value in the EA period because fundamental information is revealed at the EA. Funds with superior stock performance around EAs, when fundamental information is released, subsequently outperform those with inferior stock performance around EAs (Jiang and Zheng 2016). To the extent that AMFs speed up price adjustment in the EA window, AMFs play an important role in the convergence of price to fundamental value.

H4: AMF trades on the EA day are value-enhancing to them.

One behavioral bias of individual investors documented by prior literature is the tendency to trade too much and incur economically significant losses as a result of their trades (Barber and

Odean 2000; Barber et al. 2009a, 2009b). It is possible that the same behavioral biases also affect the trading decisions of allegedly sophisticated AMF managers. To shed light on whether AMFs trade too much, we test whether AMF trades are value enhancing.

Whether or not institutional investors are sophisticated is a longstanding debate in the literature. Several papers find that MFs do not have abnormal performance (Jensen 1968; Carhart 1997; Edelen 1999; Blake, Elton, and Gruber 1993). As suggested by Grinblatt and Titman (1994) and Kothari and Warner (2001), portfolio returns are noisy, and there is low power in these tests to detect abnormal returns even if they exist. Grinblatt and Titman (1994) address this concern by relying on priors about fund characteristics that determine performance, and Kothari and Warner (2001) recommend using time-series datasets on MF holdings to overcome the power issue. Other papers have found persistent outperformance in MFs (Lehmann and Modest 1987; Ippolito 1989; Grinblatt and Titman 1992; Hendricks, Patel, and Zeckhauser 1993; Daniel et al. 1997). In particular, Daniel et al. (1997) find that abnormal returns are roughly equivalent to management fees. Their results are consistent with informed traders making profits as compensation for their costs of acquiring information (Grossman and Stiglitz 1980).

Bartov et al. (2000) find that institutional ownership is negatively correlated with PEAD, which implies institutions are sophisticated. Institutions may have greater access to firm management or better processing capabilities due to economies of scale and more analysts (Bushee and Goodman 2007). Bushee and Goodman (2007) also claim that individuals allocate their wealth to institutions, which then invest their money in firms, because they perceive these institutions as enjoying informational advantages, which can be passed on to individuals through returns. However, some evidence suggests that institutions are not necessarily sophisticated investors. For example, Edelen, Ince, and Kadlec (2016) find increases in institutional ownership for overvalued stocks and decreases in institutional ownership for undervalued stocks, meaning institutions are on the wrong side of anomalies' implied mispricing.

We predict that AMF trades on the EA day are value-enhancing. AMFs buying on the EA day are less likely to be trading due to "dumb money flows" (Frazzini and Lamont 2008). When AMFs herd, their trades can be price destabilizing and result in future return reversals. Arif, Ben-Rephael, and Lee (2017) document this reversal based on institutional trading. Brown, Wei, and Wermers (2014) show that MFs herd into stocks with consensus analyst upgrades and herd out of stocks with consensus analyst downgrades, and that this behavior is price destabilizing. It is an empirical question whether AMFs herd on earnings news, and if so, whether this herding is price destabilizing. Trades that are a result of herding and investor flows are more likely to be unprofitable. Trades on the EA day are more likely to be information-driven, and AMFs likely have superior information processing abilities with respect to earnings news.

We note, however, that the profitability of EA buys and sells may not be symmetric. AMFs do not hold short positions, so they can only sell what is already in their long portfolio. As a result, their EA sells are more likely to reflect opportunity costs and less likely to reflect negative earnings information. In other words, even during EAs, they are more likely to sell because a better opportunity arises, rather than because the firm has issued a particularly negative earnings signal. On average, this feature could cause their EA sales to be less reflective of the earnings news than their EA buys.

3 METHODOLOGY AND RESULTS

3.1 AMF Trading Around EAs

The EA observations are taken from the intersection of Compustat, CRSP, and IBES data. IBES provides the timestamp of the EA, and the EA date is the IBES EA date if the announcement was made before or during trading hours, and the first trading day after the EA date if the announcement was made after trading hours. We apply a liquidity filter and restrict the sample to firms with a share price greater than $3 and market capitalization greater than $150 million at the most recent fiscal quarter end. We use the IBES timestamp, which is confirmed to be correct in a large portion of the sample (deHaan, Shevlin, and Thornock 2015). According to Table IA.4 of their paper, the EA dates during our sample period (2003-2010) have a minimum accuracy of 70.4 to 94.3 percent and a maximum of 95.9 to 98.8 percent.

We use AMF trades from Ancerno, dating from 1/1/2003 to 12/31/2010. The Ancerno dataset is uniquely suited to our setting, as it identifies the exact date and execution price of each transaction, which allows us to distinguish the trades of each institution and each fund family within the institution in the cross section and time series. The Ancerno data consist of money manager trades (client type=2) from 1997 to 2015. Although the trade-level data is available into 2015, the client identifiers, which we use to remove hedge funds from the sample, are unavailable after 2010. Post-2010, we have no data on client identifiers. For our purposes, we require identifiers, as we are interested in AMF trading behavior and therefore want to exclude a small number of hedge funds from our sample. The coverage is significantly better in the more recent period, so we choose the post-2003 period as relevant data for our analysis. Because we examine the (-25, +25) window around the EA, we restrict the sample period to EA dates between 2/9/2003 and 11/22/2010. Following Keim and Madhavan (1997), we filter the data to reduce the impact of outliers and potentially corrupt entries. Specifically, we drop transactions with an execution price lower than $1 and greater than $1,000, and we eliminate trades from orders with an execution time, computed as the difference between the time of first placement and last execution of the order, greater than one month.

To exclude hedge fund trades from our sample, we use the list of identified hedge fund client-manager pairs in Ancerno from Jame (2018).[13] In our 2003-2010 sample, 90.1 percent of all trades are AMF trades and 89.0 percent of client-manager pairs are AMFs. Although our analyses are based on 2003-2010 data, with which we can isolate AMF trades, our results are robust to an extension of the sample period into 2015 and pooling of AMF and hedge fund trades. Results pooling AMF and hedge fund trades are available upon request.[14] Our sample selection procedure, after removing hedge fund trades, results in a total of 97,159 firm-quarter EA observations for 5,656 different firms in this sample period.

For each day in the (-1, +4) window around the EA, we sum volume from all AMFs. We consider the day before the actual EA, as there is evidence that information leakage occurs prior to the EA (Beaver 1968). By trading before the EA, AMFs may be anticipating earnings news or hedging the risk provided by the information event. For each firm-quarter EA, we calculate the fraction of total AMF volume over the entire period that occurs on that day. In Figure 1, the (-1, +4) volumes, averaged across all firm-quarters, are displayed in red. The non-EA period consists of the (-25, -2) and (+5, +25) trading days around the EA. These volumes, averaged across all firm-quarters, are displayed in gray. The maximum mean AMF trading volume occurs on Day 0 and is 172 percent higher than the average non-EA period volume. This volume tapers off in the next few days after the EA. The volume on the day before the EA is 14 percent higher than in the non-EA period, but it is lower than that on almost all of the other EA-period days, Days 0 to +4.

Descriptive statistics of the raw trading data are reported in Table 1. The mean AMF trading volume on Day 0 is higher than the mean AMF trading volume on any other day in the EA

[13] The Internet Appendix of Jame (2018) provides details of the procedure to identify hedge funds.
[14] We note that hedge funds comprise a small portion of clienttype=2 trades. Hedge funds are better represented in clienttype=1 (plan sponsors), but we focus on clienttype=2 trades because we are interested in AMFs.

period, and the mean EA period trading volume is higher than the mean non-EA period trading volume. However, the median EA period trading volume is lower than the median non-EA period trading volume. These descriptives indicate that, when AMFs trade around EAs, they may trade extensively around them, but it is also common to not trade at all in the EA period. To address the concern that this distribution is driven by large AMFs or by trading in firms for which overall trading volume is high, we also compute descriptive statistics for AMF volume, scaled by total volume, on these trading days. These descriptives, in Table 2, tell a similar story. While the mean scaled AMF volume is higher on Day 0 relative to non-EA days, the median scaled AMF volume in the EA period is lower than the median in the non-EA period. For some EAs, a significant amount of AMF trading occurs in the EA period, but for the median firm, there is more AMF trading in the non-EA period than in the EA period.

A t-test comparing average AMF trading volume in the EA period vs. the non-EA period is significant for the raw variable (t-stat=28.46), but relative to total trading volume, there is a very small, marginally significant difference in EA period AMF trading vs. non-EA period AMF trading (difference<0.001, t-stat=1.83). AMFs have abnormally high trading volume in the EA period, but there is limited evidence that they participate disproportionately in EA period trading compared to the average market participant.

3.2 Effect of AMF Volume on PEAD

First, we determine whether PEAD exists in our sample. For all EAs between 2/9/2003 and 11/22/2010, we compute SUE from Compustat data. SUE is calculated as the difference between earnings in the most recent reported quarter and the one-year prior quarter, scaled by the time-series standard deviation of earnings of the previous 8 quarters (Jegadeesh, Kim, Krische, and Lee 2004). For each calendar year in which the EA occurs, we sort SUE into terciles based on cutoffs from the previous calendar year. Specifically, we compute SUE for all earnings announcements that occur in a given calendar year, of firms that pass the liquidity filter, to obtain tercile cutoff points for all earnings announcements that occur in the following calendar year. We match CRSP returns and SUE from Compustat based on extended link dates, as described in Beaver, McNichols, and Price (2007). Next, the CRSP returns are delisting-adjusted, based on Shumway (1997) and Beaver et al. (2007). For each firm-quarter, we calculate the (-1, +4) return as the 6-day EA-period return. These returns are winsorized at the 1st and 99th percentile, by fiscal quarter end date. These returns are then size-adjusted, with the market value calculated at the fiscal quarter end date and sorted into deciles based on all other stocks in the CRSP universe at that date. Before calculating the size-decile returns, we winsorize all firms' buy and hold returns in the (+4, +63) window around all dates at the 1st and 99th percentile, by date. We then subtract out the equal-weighted average (+4, +63) return, relative to the EA date, of those firms in the size decile to obtain the equal-weighted size-adjusted returns. These data requirements result in a sample of 92,178 firm-quarters for 5,149 unique firms.

For each calendar year in which the EA occurs, we sort the SUE into terciles based on cutoffs determined by EAs during the prior calendar year, and we sort market capitalization into terciles within year and SUE tercile. The size-adjusted (+4, +63) returns across SUE terciles and market cap terciles are reported in Table 3. Pooled across all years, there is a 1.8 percent difference in drift between SUE3 and SUE1 EAs, for small firms, significant with t-stat=6.18. The difference in drift is only 0.4 percent with a t-stat of 1.68 for medium sized firms, and 0.2 percent with a t-stat of 1.12 for large firms.

To test whether gross AMF volume during the EA period has an effect on PEAD, we sort EAs based on the intensity of AMF EA trading volume. Intensity of AMF EA trading volume is defined as average gross AMF volume as a fraction of total gross volume in the (-1, +4) window around the EA. We scale AMF trading by total volume because we are interested in the effect of AMF trading on price formation when it makes up a large portion of total price formation behavior (total volume). Table 4 reports results of regressions of size decile-adjusted (+4, +63) returns on the interaction of SUE tercile 3 and AMF EA trading intensity. Column (i) reports results for the pooled sample which contains all SUE tercile 1 and 3 firm-quarter observations with any AMF EA trading activity. The variable *(0, +4) Return* is the size decile-adjusted return in days (0, +4) of the EA. It is included to control for the effect of EA returns on drift. Announcements with higher absolute returns might have lower PEAD, and we include these returns to measure the effect of AMF EA volume on PEAD incremental to this effect. *AMF EA Volume* is the quintile ranking of AMF average nondirectional volume as a fraction of total trading volume in the (-1, +4) window of the EA, where this volume is an equal-weighted daily fraction across the 6 days, and the quintile ranking is done within year, SUE tercile, and size tercile. The size tercile is the tercile ranking of market cap within year and SUE tercile. SUE is ranked into terciles by year, and *SUE3* is an indicator variable for tercile 3 SUE.

In column (i), the coefficient on SUE3 is positive and significant, which suggests that PEAD is present in our pooled sample. The (+4, +63) returns for SUE tercile 3 firms are significantly higher than the equivalent returns for SUE tercile 1 firms. The interaction *SUE3×AMF EA Volume* is negative and significant, which is consistent with lower PEAD when AMF participation in the EA period is higher. Next, we split the sample by size, following the results of Table 3, which find the presence of PEAD in small firms but not in large firms and less so in medium-sized firms. Consistent with the results of Table 3, Table 4 column (ii) finds a positive and significant coefficient on *SUE3*, suggesting that PEAD is present in small firms. The coefficient on *SUE3×AMF EA Volume* is negative and marginally significant, which is consistent with lower PEAD in small firms when AMF participation in the EA period is higher.

Table 4 column (iii) presents results for medium-sized firms. The insignificant coefficient on SUE3 is consistent with no significant PEAD. The coefficient on *SUE3×AMF EA Volume* is negative and insignificant. Similarly, column (iv), which presents results for large firms, also finds no evidence of PEAD and an insignificant coefficient on *SUE3×AMF EA Volume*. In sum, our results in Table 4 are consistent with reduced PEAD in small firms when AMFs participate intensely in the EA period. High intensity of AMF gross volume during the EA window is associated with a marginally significant reduction in PEAD in small firms. This effect is incremental to the effect of EA returns on PEAD.

3.3 Speed of Price Adjustment

3.3.1 Gross AMF Volume

We examine whether nondirectional AMF trades in the EA period result in faster price adjustment. Specifically, we test whether the fraction of the (0, +63) return realized in days (0, +4) is greater when the intensity of AMF EA trading is high in the (0, +4) period. We retain only observations with very positive or very negative raw (0, +63) returns, to avoid small denominators. Specifically, we restrict the sample to (0, +63) raw returns that are in the top or bottom decile, within the year of the EA. We calculate the buy and hold (0, +4) return divided by the (0, +63) return. Size, calculated at the end of the quarter, is ranked into terciles, within year and (0, +63) return decile.

We rank nondirectional AMF EA volume in days (0, +4) as a fraction of total volume (equal-weighted fractions across the 6 days) into terciles. This ranking is done within year, return decile, and size tercile. Table 5 reports speed of price adjustment results. Row 1 displays the fraction of the return captured in days (0, +4) for small firms, decile 1 returns, and low AMF nondirectional EA volume. Row 2 displays this fraction for high AMF nondirectional EA volume, and the next row displays the difference in the two fractions, which is 0.055 across all years and significant at the 1 percent level. The next set of 5 rows displays these comparisons for small firms and decile 10 returns. The next set of 5 rows displays these comparisons for medium firms and decile 1 returns, then medium firms and decile 10 returns, then large firms and decile 1 returns, and finally large firms and decile 10 returns. For all sets of EAs, the fraction of the (0, +63) return realized in days (0, +4) is significantly greater when there is a higher intensity of AMF trading in the (0, +4) period.

Figure 2 displays the results in Table 5 in graphical form. This plot shows the average cumulative percent of the raw |(0, +63)| return realized on each day, for (0, +63) returns ranked in the top and bottom deciles, to avoid small denominators. The red solid curves display the cumulative returns for firm-quarters with high (top tercile) nondirectional AMF EA volume as a fraction of total volume in days (0, +4), and the black dashed curves display the cumulative returns for firm-quarters with low (bottom tercile) nondirectional AMF EA volume as a fraction of total volume in days (0, +4). The curves above the y-axis display the cumulative percent of total returns for top decile, or very positive, (0, +63) returns, and the curves below the y-axis display the cumulative percent of the absolute value of total returns for bottom decile, or very negative, (0, +63) returns. Higher intensity of AMF EA gross volume results in faster price adjustment in the 63 trading days after the EA. This figure is analogous to the speed of price adjustment tests in prior literature (Butler, Kraft, and Weiss 2007; Bushman, Smith, and Wittenberg-Moerman 2010; Twedt 2016).

3.3.2 Net AMF Volume

Next, we examine directional AMF trades rather than non-directional AMF trading volume. One advantage of Ancerno data is its ability to identify the side of the trade (Hu, Jo, Wang, and Xie 2017). Panel A of Table 6 shows that AMFs trade in the same direction as SUE. We scale net AMF volume in days (0, +4) of the EA by average gross AMF volume in days (-20, -2) and show that AMFs buy more on high SUE (SUE3) than on low SUE (SUE1). A t-test of the difference between these two means is significant (t=2.74). We also test whether the net number of fund families that are net buyers for an EA is related to the SUE for that EA. We find that the net proportion of fund families buying, defined as the number of fund families who were net buyers of the stock in days (0, +4) of the EA minus the number of fund families who were net sellers, multiplied by 100 and scaled by the total unique fund families trading, is on average lower for SUE1 EAs than for SUE3 EAs. A potential reason that both the SUE1 and SUE3 net buyer numbers are negative is that the disposition effect, which is the tendency to ride losses and realize gains, affects AMFs (Frazzini 2006).

In Panel B, we focus on small firms, as Table 4 showed that nondirectional AMF trades had a significant impact on PEAD in small stocks only. We study the effect of AMF directional trading on EA period returns and future drift. Concordant (discordant) AMF trading is defined as low (high) net buying for low SUEs and high (low) net buying for high SUEs. We scale net AMF volume in days (0, +4) of the EA by average gross AMF volume in days (-20, -2), because we are interested in "abnormal" directional trading by AMFs and its effect on return formation. We find that concordant (discordant) AMF trading results in a higher (lower) proportion of returns realized in the EA period and lower (higher) drift.

The first two rows of Table 6 report the median SUE1 and SUE3 EA period size-adjusted (0, +4) returns, and the median of these returns as a proportion of total size-adjusted (0, +63) returns, for small firms only. We report medians because these amounts are less noisy than the means. The SUE1 (0, +4) returns are 7.1 percent of SUE1 (0, +63) returns, while the SUE3 (0, +4) returns are 4.4 percent of SUE3 (0, +63) returns. The next two rows report results for the subset of earnings announcements for which AMFs trade concordantly, in the same direction as SUE, and the following two rows report results for the subset of earnings announcements for which AMFs trade discordantly, in the opposite direction as SUE. We scale average AMF directional (buys minus sells) (0, +4) volume by average total trading volume in days (-20, -2) and rank this measure into quintiles by year, SUE tercile, and size tercile. We define "discordant" as SUE3 firm-quarters that are also the bottom quintile of AMF directional EA volume and SUE1 firm-quarters that are also the top quintile of AMF directional EA volume. We define "concordant" as SUE3 firm-quarters that are also the top quintile of AMF directional EA volume and SUE1 firm-quarters that are also the bottom quintile of AMF directional EA volume.

For earnings announcements at which AMFs trade concordantly, SUE1 (SUE3) (0, +4) returns are 7.6 percent (26.8 percent) of SUE1 (SUE3) (0, +63) returns. For earnings announcements on which AMFs trade discordantly, SUE1 (SUE3) (0, +4) returns are -3.3 percent (26.5 percent) of SUE1 (SUE3) (0, +63) returns. A median test between the concordant and discordant return proportions is significant at 1 percent for the EA period return. Compared to the full sample, concordant trades shift the return from the future drift to the EA period return, and discordant trades shift the return to the (+4, +63) period from the (0, +4) period.

Panel C displays the median raw return accumulation for concordant and discordant AMF trading, for SUE1 and SUE3 EAs. Cumulative SUE1 (SUE3) raw returns are scaled to -100 (100) and displayed below (above) the x-axis. The return accumulation when AMFs trade in the same direction as SUE is faster than when they trade in the opposite direction as SUE. This difference in return accumulation is especially apparent in the subsample with negative earnings news. Concordant trading by AMFs seems to improve the speed of price adjustment.

3.4 Profitability of AMF Trades

Our previous tests rely on SUE, which is a noisy measure of what AMFs may trade on. There are other factors affecting AMF trading decisions in the EA period, so our next set of tests directly examines the profitability of their trades. Examining the profitability of trades allows us to test, at the transaction level, whether AMFs incorporate earnings news into prices. Prior literature finds the institutions earn higher profits on ex-dividend event days (Henry and Koski 2017). Abnormal returns to AMF trades at the EA indicate that prices move in the same direction as AMFs' trades would suggest.

Our research design involves mimicking AMF buys and sells. For each AMF buy decision, we record the execution price, then we calculate the profitability of that trade assuming a sell date 60 trading days after the purchase date. For each AMF sell decision in this window, we record the execution price, then calculate profitability assuming a buy date 60 trading days after the sell date. We then calculate the return for these trades using the execution price and the closing price on the +60 day, including distributions, and accounting for share splits and repurchases. This method includes one-way trading costs, as it uses the actual execution price of the trade, then uses the closing price on the day of the mimicked unwinding of the trade as the second "execution price." To determine whether trades are profitable on a size-adjusted basis, we adjust this return by the (0, +60) size decile return, to account for the opportunity cost of holding or shorting a size-matched portfolio of stocks. The size decile return is subtracted from the AMF buys and added to the AMF sells. The first column of Table 7 reports the size-adjusted profit of all AMF trades (in percentage points). Our sample consists of more than 40 million executed trades. The "All Trades (Size-

Adj)" column reports results for all AMF trades and shows that AMF trades are unprofitable on a size-adjusted basis.

Next, we examine whether the AMF trades at the EA are more profitable than AMF trades outside of the EA window. To compare the EA trades to non-EA trades, we match each EA buy (sell) to a non-EA buy (sell) in the same size decile and on the same day. This matching of EA trades to non-EA trades made on the same day and within the same size decile removes the systematic component of returns and accounts for the opportunity cost of holding or shorting a size-matched stock. It accounts for the market timing of EAs and information spillover effects from a given firm's EA. The remaining columns of Table 7 report the raw profit of AMF trades (in percentage points, no size adjustment). The "EA and Matched Non-EA Trades" column includes EA trades and matched non-EA trades. Our sample includes almost 1.1 million EA day trades and an equivalent number of matched trades outside of the EA window. EA day trades are buys and sells on the EA day, whereas non-EA trades are trades outside of the (-1, +4) window of the EA. In years 2006, 2007, and 2009, AMF trades have been unprofitable on a raw basis, but in the pooled sample of all years 2003-2010, their raw trade returns are positive. On average, AMF trades in our sample, which are executed on the same days as any firms' EA days, are profitable. We further separate trades into those executed on the EA day and in non-EA periods, to investigate whether variation in the profitability of their trades is due to efficient processing of earnings news and/or other reasons.

The "EA Day" and "Matched Non-EA" columns report results for the EA day versus non-EA AMF trades. EA day trades are more profitable than non-EA trades, but this difference is insignificant. We find more informative results when we split AMF trades into buys and sells. We seek to address whether: 1) AMFs have an information advantage in processing earnings news, and/or 2) AMFs trade for other reasons that are not value-enhancing.

Table 8 reports results for the EA day versus non-EA AMF trades, split into buys versus sells. The first column of Table 8 reports the raw profitability (in percentage points) of AMF EA Day buys. These buys are profitable on a raw basis. The next column reports that AMF Non-EA buys matched on the same day and same decile are also profitable on a raw basis. In the third column, we see that EA day buys are more profitable than Non-EA buys. These results suggest that AMFs have an information advantage in processing earnings news. The buys on the EA day are likely driven by information released at the EA. Compared to other trades that AMFs make on the same day, the EA trades are more profitable. The EA trades are less likely to be affected by investor flows, which can be a reason for trading decisions in non-EA periods.

Although buys are more profitable on the EA day than outside the EA window, sells are not. The next three columns of Table 8 examine the raw profitability (in percentage points) of AMF sells. The raw returns of EA and non-EA sells (i.e., the opportunity cost of not holding a stock that was sold) are negative in almost every year of the sample. These results suggest that AMFs would have been better off holding the stocks that they sold, rather than keeping the cash from the sale. However, AMFs are likely using the cash from these sells to finance other buys in their portfolio. Therefore, the sells are unprofitable based on the assumption that the cash would be sitting idle in the AMF portfolios, but likely profitable when assuming that the cash from the sale is used to buy another stock that would be even more profitable to hold than the stock that was sold. In the last column of Table 8, we report the difference in raw profitability of AMF EA versus non-EA sells. One caveat is that the pooled results for sells are driven by extreme negative results in 2008. In 2004, 2006, and 2007, sells on the EA day are more profitable than sells on non-EA days. These results are consistent with AMFs selling for opportunity cost reasons and being subject to flows, which affect the profitability of their trades. AMFs hold cash and bonds, providing a cushion for investor inflows and redemptions (Wermers 2000). However, they are still constrained in that: i) they can only sell a stock they already hold, ii) this cushion for investor redemptions does not prevent flows from affecting their returns, and iii) when a better opportunity arises, AMFs might sell a stock to provide the funds to take advantage of that better opportunity. AMFs have less flexibility on their sells than on their buys; it is more likely an AMF will make a profitable buy by choosing among all tradeable stocks than it is that the AMF will make a profitable sell by choosing stocks among its holdings to sell (i.e., the stocks held by a given AMF are a smaller set than the set of all tradeable stocks). That AMF EA sells, relative to non-EA sells, are often not value-enhancing for their portfolios is consistent with selling reflecting these constraints rather than reflecting information, in particular a negative signal, released at the EA. The insignificant difference in profitability between EA and non-EA sells is not so much a reflection of information processing skill. For this reason, we interpret the insignificant difference between EA and non-EA sell profitability as a reflection of other costs unrelated to information processing.

In sum, this section finds that the profitability of AMF buys on the EA day relative to buys on non-EA days is evidence that AMFs process earnings news efficiently. The insignificant difference between AMF EA sells and non-EA sells is likely due to other costs affecting selling decisions that do not affect buying decisions. Still, the profitability of AMF trades, both buys and sells, on the EA day is also evidence that AMFs process earnings news efficiently (untabulated 0.14 percent size-adjusted returns for trades on the EA day).[15]

3.5 AMF Profitability and EA Trading Intensity

While AMFs are on average profitable on their EA trades, and less profitable on their non-

[15] Untabulated tests comparing medians rather than means find similar results. These additional results are available upon request.

EA trades, AMF managers have varying skill levels. We expect that AMF managers that have an information advantage in processing earnings news will also trade more intensely, on a dollar volume basis, in the EA period. One advantage of the Ancerno data is that client fund family identifiers for all trades are available until the end of calendar year 2010. These identifiers are for a specific fund, fund family, or strategy, which we refer to as a "fund family" whose trading decisions fall under the realm of an AMF manager or team. We match these fund family identifiers to our sample of EAs from 2003 to 2010. Our final sample, following this procedure, consists of 41,055 unique fund families belonging to 109 unique institutions. Ranked AMF manager EA intensity, defined as the dollar volume of the fund family's trading that occurs in days (0, +2) of any firm's EA, as a proportion of total dollar volume for that fund family in the calendar year, is calculated for calendar year t-1, so we report results for years 2004 to 2010. High EA intensity is defined as decile 10 of this measure, and low EA intensity is defined as decile 10 of this measure. We calculate the 60-day profitability of trades as before, by assuming an unwinding date +60 trading days in the future. High EA intensity AMF managers' 60-day profitability of trades is 0.7 percent higher than that of low EA intensity AMF managers.

We then examine the profitability of these AMF managers' trades on the EA day and on non-EA days. The middle three columns of Table 8 report the 60-day profitability of EA day trades. EA day trades of high EA intensity AMF managers are 0.6 percent more profitable in 60 days than EA day trades of low EA intensity AMF managers. The last three columns of Table 9 report results for non-EA trades, trades that do not occur within trading days (0, +2) of firms' EAs. Non-EA trades of high EA intensity AMF managers are 0.7 percent more profitable in 60 days than non-EA trades of low EA intensity AMF managers. In sum, these results suggest that AMFs that focus more of their trading on the EA tend to make more profitable trades than their counterparts that focus less on the EA.

3.6 AMFs, Hedge Funds, and Earnings News

Our analyses have revealed that AMFs are on average unprofitable on a size-adjusted basis, but their EA day buys are more profitable than their non-EA buys (Section 3.4), and there are cross-sectional differences in AMFs' ability to make profitable trades (Section 3.5). To further support our inferences that AMFs process earnings news efficiently, we focus our next set of analyses on a small sample of hedge fund (HF) trades included in the Ancerno data. We isolate trades from the HFs identified by Jame (2018). Table 10 reports 60-day profitability results for this sample of HFs. Using the sample of more than 4 million trades, we find in the first column that HFs' trades are on average profitable on a size-adjusted basis. This result is in contrast to the unprofitable size-adjusted returns of AMF trades. This difference also validates our process of removing HF trades from the AMF sample.

The second column of Table 10 reports the raw profitability (in percentage points) of EA and matched non-EA HF trades. In the next set of columns, we also find that HFs' EA day and non-EA trades made on the same day are profitable on a raw basis. In the last column of Table 10, we find that HFs' EA day trades are more profitable than their non-EA trades, but this difference is insignificant. HFs could be trading in advance of EAs (e.g., anticipating earnings news) and making trades in non-EA periods based on other information signals. The insignificant difference in profitability for EA versus non-EA trades, in contrast to the AMF results, is not as affected by flow-induced trading or opportunity costs, because HFs can short. Due to the small sample size, we do not separately examine buys and sells.

Table 11 reports differences in profitability between our AMF and HF trades. We find in column 1 that the size-adjusted profitability (in percentage points) of AMF trades is significantly lower than that of HF trades. We also find that HF trades are more profitable than AMF trades, on the EA day and outside of the EA window. However, our sample of HF trades is small, so we urge caution in interpreting these results.

4 CONCLUSION

This study has two goals: 1) to evaluate whether AMFs make profitable trading decisions in response to quarterly earnings, and 2) to understand how AMF actions relate to the price discovery mechanism in the market. Our analysis of 149,161 firm-quarters for 6,061 unique firms has documented that AMFs have high trading volume at the EA, and that this volume has an effect on PEAD in small firms. We also find that high AMF trading volume at the EA is associated with faster price adjustment.

Our analyses shed light on institutional investors' ability to process earnings news to forecast future returns. By focusing on a short window around the EA, we infer that trades during the short window are information-driven, and we assess AMFs' impact on the convergence of stock prices to fundamental value. Previous literature has found that the short window around EAs is a period of "correction" to stock prices, as a substantial fraction of returns to various strategies are realized in the days around the EA (Sloan 1996; Jegadeesh and Titman 1993; La Porta et al. 1997). We contribute to this literature by showing that AMF trading in this short window facilitates the convergence of stock prices to fundamental value.

We also provide interesting evidence, using a sample of over 40 million executed trades, that AMFs do not make value-enhancing trades on a size-adjusted basis. We focus on the information event day, the EA day, to isolate trades that are information-driven. We find that EA information-driven buys are more profitable than buys outside the EA window, suggesting that AMFs are particularly good at forecasting returns based on fundamental information revealed at the EA. We also provide interesting evidence that AMFs that trade intensely in the EA period make more profitable trades, in EA and non-EA periods, than AMFs that do not trade intensely in the EA period.

Our results contribute to the longstanding debate on institutional investor skill. Unlike retail investors, which have been shown in prior literature to disregard accounting information and exhibit behavioral biases, our sample of AMFs has skill in incorporating earnings information into prices. Our findings suggest professional active managers who run individual investors' money may be an important agent in the market price discovery process. These findings seem particularly relevant as the move from active to passive asset management continues to gain prominence. Our results show these managers enhance price discovery within the context of earnings news releases. Clearly, further research on the skill of active managers and their effects on the market in other settings will be necessary to help round out the picture.

REFERENCES

Agarwal, V., W. Jiang, Y. Tang, and B. Yang. 2013. Uncovering hedge fund skill from the portfolio holdings they hide. *The Journal of Finance* 68(2): 739-783.

Arif, S., A. Ben-Rephael, and C. Lee. 2017. Mutual Funds and Short-Sellers: Why Does Short-Sale Volume Predict Stock Returns? Working paper. Indiana University and Stanford University. February 24.

Baker, M., L. Litov, J. A. Wachter, and J. Wurgler. 2010. Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements. *Journal of Financial and Quantitative Analysis* 45(5): 1111-1131.

Ball, R., and P. Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6(2): 159-178.

Barber, B. M., Y. T. Lee, Y. J. Liu, and T. Odean. 2009a. Just how much do individual investors lose by trading? *The Review of Financial Studies* 22(2): 609-632.

Barber, B. M., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance* 55(2): 773-806.

Barber, B. M., and T.Odean, T. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies* 21(2): 785-818.

Barber, B. M., T. Odean, and N. Zhu. 2009b. Systematic noise. *Journal of Financial Markets* 12(4): 547-569.

Bartov, E., S. Radhakrishnan, and I. Krinsky. 2000. Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review* 75(1): 43-63.

Battalio, R. H., and R. R. Mendenhall. 2005. Earnings expectations, investor trade size, and anomalous returns around earnings announcements. *Journal of Financial Economics* 77(2): 289-319.

Beaver, W. H. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 6: 67-92.

Beaver, W., M. McNichols, and R. Price. 2007. Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics* 43(2): 341-368.

Ben-Rephael, A., Z. Da, and R. D. Israelsen. 2017. It Depends on Where You Search: Institutional Investor Attention and Underreaction to News. *The Review of Financial Studies* 30(9): 3009-3047.

Berk, J. B., and R. C. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112(6): 1269-1295.

Berk, J. B., and J. H. Van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118(1): 1-20.

Bernard, V. L. and J. K. Thomas. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research* 27: 1-36.

Bernard, V. L., and J. K. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13(4): 305-340.

Bhattacharya, N. 2001. Investors' trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review* 76(2): 221-244.

Blake, C. R., E. J. Elton, and M. J. Gruber. 1993. The performance of bond mutual funds. *Journal of Business* 69(2): 371-403.

Boehmer, E., and J. Wu. 2012. Short selling and the price discovery process. *The Review of Financial Studies* 26(2): 287-322.

Brown, K. C., W. V. Harlow, and L. T. Starks. 1996. Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance* 51(1): 85-110.

Brown, N. C., K. D. Wei, and R. Wermers. 2014. Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science* 60(1): 1-20.

Bushee, B. J., and T. H. Goodman. 2007. Which institutional investors trade based on private information about earnings and returns? *Journal of Accounting Research* 45(2): 289-321.

Bushman, R. M., A. J. Smith, and R. Wittenberg-Moerman. 2010. Price discovery and dissemination of private information by loan syndicate participants. *Journal of Accounting Research* 48(5): 921-972.

Butler, M., A. Kraft, and I. S. Weiss. 2007. The effect of reporting frequency on the timeliness of earnings: The cases of voluntary and mandatory interim reports. *Journal of Accounting and Economics* 43(2): 181-217.

Campbell, J. Y., T. Ramadorai, and A. Schwartz. 2009. Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics* 92(1): 66-91.

Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of Finance* 52(1): 57-82.

Chakrabarty, B., P. C. Moulton, and C. Trzcinka. 2017. The performance of short-term institutional trades. *Journal of Financial and Quantitative Analysis* 52(4): 1403-1428.

Chan, L. K., N. Jegadeesh, and J. Lakonishok. 1996. Momentum strategies. *The Journal of Finance* 51(5): 1681-1713.

Cheng, S., A. Hameed, A. Subrahmanyam, and S. Titman. 2017. Short-Term Reversals: The Effects of Past Returns and Institutional Exits. *Journal of Financial and Quantitative Analysis* 52(1): 143-173.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105(6): 1167-1200.

Chopra, N., J. Lakonishok, and J. R. Ritter. 1992. Measuring abnormal performance: do stocks overreact? *Journal of Financial Economics* 31(2): 235-268.

Cohen, R. B., P. A. Gompers, and T. Vuolteenaho. 2002. Who underreacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics* 66(2): 409-462.

Collins, D. W., G. Gong, and P. Hribar. 2003. Investor sophistication and the mispricing of accruals. *Review of Accounting Studies* 8(2): 251-276.

Coval, J., and E. Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86(2): 479-512.

Cready, W., A. Kumas, and M. Subasi. 2014. Are trade Size-Based inferences about traders reliable? evidence from institutional Earnings-Related trading. *Journal of Accounting Research* 52(4): 877-909.

Cutler, D. M., J. M. Poterba, and L. H. Summers. 1991. Speculative dynamics. *The Review of Economic Studies* 58(3): 529-546.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *The Journal of Finance* 66(5): 1461-1499.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance* 52(3): 1035-1058.

De Bondt, W. F., and R. Thaler. 1985. Does the stock market overreact? *The Journal of Finance* 40(3): 793-805.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98(4): 703-738.

Dechow, P. M., R. G. Sloan, and J. Zha. 2014. Stock prices and earnings: A history of research. *Annual Review of Financial Economics* 6(1): 343-363.

deHaan, E., T. Shevlin, and J. Thornock. 2015. Market (in) attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics* 60(1): 36-55.

Di Mascio, R., A. Lines, and N. Y. Naik. 2016. Alpha Decay and Strategic Trading. Working Paper. Inalytics Ltd and the London Business School. May 31.

Edelen, R. M. 1999. Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics* 53(3): 439-466.

Edelen, R. M., O. S. Ince, and G. B. Kadlec. 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics* 119(3): 472-488.

El-Gazzar, S. M. 1998. Predisclosure information and institutional ownership: A cross-sectional examination of market revaluations during earnings announcement periods. *The Accounting Review* 73(1): 119-129.

Engelberg, J., R. D. McLean, and J. Pontiff. 2017. Anomalies and News. *The Journal of Finance* (forthcoming).

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2012. How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics* 105(2): 260-278.

Fama, E. F., and K. R. French. 2010. Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance* 65(5): 1915-1947.

Farnsworth, H., and J. Taylor. 2006. Evidence on the compensation of portfolio managers. *Journal of Financial Research* 29(3): 305-324.

Frazzini, A. 2006. The disposition effect and underreaction to news. *The Journal of Finance* 61(4): 2017-2046.

Frazzini, A., and O. A. Lamont. 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics* 88(2): 299-322.

French, K. R. 2008. Presidential address: The cost of active investing. *The Journal of Finance* 63(4): 1537-1573.

Gallagher, D. R., Looi, A., and M. Pinnuck. 2010. Are active fund managers collectors of private information or fast interpreters of public information?. *Accounting & Finance*, 50(3): 635-662.

Grinblatt, M., and S. Titman. 1992. The persistence of mutual fund performance. *The Journal of Finance* 47(5): 1977-1984.

Grinblatt, M., and S. Titman. 1994. A study of monthly mutual fund returns and performance evaluation techniques. *Journal of Financial and Quantitative Analysis* 29(3): 419-444.

Grossman, S. J., and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *The American Economic Review* 70(3): 393-408.

Ha, J., and J. Hu. 2017. How Smart is Institutional Trading? Working paper. Singapore Management University. January 19.

Hendershott, T., D. Livdan, and N. Schürhoff. 2015. Are institutions informed about news?. *Journal of Financial Economics* 117(2): 249-287.

Hendricks, D., J. Patel, and R. Zeckhauser. 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988. *The Journal of Finance* 48(1): 93-130.

Henry, T. R., and Koski, J. L. 2017. Ex-Dividend Profitability and Institutional Trading Skill. *The Journal of Finance* 72(1): 461-494.

Hu, G., K. Jo, Y. A. Wang, and J. Xie. 2017. Institutional Trading and Abel Noser Data. Working paper. Hong Kong Polytechnic University. December 30.

Hu, G., B. Ke, and Y. Yu. 2018. Can Transient Institutions Correctly Interpret Small Negative Earnings Surprises in the Absence of Access to Management's Private Information?. *Journal of Accounting, Auditing and Finance* 33(1): 3-33.

Ippolito, R. A. 1989. Efficiency with costly information: A study of mutual fund performance, 1965-1984. *The Quarterly Journal of Economics* 104(1): 1-23.

Jame, R. 2018. Liquidity Provision and the Cross Section of Hedge Fund Returns. *Management Science* (forthcoming).

Jegadeesh, N., J. Kim, S. D. Krische, and C. Lee. 2004. Analyzing the analysts: When do recommendations add value? *The Journal of Finance* 59(3): 1083-1124.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance* 48(1): 65-91.

Jensen, M. C. 1968. The performance of mutual funds in the period 1945–1964. *The Journal of Finance* 23(2): 389-416.

Jiambalvo, J., S. Rajgopal, and M. Venkatachalam. 2002. Institutional ownership and the extent to which stock prices reflect future earnings. *Contemporary Accounting Research* 19(1): 117-145.

Jiang, H., and L. Zheng. 2016. Active Fundamental Performance. Working paper. Michigan State University and University of California at Irvine. June.

Khorana, A. 1996. Top management turnover an empirical investigation of mutual fund managers. *Journal of Financial Economics* 40(3): 403-427.

Kothari, S. P., and J. B. Warner. 2001. Evaluating mutual fund performance. *The Journal of Finance* 56(5): 1985-2010.

La Porta, R. 1996. Expectations and the cross-section of stock returns. *The Journal of Finance* 51(5): 1715-1742.

La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny. 1997. Good news for value stocks: Further evidence on market efficiency. *The Journal of Finance* 52(2): 859-874.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. *The Journal of Finance* 49(5): 1541-1578.

Lehmann, B. N., and D. M. Modest. 1987. Mutual fund performance evaluation: A comparison of benchmarks and benchmark comparisons. *The Journal of Finance* 42(2): 233-265.

Lewellen, J. 2011. Institutional investors and the limits of arbitrage. *Journal of Financial Economics* 102(1): 62-80.

Lou, D. 2012. A flow-based explanation for return predictability. *Review of Financial Studies* 25(12): 3457-3489.

Odean, T. 1998. Are investors reluctant to realize their losses?. *The Journal of Finance* 53(5): 1775-1798.

PricewaterhouseCoopers. 2017. Active and Wealth Management Insights – Asset Management 2020: Taking Stock. Research study. PwC Asset Management Group. June.

Puckett, A., and X. S. Yan. 2011. The interim trading skills of institutional investors. *The Journal of Finance* 66(2): 601-633.

Shleifer, A., and R. W. Vishny. 1997. The limits of arbitrage. *The Journal of Finance* 52(1): 35-55.

Shumway, T. 1997. The delisting bias in CRSP data. *The Journal of Finance* 52(1): 327-340.

Sloan, R. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71(3): 289-315.

Song, Y. 2017. The mismatch between mutual fund scale and skill. Working paper. Stanford University. August.

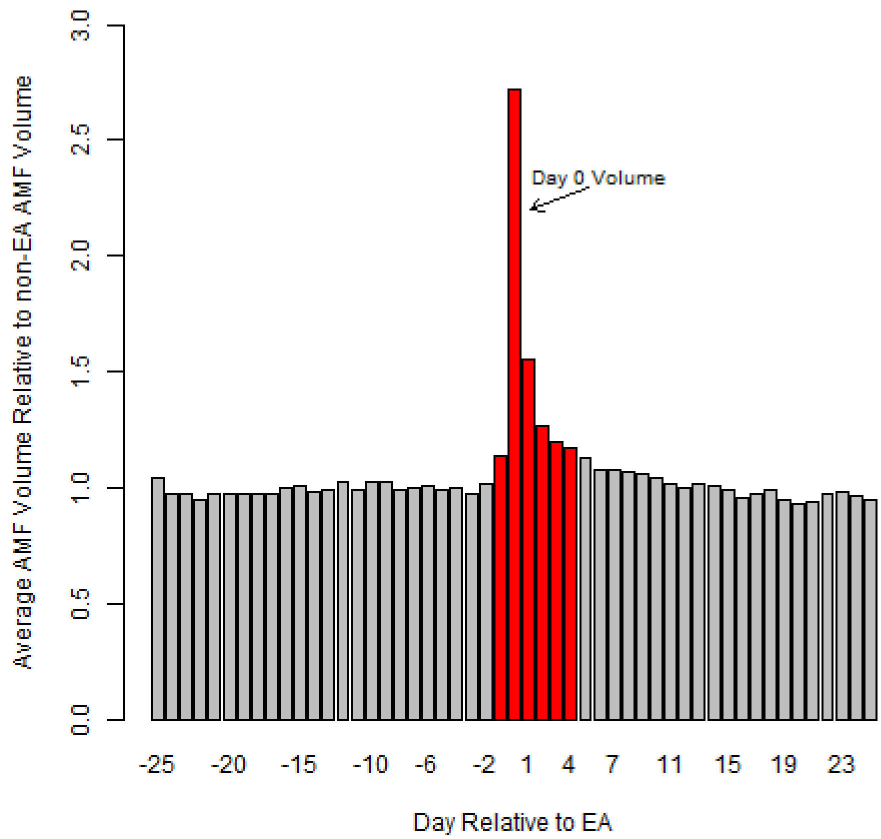
Twedt, B. 2016. Spreading the word: Price discovery and newswire dissemination of management earnings guidance. *The Accounting Review* 91(1): 317-346.

Utama, S., and W. M. Cready. 1997. Institutional ownership, differential predisclosure precision and trading volume at announcement dates. *Journal of Accounting and Economics* 24(2): 129-150.

von Beschwitz, B., S. Lunghi, and D. Schmidt. 2017. The Limits of Fundamental Arbitrage: Evidence from Detailed Hedge Fund Transaction Data. Working paper. Federal Reserve Board, Inalytics Ltd., and HEC Paris. May 12.

Wermers, R. 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance* 55(4): 1655-1695.

Figure 1: Actively Managed Fund Trading around Earnings Announcements



This graph presents the abnormal trading volume by actively managed funds (AMFs) in the 51 trading days centered around quarterly earnings announcements (EAs). Abnormal trading volume is defined as the average daily trading volume by AMFs, scaled by the average daily AMF trading volume during non-announcement days. We compute average abnormal trading volume for each firm and graph the average over all firms in our sample. The time period covered is 2003 to 2010.

Table 1: AMF Trading Volume Descriptives

	N	Mean	Std. Dev.	Min.	P25	Median	P75	Max.
Day -1 Volume	97,159	34,521	160,093	0	0	400	12,834	11,472,999
Day 0 Volume	97,159	82,391	351,779	0	0	2,000	42,440	23,071,741
Day 1 Volume	97,159	47,125	205,529	0	0	700	20,581	9,003,535
Day 2 Volume	97,159	38,645	185,197	0	0	580	16,851	19,964,303
Day 3 Volume	97,159	36,345	165,633	0	0	555	15,400	18,563,800
Day 4 Volume	97,159	35,719	152,806	0	0	500	15,021	10,625,195
Average EA (-1,+4) Daily Volume	97,159	45,791	147,687	0	466	7,591	35,829	7,572,906
Average non-EA Volume	97,159	30,341	82,549	0	1,838	8,740	27,268	5,680,543
Average (-20,-2) Volume	97,159	30,257	94,571	0	978	6,788	25,351	10,517,431

This table reports descriptive statistics for raw nondirectional AMF trading volume around the EA. Observations are total AMF share volume, at the firm-EA level, and are limited to firm-quarters with AMF trading. A t-test of EA vs. non-EA AMF volume is significant at the 1% level (t=28.46).

Table 2: AMF Trading Volume as a Fraction of Total Trading Volume, Descriptives

	N	Mean	Std. Dev.	Min.	P25	Median	P75	Max.
Day -1 Volume	97,159	0.030	0.078	0.000	0.000	0.001	0.019	1.000
Day 0 Volume	97,159	0.034	0.078	0.000	0.000	0.002	0.032	1.000
Day 1 Volume	97,159	0.032	0.078	0.000	0.000	0.001	0.024	1.000
Day 2 Volume	97,159	0.032	0.079	0.000	0.000	0.001	0.023	1.000
Day 3 Volume	97,159	0.033	0.079	0.000	0.000	0.001	0.023	1.000
Day 4 Volume	97,159	0.033	0.081	0.000	0.000	0.001	0.024	1.000
Average EA (-1,+4) Daily Volume	97,159	0.032	0.051	0.000	0.002	0.014	0.042	0.996
Average non-EA Volume	97,159	0.032	0.035	0.000	0.008	0.022	0.045	0.728

This table reports descriptive statistics for nondirectional AMF trading volume as a fraction of total trading volume around the EA. Relative to the average market participant, AMFs do not trade abnormally more during the EA period (t=1.83).

Table 3: Post-Earnings Announcement Drift

	Small	**Medium**	**Large**
2003	0.023**	-0.006	-0.011*
2004	0.023***	0.016***	-0.002
2005	0.027***	0.011**	0.014***
2006	0.019***	0.007	-0.012***
2007	0.030***	0.018***	0.031***
2008	0.034***	0.008	0.028***
2009	-0.035***	-0.035***	-0.045***
2010	0.032***	0.003	-0.007
All Years	0.018***	0.004*	0.002

This table reports the difference in size decile-adjusted (+4,+63) returns between SUE tercile 3 and SUE tercile 1 firms, for each year in 2003 to 2010 and for small, medium, and large firms. SUE is ranked into terciles by previous calendar year cutoffs, and market value is ranked into terciles within year and SUE tercile. *** indicates significance at 1%; ** at 5%; and * at 10%.

Table 4: Effect of AMF Trading Volume on PEAD

	Pooled	Small	Medium	Large
	Dependent variable:			
	(+4,+63) Return			
	(i)	(ii)	(iii)	(iv)
(0,+4) Return	0.039	0.027	0.014	0.090**
	(1.64)	(0.66)	(0.42)	(2.43)
AMF EA Volume	0.004**	0.010**	0.004	-0.002
	(1.98)	(2.48)	(1.42)	(-0.72)
SUE3	0.013**	0.032***	0.014	-0.004
	(2.21)	(2.77)	(1.42)	(-0.53)
SUE3 × AMF EA Volume	-0.005**	-0.010*	-0.006	0.001
	(-2.06)	(-1.92)	(-1.62)	(0.14)
Constant	-0.008*	-0.022**	-0.008	0.005
	(-1.69)	(-2.44)	(-1.11)	(0.78)
Adjusted R^2	0.001	0.002	0.000	0.002
Observations	22,309	7,052	7,605	7,652

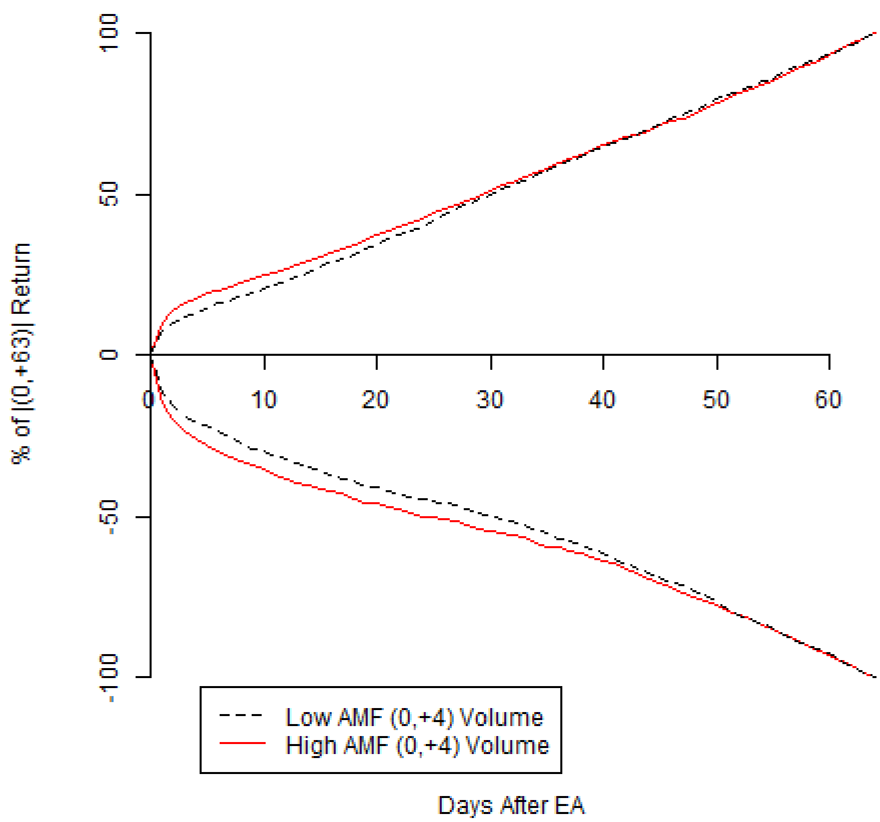
This table reports the effect of AMF nondirectional trading volume on the difference in size decile-adjusted (+4,+63) returns between SUE tercile 3 and SUE tercile 1 firms. Observations include tercile 1 and tercile 3 (low and high) SUE EAs. Intensity of AMF nondirectional trading volume in the EA period is calculated as the quintile of AMF trading volume in days (-1,+4) of the EA a fraction of total trading volume in days (-1,+4). The quintile ranking is within year, SUE tercile, and size tercile. SUE3 is an indicator variable for tercile 3 SUE. The size decile-adjusted (0,+4) return is included as a control variable. The time period covered is 2003 to 2010. *** indicates significance at 1%; ** at 5%; and * at 10%. Standard errors are clustered by firm and day.

Table 5: Effect of AMF Participation on Speed of Price Adjustment

Firm Size	(0,+60) Returns	MF Volume	All Years	N
Small	Low	Low AMF volume	0.208	905
		High AMF volume	0.264	900
		High - Low	0.055***	
	High	Low AMF volume	0.136	974
		High AMF volume	0.162	969
		High - Low	0.026**	
Medium	Low	Low AMF volume	0.222	1,031
		High AMF volume	0.286	1,025
		High - Low	0.064***	
	High	Low AMF volume	0.147	1,066
		High AMF volume	0.202	1,059
		High - Low	0.055***	
Large	Low	Low AMF volume	0.223	1,065
		High AMF volume	0.284	1,057
		High - Low	0.061***	
	High	Low AMF volume	0.158	1,092
		High AMF volume	0.212	1,087
		High - Low	0.054***	

This table reports a measure of the speed of price adjustment, the fraction of the raw (0,+63) return realized in days (0,+4), for small, medium, and large firms, and for low and high (0,+63) returns. Low (high) returns are decile 1 (10) returns, ranked by year. Market value is ranked into terciles, within year and within total return decile. AMF trading volume as a fraction of total trading volume in days (0,+4) is ranked into terciles, within year, return decile, and market value tercile, where low (high) AMF volume is tercile 1 (3). The time period covered is 2003 to 2010. In the "High – Low" rows, *** indicates significance at 1%; ** at 5%; and * at 10%.

Figure 2: Speed of Price Adjustment



This graph shows the average cumulative percent of the raw (0,+63) return realized on each day, for (0,+63) returns ranked in the top and bottom deciles, to avoid small denominators. The red solid lines display the speed of price adjustment for firm-quarters with high (tercile 3) nondirectional AMF EA volume as a fraction of total volume in days (0,+4), and the black dashed lines display the speed of price adjustment for firm-quarters with low (tercile 1) nondirectional AMF EA volume as a fraction of total volume in days (0,+4).

Table 6: AMF Directional Trading

Panel A: AMF Trading, by SUE Tercile

	Mean	Net AMFs Buying
SUE1	0.470	-3.089
SUE3	0.715	-0.758
p-value SUE1-SUE3 Difference	0.006	0.000
N	62,116	62,116

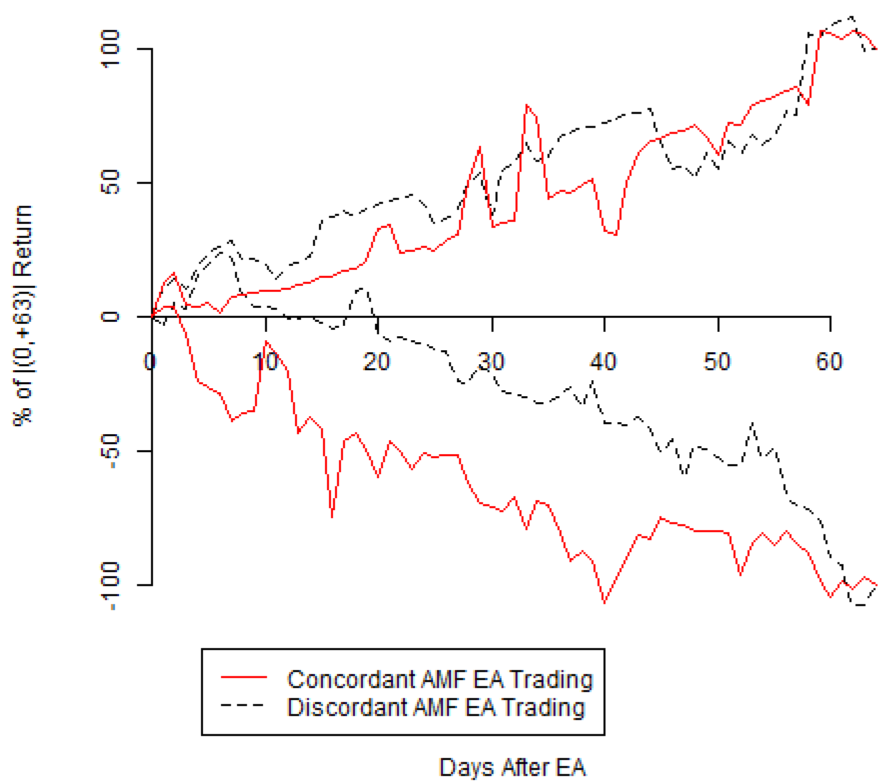
This panel shows that AMF trades during days (0,+4) of the EA are correlated with SUE. The first column reports the mean of average daily AMF net buy volume minus sell volume in the EA period, multiplied by 100 and scaled by average daily AMF gross volume in days (-20,-2) of the EA. The net buys for SUE1 announcements are significantly lower than the net buys for SUE3 announcements. The second column reports the number of AMF managers that are net buyers during the EA period, less the number of AMF managers that are net sellers, scaled by the total number of unique AMF managers trading during the EA period, in percentage points. The net proportion of AMFs that are net buyers during the EA is significantly lower for SUE1 announcements than for SUE3 announcements. The time period covered is 2003 to 2010.

Panel B: Concordant vs. Discordant AMF Trading: EA and Post-EA Returns for Small Firms

	N	(0,+4) Return	(0,+4) Return Proportion
SUE1, All	8,111	-0.012	0.071
SUE3, All	9,493	0.020	0.044
SUE1, Concordant	2,112	-0.085	0.076
SUE3, Concordant	2,993	0.075	0.268
SUE1, Discordant	2,526	-0.012	-0.033
SUE3, Discordant	1,823	0.015	0.265
Median test p-value, Concordant vs. Discordant			0.000

This panel reports the proportion of the total size-adjusted (0,+63) returns that occurs in the EA period (0,+4), for small firms with SUE in terciles 1 and 3, based on cutoffs computed in the previous calendar year. The first two rows report the median EA returns, and the median EA returns as a proportion of the total size-adjusted (0,+63) returns. The next two rows report these medians for EAs with concordant AMF trading in the EA period, defined as SUE1 EAs ranked in the bottom quintile of AMF EA directional volume and SUE3 EAs ranked in the top quintile of AMF EA directional volume, where AMF EA directional volume is defined as average daily AMF net buys minus sells in the EA (0,+4) period, scaled by average daily AMF gross volume in days (-20,-2) of the EA. AMF EA directional volume is ranked into quintiles by SUE tercile and year. The next two rows report these statistics for EAs with discordant AMF trading in the EA period, defined as SUE1 EAs ranked in the top quintile of AMF EA directional volume and SUE3 EAs ranked in the bottom quintile of AMF EA directional volume. The last row reports p-values from a median test of the concordant vs. discordant medians of size-adjusted (0,+4) returns as a proportion of the total size-adjusted (0,+63) returns.

Panel C: Median Price Adjustment for Concordant vs. Discordant AMF Trading



This panel graphs the median speed of price adjustment for concordant vs. discordant AMF EA trading, for small, medium, and large firms. The red solid lines display the speed of price adjustment for firm-quarters with discordant AMF EA trading, and the black dashed lines display the speed of price adjustment for firm-quarters with concordant AMF EA trading. The time period covered is 2003 to 2010.

Table 7: Profitability of AMF Trades

Year	All Trades (Size-Adj)	EA and Matched Non-EA Trades	EA Day	Matched Non-EA	EA - Non-EA Diff
2003	-0.087***	0.470***	0.590***	0.350***	0.240*
2004	0.064***	0.410***	0.567***	0.253***	0.314***
2005	0.182***	-0.028	0.011	-0.066	0.077
2006	-0.168***	-0.173***	-0.064*	-0.282***	0.218***
2007	0.006	-0.343***	-0.195***	-0.491***	0.297***
2008	-0.028***	0.532***	0.140***	0.924***	-0.783***
2009	-0.406***	-0.086**	-0.121**	-0.051	-0.071
2010	0.233***	0.497***	0.719***	0.275***	0.444***
All Years	-0.039***	0.075***	0.096***	0.054***	0.042
N	40,931,603	2,194,406	1,097,203	1,097,203	1,097,203

This table reports the size-adjusted profit of AMF trades in the first column and the raw profit of AMF trades in all other columns (in percentage points). The EA Day trades are matched to Non-EA trades for stocks in the same size decile and on the same day. Buys are matched to buys and sells are matched to sells. *** indicates significance at 1%; ** at 5%; and * at 10%.

Table 8: Profitability of AMF Buys and Sells

Year	EA Day Buys	Non-EA Buys	EA - Non-EA Diff, Buys	EA Day Sells	Non-EA Sells	EA - Non-EA Diff, Sells
2003	11.822***	11.372***	0.450***	-11.461***	-11.476***	0.015
2004	1.627***	1.458***	0.169	-0.575***	-1.046***	0.470***
2005	3.601***	3.478***	0.124	-3.341***	-3.375***	0.034
2006	2.324***	2.322***	0.002	-2.193***	-2.604***	0.411***
2007	-1.626***	-1.930***	0.304***	1.112***	0.822***	0.290***
2008	-7.697***	-7.367***	-0.330***	7.286***	8.482***	-1.197***
2009	11.296***	11.480***	-0.185*	-11.876***	-11.923***	0.047
2010	6.566***	5.723***	0.843***	-5.759***	-5.760***	0.002
All Years	1.980***	1.863***	0.117***	-1.713***	-1.683***	-0.030
N	537,388	537,388	537,388	559,815	559,815	559,815

This table reports the raw profit of AMF trades in all columns (in percentage points). The EA Day buys (sells) are matched to Non-EA buys (sells) for stocks in the same size decile and on the same day. *** indicates significance at 1%; ** at 5%; and * at 10%.

<u>Table 9: Profitability of AMF Trades, by Manager Type</u>

Year	All Trades			EA Day Trades			Non-EA Trades		
	High EA Intensity	**Low EA Intensity**	**High - Low**	**High EA Intensity**	**Low EA Intensity**	**High - Low**	**High EA Intensity**	**Low EA Intensity**	**High - Low**
2004	-0.445***	-0.368***	-0.077	0.877***	-6.468***	7.345***	-0.532***	-0.134	-0.398***
2005	0.424***	-0.312***	0.736***	0.740***	-1.638***	2.378***	0.383***	-0.293***	0.675***
2006	0.140***	-0.167***	0.307***	0.231*	0.118	0.113	0.105***	-0.228***	0.333***
2007	0.789***	-0.406***	1.195***	1.608***	1.996***	-0.387	0.708***	-0.450***	1.158***
2008	-0.208***	0.002	-0.210***	-0.162	1.287***	-1.449***	-0.273***	-0.049	-0.224***
2009	1.359***	-1.566***	2.924***	1.584***	2.823***	-1.238***	1.341***	-1.643***	2.984***
2010	0.548***	-0.291***	0.839***	0.494***	-1.201***	1.695***	0.489***	-0.274***	0.763***
All Years	0.353***	-0.374***	0.727***	0.604***	-0.028	0.631***	0.303***	-0.413***	0.716***
N	2,210,386	1,373,663		112,795	40,576		1,993,403	1,279,659	

This table reports the size-adjusted profit of AMF trades (in percentage points), as it varies with intensity of EA trading participation. Ranked measures are calculated for the calendar year t-1. "High EA Intensity" refers to decile 10 and "Low EA Intensity" refers to decile 1 of the measure: dollar volume of the fund family's trading that occurs in days (0,+2) of any firm's EA, as a proportion of total dollar volume in year t-1. *** indicates significance at 1%; ** at 5%; and * at 10%.

Table 10: Profitability of HF Trades

Year	**All Trades (Size-Adj)**	**EA and Matched Non-EA Trades**	**EA Day**	**Matched Non-EA**	**EA - Non-EA Diff**
2003	0.958***	0.103	-0.657***	0.864***	-1.520***
2004	0.193***	-0.108	-0.523***	0.307**	-0.830***
2005	0.055***	0.662***	0.695***	0.628***	0.067
2006	-0.225***	0.630***	1.052***	0.209	0.843***
2007	0.701***	0.192	-0.544***	0.928***	-1.473***
2008	-0.178***	1.934***	2.602***	1.266***	1.336***
2009	-0.610***	1.024***	1.207***	0.841***	0.365*
2010	-0.281***	0.547***	1.097***	-0.003	1.101***
All Years	0.055***	0.568***	0.609***	0.528***	0.080
N	4,067,753	253,906	126,953	126,953	126,953

This table reports the size-adjusted profit of HF trades in the first column and the raw profit of HF trades in all other columns (in percentage points). The EA Day trades are matched to Non-EA trades for stocks in the same size decile and on the same day. Buys are matched to buys and sells are matched to sells. *** indicates significance at 1%; ** at 5%; and * at 10%.

Table 11: Profitability of AMF vs. HF Trades

Sample	All Trades (Size-Adj)	EA and Matched Non-EA Trades	EA Day	Matched Non-EA
AMF	-0.039***	0.075***	0.096***	0.054***
HF	0.055***	0.568***	0.609***	0.528***
AMF - HF Difference	-0.094***	-0.494***	-0.513***	-0.475***

This table reports the size-adjusted profit of AMF and HF trades in the first column and the raw profit of AMF and HF trades in all other columns (in percentage points). The EA Day trades are matched to Non-EA trades for stocks in the same size decile and on the same day. Buys are matched to buys and sells are matched to sells. *** indicates significance at 1%; ** at 5%; and * at 10%.