Distracted Institutional Investors

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ABSTRACT

We investigate how distraction affects the trading behavior of professional asset managers. Exploring detailed transaction-level data, we show that managers with a large fraction of portfolio stocks exhibiting an earnings announcement are significantly less likely to trade in *other* stocks, suggesting that these announcements absorb attention which is missing for the choice of which stocks to trade. This distraction effect is more pronounced for non-passive managers that engage in active stock selection choices. Finally, we identify three channels through which distraction hurts managers' performance: distracted managers trade less profitably, incur slightly higher transaction costs and display a stronger disposition effect.

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Attention is scarce. Yet, we know very little about how limited attention affects the trading behavior of institutional asset managers—arguably the most important class of investors in financial markets today.[1] This lack of knowledge arises for two reasons. First, professional investors employ significant resources to overcome attention constraints: they hire additional research staff, acquire access to real-time news feeds and invest in computer capacities for algorithmic trading or smart order-routing. Hence, institutional asset managers are assumed to be less attention-constrained to begin with. Second, any empirical investigation in this domain faces the problem that attention is unobserved and plagued by endogeneity.

In this paper, we propose a way to address this empirical challenge and—in doing so—uncover *well-identified* evidence suggesting that attention constraints can be binding even for professional asset managers. Specifically, exploiting detailed transaction-level data for a large sample of U.S. institutional investors, we are able to identify attention shifts between different stocks that are on the "radar screen" of a particular investor. Exploring the ramifications of such attention shifts, we shed light on a number of important questions: How severe are attention constraints among professional investors? Do investors cope with them in a rational manner? And, finally, what are the channel through which attention constraints manifest themselves in investors' trading activity and performance?

Our identification builds on the premise that an investor cannot pay equal attention to all stocks. He will thus have to focus on a subset or "watchlist" of stocks. To see the idea, consider the following example: There are two investors—1 and 2. Investor 1 watches stocks A and B. Investor 2 watches stocks A and C. Suppose there is important news about stock B, but not

[1] Stambaugh (2014) reports that, at the end of 2012, roughly 22% of U.S. equity was directly owned by individuals. The flip side of this is that more than 75% of equity ownership is delegated in one way or another.

about stock C. Under limited attention, we expect investor 1 to pay less attention to stock A compared to investor 2. The reason is that, unlike investor 2, investor 1 needs to digest and respond to the news of stock B, which distracts him from trading in stock A. In another period, stock C may have important news and we would then expect investor 2 to be distracted relative to investor 1. By comparing the trading of investors 1 and 2 in the same stock, our identification exploits such attention redirections at the *investor-stock-time level*.

An appealing feature of the three-dimensional data structure (investor×stock×time) is the rich cross-sectional and time-series variation in investor distraction, which we exploit in our regression approach. In particular, through high-dimensional fixed effects, we absorb a large fraction of the variation in trading activity which could be a source of endogeneity. For example, whether or not a stock has important news in a given week is itself an important determinant of trading activity. The inclusion of *stock×date* fixed effects ensures that our results are not driven by such stock-level effects. Similarly, institutions may have different preferences for certain stocks, and these preferences could be correlated with their trading response. *Stock×manager* fixed effects control for such time-invariant preferences. In effect, our results are identified from comparing the trading activity *of different investors in the same stock at the same point in time*. We view our identification strategy to be a significant improvement over prior studies in this field.

Our institutional transaction data comes from ANcerno Ltd, a consulting firm that helps institutional investors to monitor their trading costs. Prior research finds that ANcerno trades represent approximately 10% of all institutional trading volume in the U.S. and that they are not significantly different from trades made by the average U.S. institutional investor (Puckett and Yan, 2011; Anand et al., 2012). The key feature of this data is that, in addition to detailed trading records, it provides a unique identifier for the trading institutions. This enables us to implement our identification strategy at the level of the institutional investor.[2]

Specifically, by following institutional investors over time, we construct two different versions of institutional "watchlists"; i.e., stocks that these investors pay attention to. Our first version, which we label *ANcerno watchlist* assumes that all stocks that the investor traded in the previous 12 weeks are on the investor's watchlist. The second version, which we label *13f watchlist*, is based on portfolio holdings at the end of the previous quarter as reported on form 13f. We verify that both watchlists highly predict future trading, and much better so than randomly-assigned placebo watchlists. Hence, both watchlists capture investor attention as intended. At the same time, they are sufficiently different so that showing results for both watchlists provides an important consistency check for our approach. [3]

We use quarterly earnings announcement dates to proxy for important stock news. Indeed, earnings announcements are arguably the most important recurring news events for individual stocks, justifying their preeminent role in the literature on public information disclosures (see, e.g., Beaver, 1968; Aharony and Swary, 1980; Bernard and Thomas, 1989; Kim and Verreccia, 1994). Institutional investors have the professional mandate to keep their fingers on the pulse of stock market developments. As such, they routinely attend earnings conference calls and, when the news is substantial, they may swiftly rescale their position (e.g., Bushee et al, 2011).

[2] Ideally, we would want to conduct our analysis at the fund-level. Unfortunately, the ANcerno data does not provide a unique fund identifier, and we are thus forced to work at the level of the institution. To the degree that attention constraints really operate at the fund-level, our distraction measures contain measurement error which could lead to an attenuation bias. Hence, the distraction effects documented in this paper can be understood as a lower bound estimate of the real attention constraints faced by institutional investors.

[3] Two reasons are responsible for the limited overlap. First, since the 13f watchlist requires a valid link between ANcerno and 13f, we lose a non-trivial number of institutional investors in this subsample. Second, even when there is a link, recent trading and prior holdings are not the same. A manager can make frequent round-trip trades in a stock (in which case it only appears in the ANcerno watchlist), and he can hold on to a stock bought long time ago (in which case it only appears in the 13f watchlist).

All this requires attention[4]—attention that we argue is missing for trading in other stocks. Our primary distraction proxy is thus the (weighted) fraction of stocks on the investor's watchlist that exhibit an earnings announcement in a given period.[5] Importantly, when we construct the distraction measure for a given stock and investor, we calculate this fraction by summing over all *other* stocks on the investor's watchlist. Thus, our measure captures distraction coming from other stocks on the watchlist.

Our first finding, summarized in Figure 1, is that institutional investors are significantly less likely to trade in a given stock when there are many earnings announcements for other stocks on their watchlist. An increase from the bottom to the top quartile of distraction reduces the propensity to trade in a given stock by 3-4%. For the subset of managers that follow active investment strategies; i.e., those that are not identified as quasi-indexers according to the investor classification by Bushee and Noe (2000) and Bushee (2001), the effect increases to up to 8%. As explained earlier, these results obtain in panel regressions that control for both stock×time and stock×manager fixed effects, thereby removing endogeneity concerns arising from unobserved stock-level shocks or fixed investor preferences.

In contrast to the strong effect at the extensive margin, we find no distraction effect at the intensive margin. That is, conditional on trading in a given stock, institutional investors do not trade less when there are many earnings announcements for watchlist stocks. This no-result stands in sharp contrasts to standard models of information acquisition in which inattentive

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[4] This is confirmed by Hirshleifer et al. (2009) who show that the incorporation of earnings news is delayed on days with a large number of earnings announcements.

[5] The weights correspond to the relative importance of a stock in the watchlist, where relative importance is measured by the fraction of dollar volume for the ANcerno watchlist and by the fraction of portfolio holdings for the 13f watchlist.

investors adjust at the intensive margin how much information to gather (e.g., Verrecchia, 1982; Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016). Instead, our results suggest that, even among professional traders, attention is better modeled in terms of a fixed cost to searching and trading in a particular stock (akin to the recognition cost in Merton, 1987; see also Abel et al., 2007; Chien et al., 2012).

We then conduct a number of sample splits to shed light on which type of managers are more distracted. We find that the distraction effect is stronger for managers that trade actively, where activeness is proxied by the intensity of rebalancing trades as opposed to flow-induced trades. Since the former involve a stock selection choice, whereas the latter amount to a mechanical rescaling of existing positions, we expect rebalancing trades to be more susceptible to distraction and this is what we find. We further show that our results are concentrated for institutions with a diverse watchlist across industries. This is intuitive as a stock's earnings announcement is also news to other stocks in the same industry. Hence, institutions with a high industry concentration may be attracted to rather than distracted from trading stocks when there are earnings announcements for other watchlist stocks in the same industry.

Next, we identify two channels through which distraction affects managers' performance. First, distraction leads managers to make poorer trading decisions. Compared to non-distracted managers trading in the same stock, distracted ones have past-trade returns over the next four weeks that are 20 basis points lower (40 basis points in the subsample of quasi-indexers). Second, we find that distracted managers incur slightly higher transaction costs on their trades. These findings are consistent with rational attention models, where the lack of attention manifests itself in obtaining less precise trading signals and less favorable execution prices.[6] We acknowledge, however, that the magnitudes of these effects is relatively modest.

Finally, we conduct an in-depth analysis of the channels that appear to explain observed attention choices. We start with testing an important corollary of the rational attention paradigm. Specifically, we test whether the distraction effect that we document for trading propensity is reduced for stocks facing high uncertainty. Rational attention theory predicts that investors should keep paying attention to such stocks even as the overall attention constraint becomes more binding. We do not find this in the data, however. Probing for alternative (i.e., behavioral) factors that seem to mediate the distraction effect, we uncover two additional findings. First, the distraction effect on trade and in particular sell decisions is pronounced for stocks that trade at a loss. We argue that this finding is consistent with recent literature suggesting that information can have a direct effect on investors' utility (Karlsson et al., 2009; Sicherman et al., 2015), prompting them to avoid unpleasant information when they have an excuse in the form of a distracting event. We also find that this behavior exacerbates the disposition effect (Shefrin and Statman, 1985)—i.e., the well-documented tendency of investors to hold on to losing stocks while selling winning ones. Second, we document that salience, which is found to strongly attract attention (Barber and Odean, 2008; Bordalo et al., 2013), mitigates the distraction effect. Overall, these results cast doubt on the ability of rational attention models to explain the observed trading behavior of institutional investors in the ANcerno sample. Rather, they suggest that, even for these professional investors, attention allocation decisions are influenced by subconscious and/or psychological factors such as a stock's salience and emotions toward gains and losses.

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[6] For trade profitability, see our rational attention model in appendix B. For transaction costs, the result can be rationalized by microstructure models suggesting that limited attention exposes limit order users to the risk of being "picked-off" or not executed. These effects could be at work even when order execution is outsourced to brokers, as distracted institutions may send their orders with delay and thus higher urgency.

Our paper contributes to the literature on inattention in financial markets (see, for instance, Cohen and Frazzini, 2008, DellaVigna and Pollet, 2009, and Hirshleifer et al., 2009). While this literature has been burgeoning, there are only few papers that specifically focus on professional investors—presumably because these investors are assumed to be less attention constrained to begin with. Fang et al. (2014) show that certain mutual funds persistently buy into stocks that have been covered in the media, and that these funds underperform relative to other funds. They interpret their findings as indirect evidence for the presence of attention constraints among this subset of mutual funds. Lu et al. (2016) collect a sample of marriage and divorce events for hedge fund managers and find that their performance suffers during those events. Ben-Rephael et al. (2017) propose search volume on Bloomberg terminals as a proxy for institutional attention and show that it correlates with the timely incorporation of earnings news. Kempf et al. (2016) explore a similar identification approach to ours, but aggregated and at lower frequency, to study how shareholder distraction affects corporate actions. They find that firms with distracted shareholders engage more in value-destroying acquisitions, presumably because of less intense monitoring. By looking at individual trades of institutional investors, our paper improves on the identification and allows studying the *exact channel* of how inattention affects managers' trading behavior and performance.

The paper proceeds as follows. Section I presents our empirical hypotheses. Section II describes the data. Section III introduces the identification approach. Section IV considers the effect of institutional distraction on trading activity. Section V studies how distraction affects performance. Section VI investigates whether observed attention choices are more in line with rational or irrational attention models. Section VII presents robustness checks and Section VIII concludes.

I. Hypotheses

In our empirical analysis, we focus on four outcome variables that are well-suited in the context of our identification strategy:[7] (1) investors' trading propensity (i.e., their decision to trade or not), (2) trading volume (i.e., how much they trade conditional on trading), (3) trade profitability and (4) incurred transaction costs. We argue that our collective approach allows us to shed light on the inner workings of investors' attention allocation processes. In this section, we briefly review the theoretical and empirical literature in order to derive the empirical predictions pertaining to these outcome variables.

A. Rational Attention Models

Undoubtedly, the best-developed theoretical framework for understanding investors' attention choices is the *rational attention* paradigm. Although there are nuances between specific models, they all share a common thrust: investors are fully cognizant of their attention constraints and cope with them in a rational manner. For instance, some models assume that investors face fixed *search costs* for deciding in which stock to trade (akin to the recognition cost in Merton, 1987; see also Abel et al., 2007, 2013; Chien et al., 2012). Distracted investors are less likely to incur this cost, leading them to forego trading. To capture such an *extensive margin effect*, we define a variable $trade\ dummy_{imt}$ that takes on the value one if manager m trades stock i in week t and zero otherwise. When investors are short-sale constrained, the search costs for buy decisions—and thus any potential distraction effect—far exceed the ones for sell decisions (Barber and Odean, 2008). It is not clear, however, whether the institutional investors in our

[7] As explained earlier, our identification gains its strength by exploiting the variation in trading activity of different investors in the same stock at the same point in time. As such, candidate outcome variables need to be at the individual-trade level.

sample are short-sale constrained.[8] Hence, we define dummy variables that separately flag buy and sell decisions.

Another popular branch of rational attention models assumes a one-to-one mapping between attention spent on learning about a given stock and the *precision* of the resulting trading signal (e.g., Verrecchia, 1982; He and Wang, 1995; Vives, 1995; Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016). As we showcase in appendix B, these models invariably predict that distracted investors make fewer profits from trading and choose to trade less aggressively. Accordingly, we expect to see a reduction at the intensive margin of trading, which we measure by $trading\ volume_{imt}$ (defined as the logarithm of dollar trading volume conditional on manager m trading stock i in week t), as well as a reduction in $trade\ profitability_{imt}$ (defined as the post-trade stock return, multiplied by minus one for sells).

Although rarely modeled explicitly, the rational attention theme would also seem to carry over to the microstructure domain. For instance, one may hypothesize that limit orders yield better prices but require more attention (because limit orders give rise to the risk of being picked off and/or not being executed).[9] Attention-constrained investors may hence decide to use market orders instead of limit orders. Alternatively, they may spend less time looking for the best quotes and/or bargaining with brokers. These effects could be at work even when investors outsource trade execution to their brokers, because distracted investors may send their orders with delay and thus higher urgency. To study whether distraction causes a reduction in the

[8] According to Jame (2016), the ANcerno data contains short-sales, but it is not possible to distinguish them from other sales.

[9] Dugast (2016) presents a model of limit order trading under with infrequent monitoring due to limited attention. Moreover, we believe that such an intuition can arise naturally in models of endogenous limit order trading as in Handa and Schwartz (1996) and Goettler et al. (2005, 2009).

transaction costs incurred by investors, we define the $relative\ transaction\ spread_{imt}$ as the difference between the execution price and the previous day's closing price for buys (and vice versa for sells), scaled by the previous day's closing price.

Finally, rational attention models make unequivocal predictions about the comparative statics of distraction effects in the cross-section of stocks. Specifically, they predict that investors reallocate their attention on the basis of a cost-benefit analysis. As such, investors should be less likely to divert attention from stocks that matter more to their utility (Corwin and Coughenour, 2008). Indeed, our rational attention model with risk-averse investors shown in appendix B predicts that, as the attention budget tightens, investors withdraw relatively more (less) attention from low-(high-) uncertainty stocks. In our empirical analysis, we study how distraction effects interact with proxies for the uncertainty of a stock (e.g., whether there is an immanent earnings announcement or large realizations of trading volume and absolute returns).

B. Alternative Attention Models

When it comes to alternatives to the rational attention paradigm, the situation is admittedly not very satisfying. Instead of facing a unified framework, we are left with different pieces of evidence hinting at the importance of, e.g., salience and emotions for understanding observed attention allocation behavior. Here, we discuss two potential behavioral influences that yield empirical predictions which contrast with those from rational attention models.

The first factor we consider concerns investors' emotions felt toward paper gains and losses. A growing literature in behavioral economics suggests that information about such gains and losses may directly affect the utility of economic agents, over and above its indirect effect on utility through affecting agents' choices (Caplin and Leahy, 2001; Brunnermeier and Parker, 2005; for a survey see Golman et al., 2017). A natural implication of such models is that agents may choose to selectively avoid information that they expect to be bad. Studying the online login behavior for a sample of 401k retirement plans, Karlsson et al. (2009) and Sicherman et al. (2016) find strong evidence for what they dub the "ostrich effect": during market downturns, investors with equity exposure are significantly less likely to log into their pension accounts.[10] We posit that attention-constrained investors may be particularly prone to engage in such behavior: when choosing which portfolio stock not to pay attention to, distracted investors may choose the one that is trading at a loss in order to avoid the disutility associated with it. Put differently, investors may unconsciously use distracting news coming from other stocks as an excuse why they cannot closely follow that particular stock. A similar prediction arises in models that assume investors derive utility from *realizing* gains and losses (Barberis and Xiong, 2012; Ingersoll and Jin, 2013): when a realization-utility investor anticipates that he does not want to act on bad information (i.e., realizing a loss), he may decide to stop paying attention to a losing stock when he is distracted.

In our empirical analysis, we study how distraction effects interact with a stock's past return. Based on the previous discussion, we expect a stronger distraction effect—especially for sell decisions—for portfolio stocks trading at a loss (i.e., when there is an existing long position). This prediction also suggests a connection between inattention and the disposition effect; i.e., the well-known tendency of investors to prefer selling positions trading at a gain compared to those trading at a loss (Shefrin and Statman, 1985).[11] Indeed, if distraction causes investors to

[10] This behavior is even observable over weekends, where the information gleaned from logging into the portfolio cannot be used for trading.

[11] While this behavior is most strongly observed for individual investors (Odean, 1998; Grinblatt and Keloharju, 2001), Grinblatt and Han (2005) and Frazzini (2006) find evidence that it also applies to institutional investors.

focus on their winning positions at the expense of their losing ones as we posit, we also expect distraction to exacerbate the disposition effect. We test this hypothesis using a standard measure of an (institutional) investor's propensity to succumb to the disposition effect (Odean, 1998).

Another important driver of observed attention choices is salience. Barber and Odean (2008) document that salient stocks exhibit net-buying pressure from individual investors. Hartzmark (2015) finds that both institutional and retail investors are more likely to sell portfolio stocks that rank either best or worst in terms of relative performance since purchase, consistent with the idea that these portfolio positions are more salient to the investor. Bordalo et al. (2013) explores the asset pricing implications of a model in which investors overweight salient asset payoffs.[12] Cosemans and Frehen (2017) find consistent evidence in the cross-section of stock returns. A common theme of this literature is that salience draws attention at a subconscious level, more or less outside of the control of the investor. As such, we expect that a tightening of the overall attention constraint has little effect on salient stocks, thereby mitigating the distraction effect. In our analyses, we test whether the distraction effect is less pronounced for salient stocks, using the extreme rank measure proposed by Hartzmark (2015).

II. Data

A. Institutional Trading Data

[12] Bordalo et al. (2014, 2015) write down consumer choice models in which economic agents overweight salient attributes of a product.

We obtain institutional trading data from ANcerno Ltd (formerly known as Abel Noser Solutions), a leading transaction cost consultant for institutional investors.[13] Puckett and Yan (2011) report that ANcerno trades represent approximately 10% of institutional trading volume in U.S. equities. While institutional investors subscribing to ANcerno are relatively large, their trades and stock holdings have been found to be comparable to those of the average investor in the universe of institutional asset management. Our sample period starts in January 1999 and ends in June 2011, after which ANcerno stopped the provision of an identifier for the trading institution.

Each row in the ANcerno dataset represents an executed trade, including information on the date and time of the trade, identity of the stock traded, trade direction (buy or sell), number of shares traded, transaction price, and commissions paid. One crucial feature of the ANcerno data for our purpose is that it contains a unique identifier corresponding to the management company executing the trade (*manager code*). We also have access to a reference file that links manager codes to the names of those companies. Ideally, we would want to have identification at the fund-level; however, the ANcerno data does not provide this information.[14] Hence, we are forced to conduct our analysis at the manager-level. We have 835 different managers in our sample.

[13] Previous papers using this data include Goldstein et al. (2009), Chemmanur et al. (2009), Puckett and Yan (2011), Anand et al. (2012), Franzoni and Plazzi (2015), Eisele et al. (2016), Hu et al. (2014), Jame (2016), Chakrabarty et al. (2016), Ben-Rephael and Israelson (2014) and Goetzmann et al. (2016).

[14] ANcerno contains an additional variable called *clientmgrcode*. However, interactions with ANcerno as well as our reading of the literature convince us that this is not a unique fund identifier. For instance, Jame (2016) writes (see footnote 4): "discussions with ANcerno representatives indicate that different *Clientmgrcodes* within a client-manager generally do not reflect different fund products."

In order to gauge the performance of institutional trades over various holding periods, we map stock returns from CRSP onto the ANcerno trades.[15] Since we conduct our main analyses at the manager-stock-time level, working at daily frequency becomes computationally infeasible. We therefore aggregate trades at weekly frequency.

B. Link to 13F

Using the manager names available to us, we hand-match ANcerno managers to institutional holdings data reported in 13f.[16] We are able to find corresponding 13f information for 670 out of the 835 managers in our sample. This match serves several purposes. First, we use it to obtain a link to static investor characteristics reported on Brian Bushee's website. We are particularly interested in the classification of managers into "quasi-indexers" and others,[17] as we expect distraction effects to be weaker for managers following passive investment strategies. Second, we construct a matched sample between ANcerno and 13f which allows to control for the level and change of managers' assets under management. Third, as detailed below, we exploit holdings data to assemble the list of stocks held by each manager at the end of the previous quarter.

C. Watchlist Construction

Our identification rests on the assumption that investors pay more attention to some stocks than to others. We say that investors have a *watchlist* of stocks. We construct two different

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[15] See Appendix A.1 for details.

[16] See Appendix A.2 for details.

[17] More precisely, Bushee and Noe (2001) and Bushee (2002) classify managers into three categories: quasi-indexers, transient and dedicated investors. The latter two categories differ mainly in their trading activity. Since results for these two categories are similar and since we have no expectation as to which group should be more affected, we merge them in our analysis. The investor classification data is available at: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.

watchlists for each manager-week pair. Our first version, labelled *ANcerno watchlist*, reflects past trading. More specifically, a given stock i enters the watchlist of manager m in week t when the manager was trading the stock in the previous 12 weeks. Let w_{imt}^{a} be the watchlist weight of stock i, defined as the share of past trading volume by manager i going to the stock:

$$w_{imt}^{a} = \frac{\text{trading volume in stock } i \text{ in the past 12 weeks}}{\text{total trading volume in the past 12 weeks}}$$

Below, we use this weight when we construct average distraction measures across watchlist stocks.

Our second watchlist, labelled *13f watchlist*, is based on portfolio holdings: a given stock i enters this watchlist if manager m reported a positive holding in the stock at the end of the quarter prior to week t. Let w_{imt}^{h} be the portfolio weight of stock i, defined as:

$$w_{imt}^{h} = \frac{\text{dollar value of position in stock } i \text{ at the end of the previous quarter}}{\text{total dollar value of positions at the end of the previous quarter}}$$

Note that there is only a limited overlap between the trade-based ANcerno watchlist and the holdings-based 13f watchlist. The reason for this is that trades and holdings are fundamentally different: For instance, a manager can quickly trade in and out of a stock, in which case the stock only enters the trade-based watchlist. Alternatively, a manager can report holdings for stocks which he did not trade recently, in which case the stock is only in the holdings-based watchlist. As such, we prefer to report results using both watchlists.

D. Trade Persistence

If our watchlists capture stocks that managers are paying attention to, we expect those stocks to be traded with higher propensity than a random sample of stocks. To test this prediction, we construct randomly-assigned placebo watchlists in the following way. First, we randomly reshuffle the trades and holdings data, while maintaining differences in trade (holding) intensities across managers and stocks.[18] Second, we use this reshuffled data to construct new trade-based and holdings-based watchlists (called ANcerno-placebo and 13f-placebo). We then compare the fraction of watchlist stocks that are traded in the subsequent week across the different watchlists. Table 1 Panel B shows that, for the ANcerno and the 13f watchlists, the average fraction of traded watchlist stocks equals 20.4% and 13.3%, respectively, whereas it hovers around 3-4% for the placebo watchlists. These differences are highly statistically significant and give us confidence that our watchlists indeed capture stocks that are on the "radar screens" of ANcerno investors.

E. Earnings Announcement Dates

We study how news events in some watchlist stocks affect trading in other watchlist stocks. To proxy for news events, we use earnings announcement dates from I/B/E/S and Compustat. Earnings announcements constitute the most important recurring news releases for individual firms;[19] they receive significant media attention and institutional investors routinely attend earnings conference calls. As such, they are well suited for our analysis.

Following DellaVigna and Pollet (2009), we use the earlier of the dates in I/B/E/S and Compustat when the two dates do not coincide for the same fiscal quarter. We drop the earnings announcement when the firm had another announcement less than 11 days earlier.

[18] Specifically, when a manager was trading (holding) 100 different stocks in the original data for a given week, the placebo watchlists will also feature 100 different stocks (which are randomly assigned) for this manager in that week.

[19] See, e.g., Beaver (1968), Aharony and Swary (1980), Bernard and Thomas (1989), and Kim and Verreccia (1994).

We define an earnings announcement dummy, $EA\ dummy_{it}$, that takes the value of one if firm i had an earnings announcement in week t and zero otherwise.[20] Overall, we have 274,840 earnings announcement weeks, representing roughly 8% of all stock-week observations in our sample period.

III. Methodology

A. Distraction Measure

The key idea that we exploit in this paper is that different managers are exposed to different news shocks over time. Thus, managers paying attention to the same stock at the same time are differentially distracted by other news.

We now explain how we construct our distraction measure. Recall that w_{jmt}^{a} and w_{jmt}^{h} are the weights of stock j in manager m's trade-based and holdings-based watchlist, respectively, and that $EA\ dummy_{jt}$ flags stocks with an earnings announcement. For a given stock i, manager m and week t, our distraction measure is the weighted fraction of watchlist stocks with an earnings announcement:

$$distraction_{imt} = \frac{\sum_{j \neq i} w_{jmt}^{x} \times EA\ dummy_{jt}}{\sum_{j \neq i} w_{jmt}^{x}}$$

where $x \in \{a, h\}$. Importantly, the weighted average is formed over all watchlist stocks *excluding* the stock in question. Hence, the measure is not affected by whether stock i itself has

[20] Earnings announcements on a Friday are treated slightly differently. As we don't have the exact time of the announcement, we are not sure whether the earnings news is priced in on Friday or on Monday of the following week. For this reason, $EA\ dummy$ is set to one for both weeks t and $t+1$ when the announcement occurred on a Friday.

an earnings announcement. Note also that our distraction measure always lies between 0 and 1 by definition.

Table 1, Panel A shows descriptive statistics for our distraction measure and the other variables used in this study. We see that, for the median manager in our samples, roughly 3.1% of watchlists stocks exhibit an earnings announcement in a given week. The standard deviation of this measure exceeds 10%, ensuring that we have sufficient variation in distraction. We also see that the median manager in the ANcerno sample trades a given watchlist stock approximately on three different days over the course of 12 weeks and has a weekly trading volume of 1.3$ billion. For the 13f sample, the median manager trades slightly less but has more assets under management.

[Include Table 1 here.]

B. Regression Methodology

Our main regression specification is

$$y_{imt} = \alpha_{it} + \alpha_{im} + \beta\ distraction_{imt} + \gamma\ trade\ number_{imt} + \delta\ managercontrols_{mt} + \varepsilon_{imt} \quad (1)$$

where y_{imt} is one of the four outcome variables introduced above. In principle, each manager could trade every available stock, resulting in an enormous data matrix of possible trades. Working with such a dataset is neither feasible nor desirable (because there would be zero trading for a vast majority of observations). We therefore estimate specification (1) only on the subset of watchlist stocks for each manager.

One crucial feature of our empirical setting is the three-dimensional data structure, which enables us to soak up a great deal of the cross-variation in trading activity through the inclusion of various fixed effects. For example, in any week, certain stocks happen to attract significant trading, perhaps because they exhibit an earnings announcement or are the target of takeover speculation. Suppose further that distracted managers concentrate on such attention-grabbing stocks (Barber and Odean, 2008), whereas non-distracted ones also trade in other stocks. As a result, distracted managers could appear as being relatively more active, which would confound our identification. Next, consider the stock-manager dimension. Different managers choose to trade different stocks for reasons which are largely unobserved. To the extent that such predispositions correlate with our distraction measure, a naïve comparison of the trading activity across distracted and non-distracted managers is again bound to be problematic. The inclusion of stock×date (α_{it}) and stock×manager (α_{im}) fixed effects in specification (1) immunize us against these and related concerns.[21]

In addition to these high-dimensional fixed effects, we include a number of control variables. First, because trading is relatively sticky, we include a measure of past trading activity. Specifically, $trade\ number$ is the number of days in which manager m traded stock i within the previous 12 weeks. Second, to account for time-varying manager characteristics, we include several proxies of manager size: the logarithm of the manager's dollar trading volume in the past 12 weeks and the level and change of assets under management at the end of the previous quarter. Note that with the inclusion of the latter two controls, our sample reduces to the subset of manager-quarters for which we could find corresponding 13f holdings. Hence, we show

[21] As our identification draws on the comparison *across* managers with different levels of distraction, we cannot include fund×date fixed effects in our specification. Indeed, we can show that, when such fixed effects are included, distraction for non-announcing stocks is not distinguishable from attraction to announcing stocks. In other words, the within-manager variation in our distraction measure is not meaningful in our setting.

results with and without the inclusion of these controls. Standard errors are clustered at the manager level.

IV. Distraction and Trading Activity

A. Baseline Results

In this section, we examine how distraction affects trading activity. Table 2 shows the results for the propensity to trade (trade dummy)—first for all trades (columns 1-2) and then for buys and sells separately (columns 3-6). Panels A and B reveal a pervasive distraction effect for both the ANcerno and the 13f watchlist. Based on the exact specification, we find that a one standard deviation increase in our distraction measure reduces the probability to trade by 2.2% to 3.3% relative to its unconditional mean. While the effect is not very large, it is important to note that this is the average effect across all types of managers, including those that follow passive investment strategies and which are therefore unlikely to be affected by distraction. Thus, the effect is economically meaningful. In appendix C, we show that the distraction effect does not revert in subsequent weeks. To the contrary, we find that the tendency to trade fewer stocks persists (with decaying magnitude) for up to two weeks before turning insignificant. Hence, managers do not catch up on missed trades once the distraction subsides.

[Include Table 2 here.]

Peress and Schmidt (2016) find that distracted retail investors buy but do not sell fewer distinct stocks. In contrast, we find a symmetric effect for the buy and sell decisions of institutional investors (columns 3-6). This makes sense: contrary to retail investors, institutional investors have much larger portfolios and some routinely go short. Hence, conditional on having decided to sell, a retail investor can only choose among the handful of portfolio stocks, whereas an institutional investor faces a much larger choice set. Since a complex choice is more susceptible to distraction, this explains why there is a significant distraction effect for institutional sells but not for retail ones.

In Table 3, we study the impact of distraction on the intensive margin of trade; i.e., the decision of how much to buy or sell conditional on trading. As argued above, rational attention models invariably predict that paying less attention leads investors to trade less aggressively. In contrast to this prediction, we find no evidence that distracted managers curb back the dollar volume of their trades (conditional on trading). Based on the estimated standard error, we can reject any intensive margin effect that exceeds 2.4% of the average dollar volume per standard deviation increase in distraction. Hence, even if such an effect exists, its economic magnitude would be small. The failure to support this basic prediction of rational attention models is noteworthy since, if these models are to explain any investor behavior, we expect them to explain best the behavior of professional investors.

[Include Table 3 here.]

Overall, these results suggest that it is the decision of which stocks to trade that requires the most attention—and which is thus most affected by distraction. Hence, they are most consistent with models that feature a *fixed search cost* for deciding which stock to trade (as in Merton, 1987; Abel et al., 2007; Chien et al., 2012; Abel et al., 2013).

B. Quasi-Indexers

If our results are due to investor distraction as we posit, we expect them to be concentrated for certain types of managers. For example, some managers may openly or covertly mimic an index.

Since such passive investment strategies require little attention, there is no scope for distraction. We use the investor classification by Bushee and Noe (2000) and Bushee (2001) to sort managers into "quasi-indexers" and others and repeat our regression analysis for these two groups.[22] Table 4 shows the results. We see that the distraction effect is highly concentrated in the group of non-indexers: the effect for quasi-indexers is either very small (for the ANcerno watchlist, column 1) or non-existent (for the 13f watchlist, column 3). In contrast, the effect for the non-indexers is double the magnitude of the baseline effect documented in Table 2, with a one standard deviation increase in distraction leading to a 4.5%-7.2% reduction in the propensity to trade. As shown at the bottom of the table, the differences between the two subgroups are statistically significant for both the ANcerno and the 13f sample.

[Include Table 4 here.]

C. Additional Sample Splits

In this subsection, we provide additional sample splits for the trade propensity dummy to examine which type of managers are more distracted. Each row in Table 5 represents one sample split, including a test statistic for the difference (columns 4 and 8). For brevity, we only show the coefficient on the distraction measure, although we always run the full specification with all controls.

[Include Table 5 here.]

Our first two sample splits are meant to reinforce the point that active management requires more attention and thus suffers more from inattention. First, we classify managers into terciles

[22] Because we are only able to classify a manager when we can link him to 13f data, we don't lose additional observations by including the 13f controls (level and change in assets under management). Hence, we only show results that include these controls.

based on their average watchlist *turnover* (defined as dollar trading volume over the total market capitalization of the watchlist portfolio). Managers that only trade to invest/divest as a function of fund inflows/outflows are likely to score low on this measure and hence we expect them to be less distracted. Row 1 in Table 5 confirms this expectation: distraction is strongest for the managers with high turnover, whereas low-turnover managers do not appear to be distracted at all. These differences are statistically significant.

Second, we attempt to separate between rebalancing and flow-induced trades. The idea is that rebalancing trades involve stock selection and are thus prone to distraction. Instead, flow-induced trades lead to a mechanic rescaling of existing positions. To capture the degree of flow induced vs. rebalancing trades, we calculate, for each week, the minimum of a manager's dollar buys and dollar sells, divided by his total trading volume.[23] We then take the average across weeks and call this measure *trade activeness*. Managers that score high on this measure buy and sell a lot at the same time, thereby rebalancing their portfolios from one stock to another. Managers that score low on this measure either buy or sell in a given week, presumably because they are responding to in- and outflows to and from their funds. We then run our analysis separately for managers in the bottom, middle and top tercile in terms of this trade activeness measure. Row 2 shows that, as expected, we find the strongest distraction effect for managers with high trade activeness; i.e., those managers that make active rebalancing decisions on a regular basis. For the top group, a one standard deviation increase in distraction is associated

[23] This measure is similar in spirit to the portfolio turnover proxy used in Wermers (2000) and Brunnermeier and Nagel (2004), except that we scale by total trading volume rather than portfolio holdings.

with a 4.7%-7.3% reduction in the propensity to trade, whereas there is no discernible distraction effect for the bottom group. These differences are again statistically significant.

Our third sample split is meant to disentangle between the distraction effect and the information effect of earnings news. The idea is that for stocks in the same industry as the announcing stock, the announcement provides information and may thus attract rather than distract investors' attention (e.g., Patton and Verardo, 2012). Such a confounding effect should be particularly strong for managers with concentrated industry portfolios and hence we expect to find a weaker distraction effect for this group. We therefore sort managers into terciles based on the average Herfindahl index of their watchlist stocks across the Fama-French 49 industries. Row 3 shows that, consistent with our expectation, the distraction effect is largest for the group of managers with low industry concentration (although the difference is only significant for the ANcerno watchlist).

Forth, we split managers by average assets under management over the sample period.[24] Row 4 in Table 5 shows that managers of all size appear to be distracted (except for large managers with the 13F watchlist, where the effect is insignificant). At first sight, the economic magnitude of the distraction effect seems to be larger for big institutions, although the difference is marginally significant at best. It turns out that these magnitudess are misleading, however, as the underlying propensity to trade is higher for large institutions. When scaled appropriately, the economic magnitude of the distraction effect appears comparable across size groups (a one

[24] For this sample split, we do not classify managers into equal terciles, because this results in model overfitting for the tercile of managers with low assets under management. This is because small managers' watchlists do not overlap enough, which means that our full model with the inclusion of stock×week and manager×stock fixed effects is poorly identified. Instead, to balance the number of observations in the different size groups, we classify the 60% smallest institutions as low assets under management, the 20% largest institutions as high assets under management, and all others as medium assets under management.

standard deviation increase in distraction reduces the propensity to trade by 3-4% and 4-5% for small and large managers, respectively). It may nonetheless seem surprising that large institutions are as distracted as small ones. After all, large institutions presumably comprise more different funds, which should attenuate our distraction effect through measurement error. Other factors may work against this attenuation, however. First, larger institutions are typically less focused (e.g., have a lower industry concentration), which means that the distraction effect will be less confounded by the information effect of earnings news (see above). Second, even when an institution has many funds, some trading decisions may yet be taken at or depend on input from the institutional level (for example, because trades are executed by a single trading division, because the same research division gives recommendations for all funds within the institution, or because trades are authorized by a group-wide risk management division).

The argument that less focused institutions are more prone to distraction also explains the results for our fifth sample split, where we find a stronger distraction effect for managers with a large number of watchlist stocks (Table 5 row 5). Sixth, we sort managers by average trading profits, measured as the mean (watchlist-weighted) return of the watchlist portfolio over a 48 weeks horizon. There is a tendency for managers with low or medium profits to be more distracted than those with high profits, but these differences are not significant. This evidence is consistent with skilled managers relying less on (public) earnings news, presumably because they are able to uncover valuable private information (Kacperczyk and Seru, 2007).

Finally, we check whether distraction is stronger or weaker for the 75 hedge funds in our sample.[25] We have no particular prior for this exercise: On the one hand, hedge funds are more likely to follow active investment strategies, which should make them prone to distraction. On the other hand, hedge funds are more focused and are more likely to employ trading algorithms, which should limit their capacity to be distracted. Our results, shown in Table 5 row 7, appear more consistent with the second interpretation, as the distraction effect for hedge funds is not statistically significant. We acknowledge, however, that the insignificance could also arise from low statistical power, as the economic magnitude of the distraction effect is not much different from the one for the other institutions.

In summary, the results from this section show that news events absorb attention that is missing for trading in other stocks—especially for managers that follow active investment strategies across different industries.

V. Distraction and Performance

In this section, we study whether distraction affects managers' performance. We consider two possibilities: distracted managers may trade less profitably and incur higher transaction costs.

A. Trade Profitability

To study whether distraction affects trade profitability, we repeat our panel regression from specification (1) with the post-trade return as the dependent variable. For buys, the post-trade return is simply the stock return over the subsequent 4 weeks. For sells, it is the stock return

[25] We thank Russell Jame for providing the hedge fund identifiers (described in Jame, 2016).

over 4 weeks times minus one.[26] We choose a holding horizon of 4 weeks as it strikes us as a reasonable compromise between allowing sufficient time for the information upon which the trade was based to accrue and between the added noise that is inherent in choosing a larger holding horizon. Moreover, Puckett and Yan (2011) document that a substantial fraction of round-trip trades is made within one quarter and that these trades are substantially more profitable than those that spread across quarters.

Note that, since our identification approach relies on comparing different trades made by different managers in the same stock at the same time (i.e., because we include stock×time fixed effects), our regression approach essentially compares managers' ability to be on the "right side of a trade."[27] In other words, we test whether distracted managers, compared to less distracted ones, are more likely to buy (sell) stocks that subsequently underperform (outperform). As argued in Section I, this is a clear prediction of any type of attention model in which there is a link between attention and signal precision (see our model in appendix B).

Table 6, Panel A shows the results for the overall sample. The 13f watchlist reveals a statistically significant distraction effect on trade profitability: a one standard deviation increase distraction decreases the average post-trade profitability over the four weeks from roughly 0.1% to -0.1%. Thus, while the institutional managers in our sample on average earn money with their trades, they begin losing money when they are distracted. For the ANcerno watchlist, the distraction effect is comparably in size but only marginally significant. Panel B

[26] Buys (sells) here mean trading weeks in which the manager's net trade imbalance is positive (negative), meaning that he bought (sold) more of the stock than he sold (bought).

[27] This also explains why our results are virtually unchanged when we use any type of risk-adjusted returns.

further shows that this distraction effect is pronounced for the group of non-indexers—with a magnitude that is twice as large as the one for the baseline sample. Here, the results are also statistically significant at the 5% level for both watchlists. In contrast, managers classified as quasi-indexers do not see a reduction in their trade profitability when a large fraction of watchlist stocks report their earning figures. This absence of a distraction effect is consistent with the idea that quasi-indexers do not choose which stocks to trade, and hence do not engage in a decision making process that is prone to distraction.

[Include Table 6 here.]

B. Transaction Spread

We now examine whether differences in distraction affect the order execution quality for managers trading in the same stock. To this end, we regress a measure of managers' incurred transaction costs on distraction in our usual panel regression framework (specification (1)). Given the inclusion of stock×date and stock×manager fixed effects, we are essentially testing whether distracted managers trade at worse prices compared to non- distracted ones.

Our proxy for order execution quality is the average relative transaction spread, defined as the difference between the transaction price and the previous day closing price for buys (and the same difference times minus one for sells), scaled by the previous day closing price. We then average (weighted by trading volume) the incurred spreads for buys and sells for each manager-stock-week. Transaction spreads are missing when a manager does not trade the stock in a given week.

Using this measure as the dependent variable in Table 7, we find weak support for the notion that distraction hurts execution quality: for both the ANcerno and the 13f watchlists, the effect of distraction is significantly positive but economically small (Panel A). A one standard deviation increase in distraction leads to a rise in transaction spread of about 2.5% relative to its unconditional mean (see Table 1). Panel B, further shows that this distraction effect has a similar magnitude for quasi-indexers and other institutional investors. This suggests that, while a lack of attention does not affect the trade profitability for quasi-indexers, it can affect their trade execution quality.

[Include Table 7 here.]

Taken together, our results show that distraction hurts performance: distracted managers trade less profitably and appear to be trading at slightly worse prices.

VI. Rational or Irrational Attention Allocation

A. Rational Attention Allocation?

When investors are conscious about their attention constraints, they should reallocate their attention on the basis of a cost-benefit analysis. For example, they should be less likely to divert attention from stocks that matter more to their utility (Corwin and Coughenour, 2008). Indeed, rational attention models with risk-averse investors predict that, as the attention budget tightens, investors withdraw relatively more (less) attention from stocks with low (high) ex-ante uncertainty (see appendix B). We now test whether ANcerno managers behave as prescribed by this type of theory.

In Table 8, we return to the trade propensity regressions and interact our distraction measure with measures of stock-level uncertainty.[28] The first interaction variable is an earnings announcement dummy, which flags weeks in which the stock has an earnings announcement. Since these announcements can be anticipated, attention-constrained investors can rationally choose to remain attentive to them, in which case we expect the distraction effect on the trading propensity to be reduced. The results, shown in columns 1-2, reveal that this is not the case: managers are equally distracted in announcement weeks compared to other weeks. In our second and third test, we define high-uncertainty stocks as those experiencing above-median absolute returns or share turnover. Table 8, columns 3-6, shows that the distraction effect, rather than being weaker, is actually stronger for stocks with high absolute returns and turnover—the exact opposite of what one would expect under rational attention allocation.

[Include Table 8 here.]

One potential interpretation of this result has to do with the so-called “ostrich effect”—investors’ tendency to avoid attending to bad news (Karlsson et al., 2009; Sicherman et al., 2016). The reasoning behind the ostrich effect is that information can have a direct impact on utility (Caplin and Leahy, 2001; Brunnermeier and Parker, 2005), so that facing bad news comes with the experience of a disutility. As such, investors have an incentive to look away when there is troubling news about a watchlist stock and we posit that the distraction from earnings announcements in other watchlist stocks may give them the excuse to do so.

[28] In our panel regressions, the level effect of these uncertainty measures is subsumed by the inclusion of stock×week fixed effects.

While this account is admittedly somewhat speculative, it raises the question whether attention allocation decisions can interact with and be influenced by behavioral biases and/or emotions. We now explore this possibility in more detail.

B. Exacerbating Behavioral Biases?

While an all-encompassing behavioral alternative to the rational expectation framework does not yet exist, there are some stylized facts and modelling ideas to understand behavioral cues that trigger attention/inattention. One prominent idea in this domain—the so-called *ostrich effect*—springs from belief-based utility and describes an "active information avoidance" (Caplin and Leahy, 2001; Brunnermeier and Parker, 2005; see Karlsson et al., 2009; and Sicherman et al., 2016, for empirical evidence using data on online account logins). At the heart of these models lies the assumption that information can have a direct impact on utility ("hedonic value") that is separate from its usefulness. In similar spirit, models with *realization utility* assume investors derive additional utility from realizing gains and losses over and above the utility derived from paper gain/losses (Barberis and Xiong, 2012; Ingersoll and Jin, 2013).[29]

Motivated by these theories, we study how the distraction effect for the trading propensity interacts with the past return of a stock position (measured over the previous 4 weeks). The idea is that distracted managers may choose to selectively overlook stocks that have done poorly in order to avoid facing the negative emotions associated with acknowledging a trading loss. Panels A and B of Table 9 show the results of this exercise. As indicated by the positive albeit weakly significant interaction coefficient shown in columns 1-2, the distraction effect is

[29] Using measures of neural activity obtained from functional magnetic resonance imaging (fMRI), Frydman et al. (2014) find evidence consistent with such type of preferences.

somewhat less pronounced for stock positions that trade at a gain. The flip side of this is that, consistent with an ostrich-type behavior, distracted investors are particularly unlikely to trade in stocks that have had low returns.

[Include Table 9 here.]

The realization utility framework further predicts that the interaction between distraction and past stock performance should depend on the type of the trade: when a stock has done poorly, investors with an open long position may be particularly reluctant to sell the stock (as this would lock-in a trading loss) but they may be fine buying it. Given that this argument relies on there being an outstanding position in the stock, we expect it to apply more strongly for the 13f watchlist (which is based on portfolio holdings). The results shown in columns 3-6 of Table 9 confirm this prediction: distracted investors are less likely to sell stocks with low returns, but are not less likely to buy them. For the 13f watchlist, this interaction effect is statistically significant at the 5% level.

These results lend support to theories assuming that information has a direct utility impact which can be magnified by paying attention to and/or trading on it (e.g., Karlsson et al., 2009; Barberis and Xiong, 2012). Moreover, the fact that we find a stronger distraction effect for sells following low returns hints at a connection to the disposition effect—i.e., the well-documented tendency that investors sell their winners too early while holding on to their losers (e.g., Shefrin and Statman, 1985; Odean, 1998). We explore this connection below.

C. Interaction with Salience

A recent strand in the behavioral economics literature argues that an important driver of attention allocation decisions is salience (Bordalo et al., 2014; 2015), broadly defined as how much an attribute of a certain product (e.g., the payoff of a financial asset) stands out compared to the same attribute of the average product in a choice set.[30] Perhaps one of the cleanest pieces of evidence consistent with salience-based decision making is the "rank effect" documented by Hartzmark (2015): investors are significantly more likely to sell the worst and best performing positions of their portfolios, presumably because those are more salient.[31]

In this subsection, we explore how the distraction effect interacts with the salience of a stock position, which we proxy for using an *extreme rank dummy* as proposed by Hartzmark (2015). Specifically, we define the *extreme rank dummy* to be equal to one if the return of a watchlist stock was the lowest or highest over the previous four weeks compared to all other watchlist stocks for a given investor. We then interact this variable with our distraction measure in our baseline specification. Since salient stocks catch investors' attention rather automatically (i.e., without involving a deliberate choice on the part of the investor), we expect the distraction effect to be mitigated for salient stock positions.

Our results, shown in Table 10, confirm this intuition: the distraction effect is almost fully reversed for stock positions that rank at the bottom or at the top in terms of past performance relative to the managers' other watchlist stocks. Another interpretation of this finding is that the importance of salience for explaining which stocks are traded is exacerbated at times when attention is scarce. All these results are more pronounced for sell decisions, which Hartzmark

[30] Bordelo et al. (2013) and Cosemans and Frehen (2017) document the implications of Salience Theory for asset pricing. Barber and Odean (2008) find evidence of salience-induced buying pressure from retail investors.

[31] Because a stock's performance ranking varies investor-by-investor, Hartzmark (2015) is able to rule out that this behavior is explained by stock-specific factors. Moreover, he also finds a similar rank effect for an economically meaningless ranking based on an alphabetical ordering of portfolio positions.

(2015) shows to be more affected by the rank effect.[32] Finally, note that the level effect of the extreme rank dummy is significantly positive, implying that extremely ranked stocks are more likely to be traded (especially sold). Thus, the rank effect shows up unconditionally in our sample of ANcerno trades.

[Include Table 10 here.]

D. Distraction and Disposition Effect

The disposition effect is one of the most robust facts about the trading behavior of individual as well as institutional investors and describes their preference for selling stock positions trading at a gain compared to ones trading at a loss.[33] In this subsection, we investigate the possibility that inattention can exacerbate the disposition effect. The literature suggests two reasons why this might be the case: First, there is evidence that investors can learn to avoid the disposition effect with conscious effort and experience (Feng and Seasholes, 2005; Seru et al., 2010). In similar spirit, we argue that investors may require attention/mental effort in order to avoid succumbing to the disposition effect. Second, under realization utility preferences, a distracted investor may choose to forgo selling a loser (so as to further delay its realization) while still selling his winners. Our evidence presented in Table 9 was consistent with this view.

Here, we directly measure the extent of the disposition effect at the manager-week level and explore how it correlates with our distraction proxy. Following Odean (1998), the disposition effect measure is calculated as the proportion of gains realized (PGR) minus the proportion of

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[32] Compare Table 4 in Hartzmark (2015) with Table IA.25 of the accompanying internet appendix.

[33] For individual investors, see Shefrin and Statman (1985), Odean (1998) and Grinblatt and Keloharju (2001). For institutional investors and asset pricing implications, see Grinblatt and Han (2005) and Frazzini (2006).

losses (PLR) realized. Specifically, for each manager, we keep track of the average purchase price for all open stock positions (based on that manager's trading history). Then, for each week in which the manager sells at least one stock, we calculate the PGR (PLR) as the number of positions sold at a gain (loss) over the total number of positions that could have been sold at a gain (loss) in that week and take the difference. Unconditionally, we find a statistically significant disposition effect of 1.18 percentage points (t-statistic of 3.5). To ensure that there is no mechanical relation between the dependent and the independent variable, we exclude earnings announcement stocks before calculating the disposition effect measure.

Table 11 shows the results from regressing the disposition effect measure on our distraction proxy aggregated at the manager-week level.[34] Manager and time fixed effects are included to soak up all time-invariant variation (controlling for, e.g., return seasonalities coinciding with the earnings season) and manager-invariant variation (controlling for, e.g., a manager-specific predisposition to succumb to the disposition effect). We also control for managers' watchlist sizes and past trading volumes.

[Include Table 11 here.]

As shown in Table 11, column 1, we find a significantly positive association between distraction and the extent of the disposition effect for the specification with manager and month fixed effects: a one-standard deviation increase in distraction leads to an increase in the disposition effect of about 0.1 percentage points, representing a relative increase of about 8.5%. The effect shrinks and becomes less significant, however, when the month fixed effects are replaced by

[34] The aggregated distraction measure simply equals the (weighted) fraction of watchlist stocks that have an earnings announcement in a given week.

finer week fixed effects, suggesting that it was driven in part by variation of average distraction over time (which is itself driven by the earnings season). Overall, the results are (weakly) consistent with the idea that distracted managers are more prone to the disposition effect. At a broader level, they suggest that the impact of behavioral biases can be countered by devoting costly cognitive resources (i.e., attention/mental effort)—implying that those biases are exacerbated when attention is missing.

VII. Robustness

In this section, we present robustness checks for the effect of distraction on our four variables of interest. Table 12, Panels A-D contain the results. For brevity, we only show the coefficient on the distraction measure, although we always run the full specification with and without 13f controls.

[Include Table 12 here.]

In our first robustness check, we calculate the distraction measure as before, except that we now exclude from the calculation not only the stock in question, but all stocks in the same Fama-French 49 industry. The idea is that earnings announcements may represent important economic news events for all stocks in the same industry, and hence distraction would be better defined by looking at earnings announcements among stocks in *other* industries. As shown in row 1 of Panels A-D, distraction continues to have a negative effect on the trading propensity and trade profitability, a positive effect on transaction costs, and an insignificant effect on trading volume.

Second, we address the concern that our results could be driven by institutional capital or risk management constraints. When such constraints are binding, an institution's decision to trade upon the earnings announcement of a watchlist stock is certainly interlinked with its decision to trade in other stocks. We argue, however, that in its most straightforward interpretation, such an explanation will predict the opposite of what we find. For example, suppose an institution wants to buy a stock with a positive earnings surprise. If the institution is capital constrained, it may need to sell another position in order to finance this purchase. But then we would expect to find *more* and not less trading of other watchlist stocks when there are many earnings announcements. Hence, a more subtle variant of this explanation is needed to explain our results. For instance, one may argue that institutions are reluctant to close existing positions but hold a certain cash balance (or face a limited risk-taking capacity) for entering new trades. Buying the announcing stock will then mean there is less money (or risk-taking capacity) for buying other stocks.

To control for this possibility, we include the (logarithm of the) total amount traded in announcing stocks as a control variable (while excluding all stock-weeks with an earnings announcement). The idea is that, if our results are driven by capital constraints, then it should be the actual trades in announcing stocks that matter. In other words, if an institution does not trade on the earnings announcement (so that the capital constraint is unaffected), there is no reason to expect it to trade less in other stocks. Focusing on the trading propensity, Panel A, row 2 shows that both the statistical and economic significance of the measured distraction effect is largely increased by the inclusion of the control (which itself has a significantly positive coefficient, not shown for brevity). This could mean that the true distraction effect was indeed attenuated by the presence of capital/risk management constraints (as conjectured in the "straightforward" interpretation above). We nevertheless prefer the specification without this control, because the decision to trade in announcing stocks is certainly endogenous (and not predetermined as for the other controls). For the other outcome variables, the inclusion of this control has virtually no effect.

Third, we modify the distraction measure to take into account the surprise of the earnings announcement. The idea is that a more surprising earnings announcement requires more attention to digest, therefore causing a stronger distraction effect. To test whether this is the case, we follow standard practice and calculate the earnings surprise as the difference between the actual earnings figure and the median earnings forecast reported in I/B/E/S, scaled by the stock's price five days prior to the announcement. We then take the absolute value of the earnings surprise and group the resulting measure into quintiles. Finally, we replace the earnings announcement dummy in our definition of the distraction measure by the absolute earnings surprise quintile:[35]

$$distraction(EA\ surprise)_{imt} = \frac{\sum_{j \neq i} w_{jmt}^{x} \times |EA\ surprise\ quintile|_{jt}}{\sum_{j \neq i} w_{jmt}^{x}}$$

When we repeat our analyses with this modified distraction measure, we again find a significantly negative distraction effect for the trading propensity and trade profitability, as well as an increase in transaction costs (see row 3 in Panels A-D). In terms of economic magnitude, a one standard deviation increase in distraction (24%), causes a drop in the propensity to trade by about 2-3%, which is comparable to what we found in our baseline case

[35] In order not to lose all the observations when there is no earnings announcement, we set the absolute earnings surprise quintile to zero for stock-weeks in which there was no earnings announcement. The absolute earnings surprise quintile thus takes on values from 0 (no announcement), over 1 (small earnings surpise) to 5 (large earnings surprise).

(see Table 2). For the other outcome variables, the economic magnitudes are again similar to those from before.

In our final robustness check, we redefine once more our distraction measure in order to remedy one unappealing feature of the original definition. To see the issue, suppose a manager has three watchlist stocks: stock A with a weight of 0.4, stock B with a weight of 0.4, and stock C with a weight of 0.2. Suppose further that stock A has an earnings announcement. With the original definition, the distraction measure would be 0 for stock A, 2/3 for stock B and 1/2 for stock C. Thus, it would appear as if distraction is higher for stock B compared to stock C, although this difference is only due to the respective watchlist weight that is excluded. In other words, the within-manager variation in our original distraction measure is not likely to be very meaningful.

For this reason, we now calculate distraction as:

$$distraction(alternative)_{imt} = \sum_{j \neq i} w_{jmt} \times EA\ dummy_{jt}$$

In the example above, this definition yields a distraction of 0 for stock A, and 0.4 for stocks B and C. Hence, distraction now appears similar for stocks B and C. We repeat our regressions with this new measure, after excluding earnings announcements from the sample. Now distraction *only* varies across manager-weeks (while being the same for all stocks of the same manager). As shown in row 4 of Panels A-D, our results for all four outcome variables are qualitatively and quantitatively similar to those from before.

VIII. Conclusion

Exploring detailed transaction records, we investigate and quantify attention constraints among professional asset managers. These investors employ significant resources to overcome attention constraints: they hire research staff, acquire access to real-time news feeds and invest in computer capacities for algorithmic trading or smart order-routing. We find that, despite of these efforts, attention constraints occasionally appear to be binding. Specifically, we find that managers with a large fraction of watchlist stocks exhibiting an earnings announcement are significantly less likely to trade in other stocks compared to non-distracted managers, but—conditional on trading—they do not trade in smaller amounts. We further present evidence that distracted managers trade less profitably and incur higher transaction costs, although both of these effects are economically small.

Our trade-level analysis allows us to study in great detail the drivers of institutional investors' attention allocation decisions. Doing so, we document a number of facts that are hard to square with rational attention models: First, the absence of a distraction effect at the intensive margin of trading speaks against models in which attention-constrained investors gather less precise trading signals—a standard assumption in rational attention models (e.g., Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016). Second, we do not find that the distraction effect is less pronounced for stocks with high uncertainty, even though paying attention to such stocks is clearly in the interest of investors. Third, we do on the other hand find that the distraction effect is weaker for watchlist stocks that trade at a gain, suggesting that distracted managers redirect their attention in a way that makes them feel better. This exacerbates the disposition effect, and should therefore hurt managers' overall performance. Finally, we show that the distraction effect is mediated by a stock's salience.

Overall, our results shed a sobering light on the ability of rational attention models to explain the observed trading behavior of institutional investors. Rather, they suggest that, even for these professional investors, attention allocation decisions are influenced by subconscious and/or psychological factors such as salience and emotions toward gains and losses. This calls for more research to better understand what really drives attention allocation decisions.

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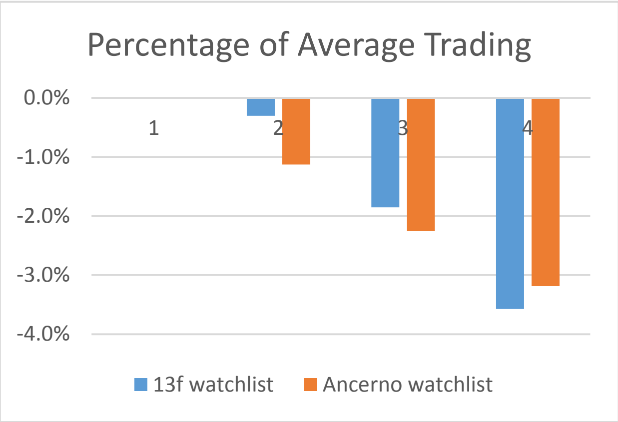
Figure 1: Distraction and Trading Propensity

This figure shows the economic magnitude of the distraction effect for different distraction quartiles. The economic magnitude is measured as the reduction in the propensity to trade, relative to its unconditional mean. The numbers come from regressions similar to the ones in Table 2, except that the continuous distraction measure is replaced by quartile dummies. The numbers for quartiles 2 to 4 show the additional distraction relative to quartile 1 (least distraction). Panel A shows the quartile results for the overall sample that includes all managers. Panel B shows the quartile results for the subset of managers that are classified as non-indexers according to Bushee and Noe (2000) and Bushee (2001). The orange and blue bars show results for the ANcerno trade-based and 13f holdings-based watchlists, respectively.

Panel A: All managers



Panel B: Non-indexers only

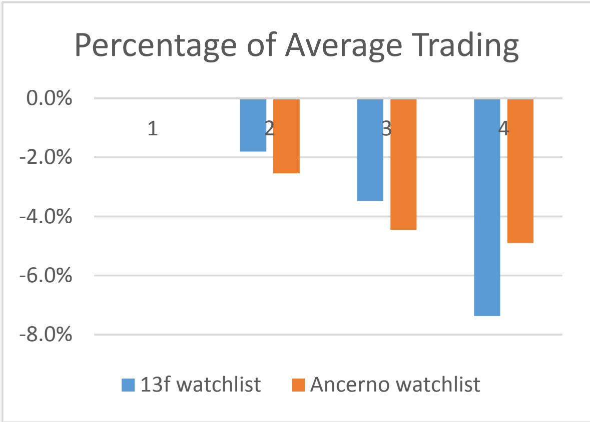


Table 1: Summary Statistics

This table describes the data used in our study. In Panel A, we show summary statistics for all variables used in our panel regressions. The "ANcerno sample – full" contains all stock-manager-week combinations that are part of the ANcerno watchlist. The "ANcerno sample – 13f match" contains the subsample of "ANcerno sample – full" for which we could match 13f holdings data at the end of the previous quarter. The "13f based sample" contains all stock-manager-week combinations that are part of the 13f watchlist. *Distraction (ANcerno)* is defined as the weighted fraction (in %) of a manager's watchlist stocks that have an earnings announcement. For the ANcerno watchlist, the weights correspond to the fraction of trading volume in the particular stock over the past 12 weeks. For the 13f watchlist, the weights correspond to the fraction of portfolio holdings in the particular stock at the end of the previous quarter. *Stocks on watchlist* is the logarithm of the number of stocks on the manager's watchlist. *Trade volume* is the weekly trading volume in the stock (if it is positive) in million $. *Trade number* is the number of days on which the stock was traded in the last 12 weeks. *Trade volume manager* is the total trading volume of the manager in the past 12 weeks (in m$). *Trade (dummy)* is a dummy variable equal to one if the manager trades the stock in that week. *Buy (dummy)* is a dummy variable equal to one if the manager bought the stock at least once in the week. *Sell (dummy)* is a dummy variable equal to one if the manager sold the stock at least once in the week. *Trade profitability* is the post-trade return for buys and the post-trade return times minus one for sells. Post-trade returns are calculated over the subsequent 4 weeks of the transaction week. *Relative transaction spread* is the difference between the transaction price and the previous day closing price for buys (and the same difference times minus one for sells), scaled by the previous day closing price. *Assets under Management* is the amount of assets under management according to 13f (in b$). *Change in AuM* is the percentage change in assets under management of the manager in the preceding quarter. In Panel B, we report results of a trade persistence analysis at the manager-week level. For each watchlist (ANcerno and 13f), it shows the mean number of stocks on the watchlist, the mean number of those stocks that are traded in the next week, and the fraction of the two. This fraction is compared to a similar fraction of traded stocks for a Placebo watchlist; ie., a randomly-assembled watchlist. The last column reports the *t*-statistic of a difference-in-mean test clustered at the manager-level. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary statistics for all variables

	ANcerno sample - full			ANcerno sample - 13f match			13f based sample		
	Median	Mean	StD	Median	Mean	StD	Median	Mean	StD
Distraction	3.1	7.9	10.3	3.1	7.8	10.3	3.1	8.1	10.8
Stocks on watchlist (log)	6.62	6.42	1.20	6.44	6.31	1.24	7.18	6.90	1.12
Trade volume (m$)	0.12	1.87	11.04	0.15	2.03	12.11	0.16	2.16	12.80
Trade number (t-12,t-1)	3	7.5	10.6	3	8.3	12.3	0	3.1	9.0
Trade volume manager (t-12,t-1) (b$)	1.3	10.7	24.7	1.3	12.7	26.3	0.2	6.1	19.0
Trade (dummy)	0.00	0.28	0.45	0.00	0.29	0.46	0.00	0.11	0.32
Buy (dummy)	0.00	0.18	0.38	0.00	0.20	0.40	0.00	0.08	0.27
Sell (dummy)	0.00	0.18	0.38	0.00	0.18	0.38	0.00	0.07	0.25
Trade profitability (%)	0.02	0.05	13.86	0.07	0.09	14.10	0.08	0.09	13.98
Relative transaction spread (%)	0.17	0.41	1.03	0.16	0.38	1.01	0.16	0.37	0.99
Assets under Management (b$)				10.1	90.2	149.0	19.1	99.5	154.6
Change in AuM (%)				2.8	2.2	14.2	2.6	2.5	13.8
Number of Observations	57,382,705			17,900,548			40,436,769		

Panel B: Trade persistence for ANcerno and 13f watchlists

	Mean # stocks on watchlist	Mean # traded stocks on watchlist	Fraction traded (in %)	Placebo: Fraction traded (in %)	t-statistic of difference
ANcerno watchlist	275.75	82.36	20.43	4.16	(39.93)***
13f watchlist	486.83	64.58	13.30	3.45	(11.87)***

Table 2: Distraction and Trading Propensity

This table shows results of stock-manager-week level regressions of managers' trading propensity on the distraction measure (specification (1) in the text). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. In columns 1-2, trading propensity is measured by a dummy that takes the value one if the manager trades a given stock in a given week and zero otherwise. Columns 3-4 and 5-6 separate between the buy and sell propensity, respectively. Panel A shows results for the ANcerno watchlist; Panel B shows results for the 13f watchlist. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: ANcerno watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0611***	-0.0837***	-0.0473***	-0.0486***	-0.0319***	-0.0660***
	(-4.57)	(-4.34)	(-4.26)	(-3.78)	(-3.24)	(-3.38)
Stocks on watchlist (log)	0.0175***	0.0089	0.0111***	0.0031	0.0136***	0.0015
	(4.46)	(1.37)	(3.47)	(0.64)	(4.33)	(0.21)
Trade volume manager (t-12,t-1) (log)	0.0167***	0.0191***	0.0080***	0.0109***	0.0109***	0.0128***
	(6.82)	(4.99)	(3.74)	(2.84)	(6.04)	(3.62)
Trade number (t-12,t-1)	0.0154***	0.0135***	0.0135***	0.0123***	0.0144***	0.0138***
	(20.74)	(10.15)	(46.23)	(21.04)	(56.48)	(52.17)
Assets under Management (log)		0.0053		0.0073**		0.0024
		(1.32)		(2.24)		(0.64)
Change in AuM (%)		-0.0107		0.0084		-0.0244**
		(-0.75)		(0.75)		(-2.35)
Number of Observations	57,313,471	17,701,215	57,313,471	17,701,215	57,313,471	17,701,215
Adjusted-R^2	0.32	0.37	0.32	0.41	0.29	0.31
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: 13f watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0354***	-0.0353***	-0.0207***	-0.0203***	-0.0227**	-0.0228**
	(-3.25)	(-3.22)	(-3.25)	(-3.19)	(-2.32)	(-2.32)
Stocks on watchlist (log)	0.0085	0.0158	0.0044	0.0061	-0.0002	-0.0032
	(1.29)	(1.57)	(1.28)	(1.20)	(-0.05)	(-0.42)
Trade volume manager (t-12,t-1) (log)	0.0117***	0.0119***	0.0049***	0.0049***	0.0055***	0.0054***
	(4.42)	(4.39)	(3.79)	(3.78)	(4.13)	(4.18)
Trade number (t-12,t-1)	0.0158***	0.0159***	0.0140***	0.0140***	0.0147***	0.0147***
	(8.68)	(8.92)	(25.00)	(25.56)	(49.88)	(46.76)
Assets under Management (log)		-0.0087		-0.0022		0.0037
		(-1.37)		(-0.61)		(0.64)
Change in AuM (%)		-0.0040		0.0055		-0.0058
		(-0.63)		(1.52)		(-1.26)
Number of Observations	39,413,266	39,241,617	39,413,266	39,241,617	39,413,266	39,241,617
Adjusted-R^2	0.48	0.48	0.49	0.49	0.38	0.38
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Distraction and Trading Volume

This table shows results of stock-manager-week level regressions of managers' trading volume on the distraction measure (specification (1) in the text). Trading volume is measured by the logarithm of the dollar trading volume (buys plus sells) by the manager in a given stock and week. The measure is set to missing if the manager does not trade in the stock in a given week. Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Columns 1-2 show results for the ANcerno watchlist; columns 3-4 show results for the 13f watchlist. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Trading Volume (log)			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
Distraction	-0.0580	-0.1244	-0.0624	-0.0649
	(-0.51)	(-0.50)	(-0.23)	(-0.23)
Stocks on watchlist (log)	-0.5810***	-0.4582***	-0.1100	-0.2050
	(-12.63)	(-6.72)	(-1.06)	(-1.24)
Trade volume manager (t-12,t-1) (log)	0.3940***	0.3614***	0.1749***	0.1745***
	(15.90)	(8.66)	(4.83)	(4.78)
Trade number (t-12,t-1)	0.0312***	0.0262***	0.0253***	0.0247***
	(9.40)	(11.08)	(9.97)	(9.65)
Assets under Management (log)		-0.0112		0.1524
		(-0.19)		(1.15)
Change in AuM (%)		0.1428		0.0565
		(0.97)		(0.36)
Number of Observations	16,293,088	5,249,252	4,609,571	4,595,689
Adjusted-R^2	0.46	0.46	0.46	0.46
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Table 4: Trading Propensity – Excluding Quasi-Indexers

This table shows a sample split by whether a manager is a quasi-indexer or not. We run stock-manager-week level regressions of managers trading activity on the distraction measure (specification (1) in the text). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Columns 1-2 and 3-4 show results for the ANcerno watchlist and the 13f watchlist, respectively. In columns 1 and 3, we include only managers that are identified as quasi-indexers according to the classification by Bushee and Noe (2000) and Bushee (2001), while we exclude those managers in columns 2 and 4. The statistical significance of the difference between the two subgroups is reported at the bottom of the table. This significance is based on a regression model where all explanatory variables and fixed effects are interacted with a dummy equal to one if the manager is a quasi-indexer. All variables are defined in Appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Trade (dummy)			
Sample:	ANcerno watchlist		13f watchlist	
Subsample:	Quasi-indexer	Other	Quasi-indexer	Other
	(1)	(2)	(3)	(4)
Distraction	-0.0470**	-0.1272***	-0.0033	-0.0737***
	(-2.23)	(-4.36)	(-0.32)	(-2.97)
Stocks on watchlist (log)	0.0085	0.0202**	0.0231	0.0069
	(1.10)	(1.98)	(1.63)	(0.90)
Trade volume manager (t-12,t-1) (log)	0.0171***	0.0132**	0.0109***	0.0138***
	(3.12)	(2.36)	(3.56)	(4.40)
Trade number (t-12,t-1)	0.0115***	0.0159***	0.0141***	0.0174***
	(8.30)	(21.90)	(8.30)	(12.29)
Assets under Management (log)	0.0097**	-0.0031	-0.0097	-0.0020
	(2.18)	(-0.65)	(-1.42)	(-0.29)
Change in AuM (%)	-0.0393	-0.0032	-0.0052	0.0028
	(-1.58)	(-0.17)	(-0.63)	(0.31)
Number of Observations	8,028,495	6,715,463	21,990,021	11,254,609
Adjusted-R^2	0.48	0.25	0.56	0.36
Difference in Distraction (t-stat)	2.23**		2.69***	
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Table 5: Trading Propensity – Sample Splits by Manager Characteristics

This table shows results for sample splits for the stock-manager-week level regressions of managers trading propensity on the distraction measure (specification (1) in the text). Each row represents a different sample split as indicated in the row header (and explained in Section IV.C). The specification is the same as the one from Table 2. For brevity, the table only shows the coefficient on the distraction measure. Columns 1-3 and 5-7 show results for the ANcerno and 13F watchlists, respectively. Columns 4 and 8 show the test statistics of the difference between the high/yes and low/no groups. These significance tests are based on a regression model where all explanatory variables and fixed effects are interacted with a dummy equal to one if an observation is in the high/yes group and zero if it is in the low/no group. The split variables are defined as follows: 1) turnover is the manager's average dollar trading volume in watchlist stocks over their market capitalization. 2) trade activeness is defined as the minimum of a manager's dollar buys and dollar sells, divided by his total trading volume. 3) industry concentration is defined as the Herfindahl concentration index of a manager's reported stock holdings across Fama-French 49 industries. 4) Institution AuM is the institution's average assets under management. 5) Watchlist size is the average number of stocks on the institution's watchlist. 6) Average profits is the average 48-weeks ahead portfolio return of the watchlist portfolio. 7) Hedge fund is a dummy variable equal to one for hedge funds and zero otherwise (obtained from Russell Jame; explained in Jame, 2016). All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Trade (dummy)							
	ANcerno watchlist				13F watchlist			
Sample Split by:	Low/No	Medium	High/Yes	t-stats Difference	Low/No	Medium	High/Yes	t-stats Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1) Turnover	-0.0085	-0.0967***	-0.1194***	-2.60***	0.0025	-0.0395**	-0.0642**	-2.39**
	(-0.37)	(-3.10)	(-3.26)		(0.26)	(-2.60)	(-2.44)	
2) Trade activeness	-0.0148	-0.0453*	-0.1321***	-2.93***	0.0112	-0.0048	-0.0739***	-3.54***
	(-0.46)	(-1.77)	(-4.02)		(1.05)	(-0.50)	(-3.42)	
3) Industry concentr.	-0.1481***	-0.0251	-0.0446*	2.12**	-0.0418*	-0.0359***	-0.0148	1.04
	(-3.44)	(-0.98)	(-1.72)		(-1.76)	(-2.62)	(-1.23)	
4) Institution AuM	-0.0505***	-0.1111***	-0.1596**	-1.72*	-0.0186**	-0.0488**	-0.0639	-1.02
	(-3.08)	(-3.06)	(-2.61)		(-2.34)	(-2.10)	(-1.45)	
5) Watchlist size	-0.0366	-0.0374*	-0.1322***	-2.47**	-0.0122	-0.0130	-0.0409**	-1.31
	(-1.09)	(-1.70)	(-4.07)		(-0.74)	(-1.08)	(-2.23)	
6) Average profits	-0.0489	-0.1183***	-0.0254	0.48	-0.0509***	-0.0204*	-0.0431*	0.26
	(-1.36)	(-4.04)	(-0.76)		(-2.70)	(-1.76)	(-1.82)	
7) Hedge fund	-0.0848***	N/A	-0.0538	-0.77	-0.0379***	N/A	-0.0208	0.98
	(-3.82)		(-1.18)		(-3.07)		(-1.33)	
Past Trade controls	Yes	Yes	Yes		Yes	Yes	Yes	
AuM & change in AuM	Yes	Yes	Yes		Yes	Yes	Yes	
Stock×Week f.e.	Yes	Yes	Yes		Yes	Yes	Yes	
Manager×Week f.e.	Yes	Yes	Yes		Yes	Yes	Yes	

Table 6: Distraction and Trade Profitability

This table shows results of stock-manager-week level regressions of trade profitability on the distraction measure (specification (1) in the text). The dependent variable is the post-trade return for buys and the post-trade return times minus one for sells. Post-trade returns are calculated over the subsequent 4 weeks of the transaction week. Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Panel A shows the results for the whole sample. Panel B shows a sample split by whether a manager is a quasi-indexer or not. In both panels, columns 1-2 and 3-4 show results for the ANcerno watchlist and the 13f watchlist, respectively. In Panel B, columns 1 and 3, we include only managers that are identified as quasi-indexers according to the classification by Bushee and Noe (2000) and Bushee (2001), while we exclude those managers in columns 2 and 4. The statistical significance of the difference between the two subgroups is reported at the bottom of the table. This significance is based on a regression model where all explanatory variables and fixed effects are interacted with a dummy equal to one if the manager is a quasi-indexer. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Overall

Dependent Variable:	Trade Profitability			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
Distraction	-0.0097*	-0.0072*	-0.0185**	-0.0199**
	(-1.93)	(-1.71)	(-2.14)	(-2.26)
Stocks on watchlist (log)	0.0002	0.0005	0.0004	-0.0006
	(0.26)	(0.32)	(0.34)	(-0.31)
Trade volume manager (t-12,t-1) (log)	-0.0001	-0.0007	-0.0007	-0.0007
	(-0.29)	(-0.75)	(-1.27)	(-1.33)
Trade number (t-12,t-1)	-0.0001***	-0.0001***	-0.0001***	-0.0001**
	(-4.97)	(-2.72)	(-2.83)	(-2.55)
Assets under Management (log)		0.0004		0.0015
		(0.64)		(1.04)
Change in AuM (%)		-0.0026		-0.0038
		(-1.15)		(-1.00)
Number of Observations	15,735,084	4,605,102	3,936,029	3,921,673
Adjusted-R^2	0.09	0.10	0.10	0.10
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Panel B: Excluding Quasi-Indexers

Dependent Variable:	Trade Profitability			
Sample:	ANcerno watchlist		13f watchlist	
Subsample:	Quasi-indexer	Other	Quasi-indexer	Other
	(1)	(2)	(3)	(4)
Distraction	0.0028	-0.0183**	0.0046	-0.0290***
	(0.47)	(-2.52)	(0.66)	(-3.06)
Stocks on watchlist (log)	0.0002	-0.0019	0.0030	-0.0036
	(0.16)	(-1.12)	(1.59)	(-1.31)
Trade volume manager (t-12,t-1) (log)	-0.0000	0.0002	0.0003	-0.0005
	(-0.03)	(0.20)	(0.62)	(-0.64)
Trade number (t-12,t-1)	-0.0001***	-0.0001	-0.0001***	-0.0001
	(-3.77)	(-1.06)	(-4.67)	(-0.93)
Assets under Management (log)	-0.0006	-0.0003	-0.0028**	0.0013
	(-0.63)	(-0.56)	(-2.16)	(0.99)
Change in AuM (%)	0.0006	-0.0117	0.0012	-0.0084
	(0.34)	(-1.65)	(0.43)	(-1.10)
Number of Observations	1168041	1823898	909281	1759716
Adjusted-R^2	0.09	0.10	0.11	0.10
Difference in Distraction (t-stat)	1.89*		2.19**	
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Table 7: Distraction and Transaction Costs

This table shows results of stock-manager-week level regressions of transaction costs on the distraction measure (specification (1) in the text). The dependent variable is the relative transaction spread, defined as the difference between the transaction price and the previous day closing price for buys (and the same difference times minus one for sells), scaled by the previous day closing price. Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Panel A shows the results for the whole sample. Panel B shows a sample split by whether a manager is a quasi-indexer or not. In both panels, columns 1-2 and 3-4 show results for the ANcerno watchlist and the 13f watchlist, respectively. In Panel B, columns 1 and 3, we include only managers that are identified as quasi-indexers according to the classification by Bushee and Noe (2000) and Bushee (2001), while we exclude those managers in columns 2 and 4. The statistical significance of the difference between the two subgroups is reported at the bottom of the table. This significance is based on a regression model where all explanatory variables and fixed effects are interacted with a dummy equal to one if the manager is a quasi-indexer. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Overall

Dependent Variable:	Relative Transaction Spread			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
Distraction	0.0009*	0.0011**	0.0013***	0.0012**
	(1.95)	(2.53)	(2.83)	(2.55)
Stocks on watchlist (log)	0.0000	0.0001	-0.0001	0.0001
	(0.74)	(1.05)	(-0.60)	(0.38)
Trade volume manager (t-12,t-1) (log)	0.0000	0.0001	0.0001**	0.0001**
	(0.91)	(0.90)	(2.15)	(2.18)
Trade number (t-12,t-1)	0.0000	-0.0000	-0.0000	-0.0000
	(1.36)	(-0.72)	(-0.51)	(-0.14)
Assets under Management (log)		-0.0001		-0.0002
		(-1.28)		(-1.62)
Change in AuM (%)		-0.0001		0.0002
		(-0.49)		(0.42)
Number of Observations	15,299,987	4,504,960	3,852,202	3,838,117
Adjusted-R^2	0.07	0.07	0.06	0.06
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Panel B: Excluding Quasi-Indexers

Dependent Variable:	Relative Transaction Spread			
Sample:	ANcerno watchlist		13f watchlist	
Subsample:	Quasi-indexer	Other	Quasi-indexer	Other
	(1)	(2)	(3)	(4)
Distraction	0.0009*	0.0010	0.0011*	0.0010
	(1.83)	(1.64)	(1.78)	(1.59)
Stocks on watchlist (log)	0.0001	0.0003	0.0002*	0.0000
	(0.77)	(1.65)	(1.66)	(0.02)
Trade volume manager (t-12,t-1) (log)	0.0001	-0.0001	0.0001**	0.0000
	(1.03)	(-0.77)	(2.44)	(0.70)
Trade number (t-12,t-1)	0.0000	0.0000	0.0000	0.0000
	(0.97)	(0.21)	(1.12)	(0.67)
Assets under Management (log)	-0.0001	0.0000	-0.0001	0.0001
	(-1.10)	(0.44)	(-1.24)	(0.34)
Change in AuM (%)	0.0006	-0.0003	0.0010	-0.0002
	(0.91)	(-1.21)	(1.25)	(-0.52)
Number of Observations	1,831,393	1,171,891	1,767,715	912,207
Adjusted-R^2	0.05	0.05	0.05	0.06
Difference in Distraction (t-stat)	0.34		0.57	
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes

Table 8: Trading Propensity – Rational Attention Allocation?

This table shows results of stock-manager-week level regressions of managers' trading propensity on the distraction measure (specification (1) in the text). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. In columns 1-2, the distraction measure is interacted with a dummy variable that equals one if there is an earnings announcement for the given stock×week and zero otherwise (EA dummy). In columns 3-4, the distraction measure is interacted with a dummy variable that equals one if the absolute return of a given stock×week is above median and zero otherwise (HighAbsret dummy). In columns 5-6, the distraction measure is interacted with a dummy variable that equals one if the turnover of a given stock×week is above median and zero otherwise (HighTurnover). The level effects of the interaction variables are subsumed by the stock×week fixed effects. In Panel A, we conduct the analysis for the ANcerno watchlist and in Panel B for the 13f watchlist. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: ANcerno watchlist

Dependent Variable:	Trade (dummy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0607***	-0.0806***	-0.0544**	-0.0410	-0.0131	0.0076
	(-4.45)	(-4.04)	(-2.14)	(-1.21)	(-0.63)	(0.25)
Distraction×EA	-0.0019	-0.0170				
	(-0.21)	(-1.03)				
Distraction×HighAbsret			-0.0048	-0.0303*		
			(-0.41)	(-1.79)		
Distraction×HighTurnover					-0.0264**	-0.0500***
					(-2.49)	(-2.86)
Stocks on watchlist (log)	0.0175***	0.0089	0.0175***	0.0089	0.0175***	0.0089
	(4.47)	(1.38)	(4.48)	(1.39)	(4.48)	(1.39)
Trade volume manager (t-12,t-1) (log)	0.0167***	0.0191***	0.0167***	0.0191***	0.0167***	0.0191***
	(6.84)	(5.05)	(6.84)	(5.05)	(6.84)	(5.05)
Trade number (t-12,t-1)	0.0154***	0.0135***	0.0154***	0.0135***	0.0154***	0.0135***
	(20.80)	(10.28)	(20.81)	(10.27)	(20.81)	(10.27)
Assets under Management (log)		0.0053		0.0053		0.0053
		(1.34)		(1.34)		(1.34)
Change in AuM (%)		-0.0107		-0.0106		-0.0106
		(-0.76)		(-0.75)		(-0.75)
Number of Observations	56,996,731	17,253,471	56,939,099	17,237,498	56,939,297	17,237,566
Adjusted-R^2	0.31	0.36	0.31	0.36	0.31	0.36
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: 13f watchlist

Dependent Variable:	Trade (dummy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0384***	-0.0382***	-0.0164	-0.0173	0.0084	0.0083
	(-3.48)	(-3.44)	(-0.99)	(-1.05)	(0.56)	(0.55)
Distraction×EA	0.0164*	0.0157*				
	(1.84)	(1.75)				
Distraction×HighAbsret			-0.0135	-0.0127		
			(-1.55)	(-1.46)		
Distraction×HighTurnover					-0.0250***	-0.0249***
					(-2.84)	(-2.77)
Stocks on watchlist (log)	0.0085	0.0158	0.0085	0.0158	0.0085	0.0158
	(1.30)	(1.57)	(1.30)	(1.57)	(1.30)	(1.57)
Trade volume manager (t-12,t-1) (log)	0.0117***	0.0119***	0.0117***	0.0119***	0.0117***	0.0119***
	(4.44)	(4.41)	(4.44)	(4.41)	(4.44)	(4.41)
Trade number (t-12,t-1)	0.0158***	0.0159***	0.0158***	0.0159***	0.0158***	0.0159***
	(8.72)	(8.96)	(8.73)	(8.97)	(8.73)	(8.97)
Assets under Management (log)		-0.0087		-0.0087		-0.0087
		(-1.37)		(-1.37)		(-1.37)
Change in AuM (%)		-0.0040		-0.0040		-0.0040
		(-0.63)		(-0.63)		(-0.63)
Number of Observations	39,093,780	38,921,958	39,082,971	38,911,171	39,083,221	38,911,421
Adjusted-R^2	0.48	0.48	0.48	0.48	0.48	0.48
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Trading Propensity – Exacerbating Behavioral Biases?

This table shows results of stock-manager-week level regressions of managers' trading propensity on the distraction measure (specification (1) in the text). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. In columns 1-2, the dependent variable is the trade propensity; i.e., a dummy variable that takes the value one if the manager buys or sells the stock. In columns 3-4, the dependent variable is the buy propensity; i.e., a dummy that takes the value one if the manager buys a given stock in a given week and zero otherwise. In columns 5-6, the dependent variable is the sell propensity; i.e., a dummy variable that takes the value one if the manager sells the stock. In all columns, the distraction measure is interacted with the stock's return in the previous four weeks (PastReturn). The level effects of the PastReturn interaction variables is subsumed by the stock×week fixed effects. In Panel A, we conduct the analysis for the ANcerno watchlist and in Panel B for the 13f watchlist. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: ANcerno watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0610***	-0.0837***	-0.0474***	-0.0488***	-0.0316***	-0.0659***
	(-4.56)	(-4.39)	(-4.27)	(-3.84)	(-3.22)	(-3.43)
Distraction×PastReturn	0.0456	0.0492	-0.0194	-0.0292	0.0457*	0.0670*
	(1.41)	(1.59)	(-0.59)	(-0.82)	(1.94)	(1.75)
Stocks on watchlist (log)	0.0175***	0.0089	0.0111***	0.0031	0.0136***	0.0014
	(4.47)	(1.38)	(3.47)	(0.64)	(4.33)	(0.21)
Trade volume manager (t-12,t-1) (log)	0.0167***	0.0190***	0.0080***	0.0109***	0.0109***	0.0127***
	(6.83)	(5.04)	(3.74)	(2.88)	(6.05)	(3.66)
Trade number (t-12,t-1)	0.0154***	0.0135***	0.0135***	0.0123***	0.0144***	0.0138***
	(20.78)	(10.23)	(46.25)	(21.16)	(56.88)	(53.21)
Assets under Management (log)		0.0054		0.0072**		0.0025
		(1.36)		(2.27)		(0.68)
Change in AuM (%)		-0.0105		0.0084		-0.0244**
		(-0.75)		(0.77)		(-2.37)
Number of Observations	56,833,924	17,201,876	56,833,924	17,201,876	56,833,924	17,201,876
Adjusted-R^2	0.31	0.36	0.31	0.40	0.29	0.30
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: 13f watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0356***	-0.0355***	-0.0206***	-0.0203***	-0.0228**	-0.0229**
	(-3.29)	(-3.26)	(-3.27)	(-3.20)	(-2.35)	(-2.35)
Distraction×PastReturn	0.0530*	0.0537*	-0.0046	-0.0030	0.0491**	0.0478**
	(1.88)	(1.83)	(-0.18)	(-0.12)	(2.55)	(2.32)
Stocks on watchlist (log)	0.0086	0.0158	0.0044	0.0060	-0.0002	-0.0032
	(1.30)	(1.58)	(1.28)	(1.21)	(-0.04)	(-0.42)
Trade volume manager (t-12,t-1) (log)	0.0117***	0.0119***	0.0049***	0.0049***	0.0055***	0.0054***
	(4.44)	(4.41)	(3.81)	(3.80)	(4.14)	(4.19)
Trade number (t-12,t-1)	0.0158***	0.0159***	0.0140***	0.0140***	0.0147***	0.0147***
	(8.73)	(8.97)	(25.16)	(25.73)	(50.25)	(47.09)
Assets under Management (log)		-0.0087		-0.0022		0.0038
		(-1.37)		(-0.61)		(0.64)
Change in AuM (%)		-0.0040		0.0055		-0.0058
		(-0.63)		(1.53)		(-1.26)
Number of Observations	39,067,464	38,895,699	39,067,464	38,895,699	39,067,464	38,895,699
Adjusted-R^2	0.48	0.48	0.49	0.49	0.38	0.38
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Trading Propensity – Interaction with Salience

This table shows results of stock-manager-week level regressions of managers' trading propensity on the distraction measure (specification (1) in the text). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. In columns 1-2, the dependent variable is the trade propensity; i.e., a dummy variable that takes the value one if the manager buys or sells the stock. In columns 3-4, the dependent variable is the buy propensity; i.e., a dummy that takes the value one if the manager buys a given stock in a given week and zero otherwise. In columns 5-6, the dependent variable is the sell propensity; i.e., a dummy variable that takes the value one if the manager sells the stock. In all columns, the distraction measure is interacted with a dummy variable flagging a managers' watchlist stocks with the most extreme (positive or negative) past returns over the previous four weeks (ExtremeRank), which is supposed to capture the Rank Effect documented by Hartzmark (2015). The level effect of the ExtremeRank dummy variable is included in all regressions. In Panel A, we conduct the analysis for the ANcerno watchlist and in Panel B for the 13f watchlist. All other variables are defined in Appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: ANcerno watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0625***	-0.0853***	-0.0481***	-0.0492***	-0.0328***	-0.0674***
	(-4.63)	(-4.44)	(-4.29)	(-3.83)	(-3.29)	(-3.44)
Distraction×ExtremeRank	0.0504***	0.0513***	0.0285***	0.0194**	0.0325***	0.0419***
	(5.93)	(3.89)	(4.17)	(1.99)	(4.33)	(2.96)
ExtremeRank	0.0029**	0.0037*	-0.0005	-0.0004	0.0034**	0.0033**
	(2.00)	(1.68)	(-0.38)	(-0.23)	(2.45)	(2.26)
Stocks on watchlist (log)	0.0176***	0.0090	0.0111***	0.0032	0.0136***	0.0015
	(4.48)	(1.40)	(3.48)	(0.65)	(4.34)	(0.22)
Trade volume manager (t-12,t-1) (log)	0.0167***	0.0190***	0.0080***	0.0109***	0.0109***	0.0127***
	(6.83)	(5.04)	(3.74)	(2.88)	(6.05)	(3.65)
Trade number (t-12,t-1)	0.0154***	0.0135***	0.0135***	0.0123***	0.0144***	0.0138***
	(20.78)	(10.23)	(46.26)	(21.16)	(56.89)	(53.21)
Assets under Management (log)		0.0054		0.0072**		0.0025
		(1.36)		(2.27)		(0.68)
Change in AuM (%)		-0.0105		0.0084		-0.0244**
		(-0.75)		(0.77)		(-2.37)
Number of Observations	56,833,924	17,201,876	56,833,924	17,201,876	56,833,924	17,201,876
Adjusted-R^2	0.31	0.36	0.31	0.40	0.29	0.30
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: 13f watchlist

Dependent Variable:	Trade (dummy)		Buy (dummy)		Sell (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.0359***	-0.0358***	-0.0208***	-0.0204***	-0.0231**	-0.0232**
	(-3.30)	(-3.27)	(-3.28)	(-3.22)	(-2.37)	(-2.36)
Distraction×ExtremeRank	0.0421***	0.0408***	0.0143**	0.0137**	0.0334***	0.0326***
	(4.77)	(4.63)	(2.21)	(2.10)	(3.89)	(3.78)
ExtremeRank	-0.0007	-0.0007	-0.0059***	-0.0060***	0.0038**	0.0039*
	(-0.44)	(-0.38)	(-4.20)	(-4.21)	(1.99)	(1.89)
Stocks on watchlist (log)	0.0086	0.0158	0.0043	0.0060	-0.0001	-0.0031
	(1.30)	(1.58)	(1.27)	(1.20)	(-0.03)	(-0.41)
Trade volume manager (t-12,t-1) (log)	0.0117***	0.0119***	0.0049***	0.0049***	0.0055***	0.0054***
	(4.44)	(4.41)	(3.81)	(3.80)	(4.14)	(4.19)
Trade number (t-12,t-1)	0.0158***	0.0159***	0.0140***	0.0140***	0.0147***	0.0147***
	(8.73)	(8.97)	(25.16)	(25.73)	(50.26)	(47.09)
Assets under Management (log)		-0.0087		-0.0022		0.0038
		(-1.37)		(-0.61)		(0.64)
Change in AuM (%)		-0.0040		0.0055		-0.0058
		(-0.63)		(1.53)		(-1.26)
Number of Observations	39,067,464	38,895,699	39,067,464	38,895,699	39,067,464	38,895,699
Adjusted-R^2	0.48	0.48	0.49	0.49	0.38	0.38
Stock×Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Distraction and the Disposition Effect

This table shows results of manager-week level regressions of the disposition effect measure on the distraction measure (aggregated at the manager-level, as described in Section VI. Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Following Odean (1998), the disposition effect measure is calculated as the proportion of gains realized (PGR) minus the proportion of losses (PLR) realized. Specifically, for each manager, we keep track of the average purchase price for all open positions (based on their trading history). Then, for each week in which the manager sells at least one stock, we calculate the PGR (PLR) as the number of positions sold at a gain (loss) over the total number of positions that could have been sold at a gain (loss) in that week and take the difference. Unconditionally, we find a disposition effect of 1.18 percentage points (*t*-statistic = 3.5; based on standard errors clustered at the manager level). To ensure that there is no mechanic relation between the dependent and independent variable, we exclude earnings announcement stocks before calculating the disposition effect measure. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Disposition Effect = Proportion of Gains Realized – Proportion of Losses Realized			
	(1)	(2)	(3)	(4)
Distraction	1.2068***	0.9624**	0.8412*	0.6864
	(3.91)	(2.02)	(1.72)	(1.42)
Stocks on watch list (log)	-0.3784	0.3821	-0.3676	0.4003
	(-1.19)	(0.52)	(-1.16)	(0.55)
Trade volume manager (t-12,t-1) (log)	-0.0532	-0.2505	-0.0650	-0.2753
	(-0.38)	(-0.92)	(-0.46)	(-1.00)
Assets under Management (log)		0.8392		0.8512
		(1.28)		(1.29)
Change in AuM (%)		1.5901		1.6046
		(1.01)		(1.02)
Number of Observations	195,613	69,002	195,613	69,002
Adjusted-R^2	0.32	0.33	0.33	0.35
Manager fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	No	No
Week fixed effects	No	No	Yes	Yes

Table 12: Robustness Checks

This table shows robustness checks for stock-manager-week level regressions of different dependent variables on the distraction measure (specification (1) in the text). In Panel A, the dependent variable is trading propensity dummy (see Table 2). In Panel A, the dependent variable is the logarithm of trading volume. In Panel C, the dependent variable is the trade profitability (see Table 6). In Panel D, the dependent variable is the relative transaction spread (see Table 7). Each row represents a different robustness check as indicated in the row header (and explained in Section VII). For brevity, the table only shows the coefficient on the distraction measure. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Propensity

Dependent Variable:	Trade (dummy)			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
1) Exclude same industry	-0.0581***	-0.0795***	-0.0340***	-0.0338***
	(-4.50)	(-4.31)	(-3.23)	(-3.20)
2) Control for trading in EA stocks	-0.1765***	-0.1872***	-0.0903***	-0.0899***
	(-11.03)	(-8.15)	(-6.29)	(-6.24)
3) Distraction (EA surprise)	-0.0211***	-0.0273***	-0.0120***	-0.0121***
	(-3.74)	(-4.07)	(-3.04)	(-3.05)
4) Distraction (alternative)	-0.0629***	-0.0834***	-0.0419***	-0.0416***
	(-4.31)	(-4.51)	(-4.47)	(-4.44)
Past Trade Controls	Yes	Yes	Yes	Yes
AuM and Change in AuM	No	Yes	No	Yes
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Week fixed effects	Yes	Yes	Yes	Yes

Panel B: Trading Volume

Dependent Variable:	Trading Volume			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
1) Exclude same industry	-0.0429	-0.0941	-0.0896	-0.0938
	(-0.41)	(-0.41)	(-0.38)	(-0.40)
2) Control for trading in EA stocks	-0.1513	-0.2021	-0.3443	-0.3490
	(-1.09)	(-1.08)	(-0.94)	(-1.06)
3) Distraction (EA surprise)	-0.0377	-0.0258	0.0263	0.0242
	(-0.91)	(-0.31)	(0.33)	(0.30)
4) Distraction (alternative)	-0.0697	-0.1276	-0.2160	-0.2189
	(-0.70)	(-0.80)	(-1.19)	(-1.20)
Past Trade Controls	Yes	Yes	Yes	Yes
AuM and Change in AuM	No	Yes	No	Yes
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Week fixed effects	Yes	Yes	Yes	Yes

Panel C: Trade Profitability

Dependent Variable:	Trade Profitability			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
1) Exclude same industry	-0.0092*	-0.0085	-0.0175**	-0.0187**
	(-1.88)	(-1.56)	(-2.10)	(-2.20)
2) Control for trading in EA stocks	-0.0086*	-0.0082*	-0.0190**	-0.0201**
	(-1.71)	(-1.79)	(-2.11)	(-2.18)
3) Distraction (EA surprise)	-0.0030**	0.0027**	-0.0063**	-0.0065**
	(-2.05)	(1.99)	(-2.14)	(-2.20)
4) Distraction (alternative)	-0.0092*	-0.0098	-0.0205**	-0.0215*
	(-1.72)	(-1.61)	(-1.98)	(-1.88)
Past Trade Controls	Yes	Yes	Yes	Yes
AuM and Change in AuM	No	Yes	No	Yes
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Week fixed effects	Yes	Yes	Yes	Yes

Panel D: Relative Transaction Spread

Dependent Variable:	Relative Transaction Spread			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
1) Exclude same industry	0.0009*	0.0011***	0.0012***	0.0010**
	(1.68)	(2.71)	(2.73)	(2.55)
2) Control for trading in EA stocks	0.0008*	0.0010**	0.0016***	0.0015***
	(1.74)	(2.19)	(3.26)	(3.24)
3) Distraction (EA surprise)	0.0003	0.0004**	0.0004***	0.0004**
	(1.63)	(2.50)	(2.72)	(2.65)
4) Distraction (alternative)	0.0013**	0.0011**	0.0012**	0.0011**
	(2.04)	(2.16)	(2.32)	(2.31)
Past Trade Controls	Yes	Yes	Yes	Yes
AuM and Change in AuM	No	Yes	No	Yes
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Week fixed effects	Yes	Yes	Yes	Yes

Appendix A.1: Match between ANcerno and CRSP

Matching procedure: We match *stockkeys* from ANcerno to permnos from CRSP using 8-digit *cusip*-day pairs. We drop from our sample all stockkeys that have more than one cusip on any particular day.

Since the cusip field in ANcerno is missing for several trades, there are often “holes” in this match. We fill this holes in the following way: Whenever a permno shows up for a stockkey two times without any other permno being present in between, we assign this permno for all dates in between. We also assign the first permno to all prior days of this stockkey and last permno to all following dates.

Quality assessment: On average we can match over 93% of stockkey-dates to permnos. In no month is the matching quota below 90%. As a comparison: Matching on stock symbols (*ticker*) only matches 63% of stockkey-dates. In those cases where we can match stockkey and permno using both ticker and cusip, they yield the same permno in 99.5% of the cases. In those cases where they yield different permnos, the match is better using our cusip method in 99% of the cases. We measure quality of the match as the difference in logs between the average trading price in ANcerno and the CRSP closing price. The match quality is also good in an absolute sense. In only 36 out of over 11 million stockkey-date pairs is the median trading price from ANcerno outside the low-high price range given by CRSP.

Appendix A.2: Match between ANcerno and 13f

Using the manager names available to us, we hand-match between ANcerno managers (identified by *managercode*) to institutional investors in 13f (identified by *mgrno*). In doing so, we follow a conservative matching approach in order to minimize erroneous matches. We first use a string-proximity algorithm to generate a set of potential matches and then manually select the correct match from these potential matches. We are able to find mgrnos in 13f for 670 out of the 835 managers in our ANcerno sample.

Given the name-matching table, we link each managercode-quarter pair in ANcerno with mgrno-quarter pairs from 13f where available. For the managercode-quarter pairs that we can match, the match is with a unique mgrno in 92% of the cases. For the remaining 8%, there appear multiple mgrnos in 13f in that quarter with a name that matches to ANcerno. It appears that in those cases the different mgrnos represent different state branches of the same manager. We therefore aggregate the 13f holdings across those different mgrnos in those quarters. With this approach, we are able to find holding reports for 6,830 out of 19,686 managercode-quarter pairs in our ANcerno sample.

Appendix A.3: Variable Definitions

This table shows the definitions of the variables used in our study. All continuous variables are winsorized at the 1% threshold on both sides.

Variable Name	Definition	Level	Source
Distraction	Weighted fraction of a manager's watchlist stocks that have an earnings announcement, where the weights correspond to the fraction of the manager's trading volume in the stock over the past 12 weeks for the ANcerno watchlist and to the fraction of the manager's holdings in the stock at the end of the previous quarter for the 13f watchlist.	Manager-Stock-Week	ANcerno, 13f, I/B/E/S
Stocks on watchlist (log)	Logarithm of number of stocks that are on the manager's ANcerno (i.e., stocks that the manager traded in the past 12 weeks) or 13f watchlist (i.e., stocks that the manager held at the end of the previous quarter).	Manager-Week	ANcerno, 13f
Trade volume manager (t-12,t-1) (log)	Logarithm of the dollar trading volume of the manager in the preceding 12 weeks. (Ancerno)	Manager-Week	ANcerno
Trade number (t-12,t-1)	How many days in the last 12 weeks the manager traded the stock.	Manager-Week-Stock	ANcerno
Assets under Management (log)	Logarithm of the dollar amount of assets under management at the end of the previous quarter (13f)	Manager-Week	13f
Change in AuM	Relative change in assets under management from beginning to the end of the previous quarter (13f)	Manager-Week	13f
Trade (dummy)	Dummy variable equal to 1 if the manager traded the stock in that week	Manager-Week-Stock	ANcerno
Buy (dummy)	Dummy variable equal to 1 if the manager bought the stock in that week	Manager-Week-Stock	ANcerno
Sell (dummy)	Dummy variable equal to 1 if the manager sold the stock in that week	Manager-Week-Stock	ANcerno
Trading Volume (log)	Logarithm of the dollar trading volume of the manager in the stock in that week	Manager-Week-Stock	ANcerno
Trade Profitability	Compounded stock return over the subsequent four weeks for buys, minus one times the compounded stock return over the subsequent four weeks for sells.	Manager-Week-Stock	ANcerno, CRSP
Transaction Costs	The volume-weighted average relative transaction spread, which is defined as the difference between the execution price and the previous day's closing price for buys (and vice versa for sells), scaled by the previous day's closing price.	Manager-Week-Stock	ANcerno, CRSP

Appendix B: Rational Attention Model

In this appendix, we write down a simply equilibrium model in which investors are attention-constrained and behave ***rational*** about it. The model is a simplified version of Kacperczyk et al. (2016), and follows a large literature that models attention allocation through the choice of signal precisions (e.g., Peng and Xiong, 2006; Van Nieuwerburg and Veldkamp, 2010). The point here is to demonstrate that these type of models lead to straightforward predictions regarding how rational investors allocate their attention across stocks—predictions that can be tested and rejected in the data.

Setup: There are two stocks with independent fundamental values $\theta_1 \sim N(0, \sigma_{\theta 1})$ and $\theta_2 \sim N(0, \sigma_{\theta 2})$. We can interpret θ_j as the fundamental value of stock j after incorporating news about future cash-flows. $\sigma_{\theta j}$ then represents the uncertainty regarding future cash-flows news. When $\sigma_{\theta j}$ is high, there is lots of news and media coverage about stock j.

A continuum of mean-variance-investors (with identical risk-tolerance φ) trade the two stocks in a competitive market. Stock supply is noisy, $\eta_j \sim N(0, \sigma_{\eta j})$, to prevent prices from being fully revealing in equilibrium. Investors receive a signal about the cash-flow news for each stock. Let $s_{ij} = \theta_j + \varepsilon_{ij}$ be investor i's signal about stock j, where $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon ij})$, is normally distributed and independent across investors.

We assume that investors have limited attention. Let $\tau_* \equiv \sigma_*^{-1}$ denote the precision (inverse variance) corresponding to $*$ and let κ be the attention capacity of investor i (which is assumed to be the same across investors). Each investor i must choose how to allocate this attention across the two stocks:

$$\tau_{i1} + \tau_{i2} = \kappa$$

Equilibrium prices: With mean-variance preferences, investor i's optimal demand for stock j is given by

$$x_{ij} = \varphi \frac{E(\theta_j | s_{ij}, p_j) - p_j}{Var(\theta_j | s_{ij}, p_j)}.$$

This is the standard noisy rational expectations equilibrium (NREE) model when investors have dispersed information. Grossman (1976) has shown that the equilibrium price function is given by $p_j = \alpha_{j1}\theta_j + \alpha_{j2}\eta_j$, with

$$\alpha_{j1} = \tau_{\varepsilon j} \frac{1 + \varphi^2 \tau_{\varepsilon j} \tau_{\eta j}}{\tau_{\theta j} + \tau_{\varepsilon j} + \varphi^2 \tau_{\varepsilon j}^2 \tau_{\eta j}}$$

$$\alpha_{j2} = -\frac{1}{\varphi} \frac{1 + \varphi^2 \tau_{\varepsilon j} \tau_{\eta j}}{\tau_{\theta j} + \tau_{\varepsilon j} + \varphi^2 \tau_{\varepsilon j}^2 \tau_{\eta j}},$$

where $\tau_{\varepsilon j} \equiv \int_i \tau_{\varepsilon ij}\, di$ is the average signal precision. In what follows, we focus on the symmetric equilibrium in which $\tau_{\varepsilon ij} = \tau_{\varepsilon j}$ for all i.

Trading volume: Assuming that there was a previous trading round in which information was not yet dispersed (investors did not receive idiosyncratic signals) so that investors all held the same share in each stock ($x_{ij}^0 = \bar{\eta}_j$), we can interpret $E(|x_{ij} - x_{ij}^0|)$ as a measure of trading volume. In the symmetric NREE, investors' equilibrium demand reduces to

$$x_{ij} = \varphi \tau_{\varepsilon j} \varepsilon_{ij} + \eta_j .$$

It follows that investor i's trading volume $x_{ij} - x_{ij}^0$ is normally distributed with mean zero. Hence, $|x_{ij} - x_{ij}^0|$ is half-normally distributed and has an expectation of

$$E\left(\left|x_{ij}-x_{ij}^0\right|\right)=\left[\frac{2}{\pi}\left(\varphi^2\tau_{\varepsilon j}+\tau_{\eta j}^{-1}\right)\right]^{0.5}.$$

Proposition 1: *Trading* ***volume*** *is* ***increasing in investors' signal precisions ($\tau_{\varepsilon j}$)*** *and increasing in the variance of supply noise (τ_η^{-1}).*

The second part of the proposition follows from the market clearing condition which dictates that investors must accommodate supply shocks. When supply shocks are bigger, investors will have to trade more to accommodate them. The first part is more subtle as there are two counteracting effects in equilibrium. First, when information improves, risk-averse investors face a lower posterior uncertainty, $Var\left(\theta_j|s_{ij},p_j\right)$, and are thus willing to trade more aggressively. Second, investors' trading demands depend on the *dispersion in beliefs* across investors, $E\left(\theta_j|s_{ij},p_j\right)-\int_0^1 E\left(\theta_j|s_{ij},p_j\right)\,di$. It is easy to see that the dispersion in beliefs is first increasing and then decreasing in $\tau_{\varepsilon j}$: When signals are pure noise ($\tau_{\varepsilon j}=0$), beliefs equal the common prior and there is no dispersion. As signals become infinitely precise ($\tau_{\varepsilon j}\to\infty$), all investors know θ and there is no dispersion. Thus, when $\tau_{\varepsilon j}$ is large, the second effect would seem to reduce trading volume. It turns out, however, that the first effect of lower uncertainty on trading aggressiveness always dominates the second effect of lower belief dispersion, leading to an increase in trading volume. Intuitively, as $\tau_{\varepsilon j}$ approaches infinity, fundamental risk is removed and investors behave as if they were risk-neutral: they are willing to bet very aggressively on even tiny differences in beliefs.

Trading profits: Trading profits depend on the correlation between an investor's trades and subsequent returns, $Corr(x_{ij}-x_{ij}^0,\theta_j-p_j)$. The higher this correlation, the more likely it is that a given investor i buys (sells) when subsequent returns are positive (negative), implying higher trading profits.

Proposition 2*: Trading* ***profits*** *are* ***increasing in investors' signal precisions ($\tau_{\varepsilon j}$)****.*

Proof: $Cov\left(x_{ij}-x_{ij}^0,\theta_j-p_j\right)=Cov\left(\eta_j,\theta_j-p_j\right)=\alpha_{j2}\sigma_{\eta j}$ and therefore

$$Corr\left(x_{ij}-x_{ij}^0,\theta_j-p_j\right)=\frac{\alpha_{j2}\sigma_{\eta j}}{\sqrt{\sigma_{\eta j}}\sqrt{(1-\alpha_{j1})^2\sigma_{\theta j}+\alpha_{j2}^2\sigma_{\eta j}}}=\frac{\sqrt{\sigma_{\eta j}}}{\sqrt{\left(\frac{1-\alpha_{j1}}{\alpha_{j2}}\right)^2\sigma_{\theta j}+\sigma_{\eta j}}}.$$

Finally, note that $\frac{1-\alpha_{j1}}{\alpha_{j2}}$ simplifies to $\frac{\varphi\tau_{\theta j}}{1+\varphi^2\tau_{\varepsilon j}\tau_{\eta j}}$, which is decreasing in $\tau_{\varepsilon j}$. ■

Intuitively, the more precise an investor's information, the better will the investor be able to predict and trade on future returns.

Attention allocation: Let $E_i(\cdot)$ and $Var_i(\cdot)$ denote the expectation and variance conditional on information available to investor i, $\{s_{i1},s_{i2},p_1,p_2\}$, and let W_i represent investor i's final wealth. Before trading, investor i faces the following *two-step* decision problem:

$$\max_{\tau_{i1},\tau_{i2}} E\left[\max_{x_{i1},x_{i2}}\frac{1}{\varphi}E_i(W_i)-\frac{1}{2\varphi^2}Var_i(W_i)\right]$$

subject to

$$W_i=W_i^0+x_{i1}(\theta_1-p_1)+x_{i2}(\theta_2-p_2) \tag{1}$$

$$\tau_{i1}+\tau_{i2}=\kappa \tag{2}$$

$$\tau_{i1},\tau_{i2}\ \geq 0 \tag{3}$$

First, investor i allocates his attention between the two stocks subject to the additivity constraint (2) and the non-negativity constraints on signal precisions (3), which ensures that investor i cannot unlearn something that he already knew. Second, after observing signal realizations, investor i chooses optimal portfolio holdings subject to the budget constraint in (1).

The asset demand given above is the optimal solution to the second step of portfolio optimization. We now solve for the optimal attention allocation. Plugging the budget constraint and optimal trading demands into the utility function, we have for each stock

$$\frac{1}{\varphi}E\big(x_{ij}(\theta_j - p_j)|s_{ij},p_j\big) - \frac{1}{2\varphi^2}Var\big(x_{ij}(\theta_j - p_j)|s_{ij},p_j\big) = \frac{1}{2}\frac{\big[E\big(\theta_j|s_{ij},p_j\big) - p_j\big]^2}{Var\big(\theta_j|s_{ij},p_j\big)}$$

Substituting for the equilibrium price function, taking the unconditional expectation and after some algebra we are left with

$$E\left[\frac{\big[E\big(\theta_j|s_{ij},p_j\big) - p_j\big]^2}{Var\big(\theta_j|s_{ij},p_j\big)}\right] = \frac{\tau_{\theta j} + \tau_{\varepsilon ij}\big[1 + \varphi^2\big(\tau_{\theta j} + 2\tau_{\varepsilon j} + \varphi^2\tau_{\varepsilon j}^2\tau_{\eta j}\big)\tau_{\eta j}\big]}{\varphi^2\big(\tau_{\theta j} + \tau_{\varepsilon j} + \varphi^2\tau_{\varepsilon j}^2\tau_{\eta j}\big)^2\tau_{\eta j}}$$

This expression is linear in investor i's signal precision $\tau_{\varepsilon ij}$. Hence, when choosing how to allocate a unit of attention, investor i compares the marginal value of spending it on stock 1 to spending it on stock 2. For the investor to be indifferent between the two, it must be

$$\frac{1 + \varphi^2\big(\tau_{\theta 1} + 2\tau_{\varepsilon 1} + \varphi^2\tau_{\varepsilon 1}^2\tau_{\eta 1}\big)\tau_{\eta 1}}{\varphi^2\big(\tau_{\theta 1} + \tau_{\varepsilon 1} + \varphi^2\tau_{\varepsilon 1}^2\tau_{\eta 1}\big)^2\tau_{\eta 1}} = \frac{1 + \varphi^2\big(\tau_{\theta 2} + 2\tau_{\varepsilon 2} + \varphi^2\tau_{\varepsilon 2}^2\tau_{\eta 2}\big)\tau_{\eta 2}}{\varphi^2\big(\tau_{\theta 2} + \tau_{\varepsilon 2} + \varphi^2\tau_{\varepsilon 2}^2\tau_{\eta 2}\big)^2\tau_{\eta 2}}.$$

For an equilibrium in which investors pay attention to both stocks, this "attention equality" condition *must* hold. Although $\tau_{\varepsilon 1}$ and $\tau_{\varepsilon 2}$ cannot be obtained in closed form, one can prove the following comparative statics results.

Proposition 3*: The equilibrium level of attention* $\boldsymbol{\tau_{\varepsilon j}}$ *paid to stock j is* ***increasing in*** $\boldsymbol{\sigma_{\theta j}}$ *and* ***decreasing in*** $\boldsymbol{\sigma_{\theta \neg j}}$.

Proposition 4*: The sensitivity of the equilibrium level of attention* $\boldsymbol{\tau_{\varepsilon j}}$ *paid to stock j with respect to an increase in* $\boldsymbol{\sigma_{\theta \neg j}}$ *is decreasing* in $\boldsymbol{\sigma_{\theta j}}$.

Proof: Let $A \equiv \varphi^2\tau_{\eta j}$. Given that $\tau_{\varepsilon j}, \tau_{\theta j}, A > 0$, it is easy to show that:

$$\frac{\partial}{\partial\tau_{\varepsilon j}}\left(\frac{1+\big(\tau_{\theta j} + 2\tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)A}{\big(\tau_{\theta j} + \tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)^2 A}\right) < 0 \qquad \text{(i)}$$

$$\frac{\partial}{\partial\tau_{\theta j}}\left(\frac{1+\big(\tau_{\theta j} + 2\tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)A}{\big(\tau_{\theta j} + \tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)^2 A}\right) < 0 \qquad \text{(ii)}$$

$$\frac{\partial^2}{\partial\tau_{\varepsilon j}\partial\tau_{\theta j}}\left(\frac{1+\big(\tau_{\theta j} + 2\tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)A}{\big(\tau_{\theta j} + \tau_{\varepsilon j} + A\tau_{\varepsilon j}^2\big)^2 A}\right) > 0 \qquad \text{(iii)}$$

To see why these properties are sufficient for proving Propositions 3 and 4, consider what happens to the "attention equality" condition when there is an increase in, say, $\sigma_{\theta 2}$. This increases the right-hand-side of the equality condition [property (i)]. To balance the equilibrium equality condition, investors must shift attention away from stock 1 into stock 2 ($\tau_{\varepsilon 2}$ increases at the expense of $\tau_{\varepsilon 1}$), as this increases the left-hand-side and decreases the right-hand-side [property (ii)], thereby offsetting the effect of a larger $\sigma_{\theta 2}$.

By exactly how much investors must reallocate their attention in response to an increase in $\sigma_{\theta 2}$ depends on $\sigma_{\theta 1}$. When $\sigma_{\theta 1}$ is high, the left-hand-side of the equality conditions increases a lot for a given reduction in $\tau_{\varepsilon 1}$ [property (iii)]. Thus, less attention rebalancing is needed to equilibrate the attention equality condition. ■

The intuitions for these results are as follows. When stock 2 has mode pending news about its future cash-flows ($\sigma_{\theta 2}$ is high), investors reduce the heightened uncertainty by paying more attention to it. Because attention is in limited supply, this comes at the cost of paying less attention to stock 1. However, when stock 1 faces high uncertainty itself ($\sigma_{\theta 1}$ is high), then investors find it very costly to reduce their attention to stock 1. They will then resort to rebalancing less.

Bringing the model to the data: Taken together, Propositions 1-4 give us testable predictions that can be rejected in the data.

Prediction 1 (distraction effect for trading volume)*: When there is more cash-flow news about one stock, investors trade less in other stocks.*

Prediction 2 (distraction effect for trading profits)*: When there is more cash-flow news about one stock, investors make lower trading profits in other stocks.*

Prediction 3*: These distraction effects are weaker for stocks that face high uncertainty themselves.*

In principle, these predictions should hold for the entire stock market: when investors are distracted by news about one stock, they will pay less attention to all the other stocks in the market. Such distraction effects will be hard to detect, however. For one thing, with several thousand different stocks, investors only need to reduce their attention on other stocks by a tiny bit to be able to pay substantially more attention to one stock. Even more importantly, it is highly unlikely that investors pay attention to all stocks. For example, Van Nieuwerburgh and Veldkamp (2010) explain the fact that most investors are under-diversified as a result of limited attention. Merton (1987) suggests that some stocks have low investor recognition and earn higher expected returns in equilibrium. In light of this evidence, it seems natural to assume that ***investors pay attention to stocks in their portfolios*****—**after all, investors must at least have paid attention when they were buying them. [Moreover, institutional investors are often prohibited from short selling. For a short-sell constrained investor, information about portfolio stocks is more valuable than information about other stocks: while he benefits from learning about both positive and negative news about his portfolio stocks, he can only benefit from positive news about other stocks (because he cannot take action when the news is negative).]

Given this assumption, our empirical predictions can be stated as follows: when there is more news about one stock in an investor's portfolio, he will trade less and make lower profits in other stocks in his portfolio. These distraction effects should be reduced for portfolio stocks that face high uncertainty themselves.

Appendix C: Distraction and Trading Propensity – Leads and Lags

This table shows results of stock-manager-week level regressions of managers' trading propensity on *past, current and future* realizations of the distraction measure (specification (1) in the text, augmented by leads and lags for the distraction variable). Distraction is defined as the fraction of a manager's watchlist stocks that have an earnings announcement. Trading propensity is measured by a dummy that takes the value one if the manager trades a given stock in a given week and zero otherwise. Columns 1-2 and 3-4 show results for the ANcerno watchlist and the 13f watchlist, respectively. All variables are defined in appendix A.3. Standard errors are clustered at the manager level. *t*-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Trade (dummy)			
Sample:	ANcerno watchlist		13f watchlist	
	(1)	(2)	(3)	(4)
Distraction (t-1)	-0.0257	-0.0231	-0.0081	-0.0076
	(-1.34)	(-1.05)	(-0.96)	(-0.89)
Distraction (t)	-0.0776***	-0.0942***	-0.0337***	-0.0337***
	(-4.82)	(-4.51)	(-3.18)	(-3.17)
Distraction (t+1)	-0.0432***	-0.0557***	-0.0326**	-0.0332***
	(-3.80)	(-3.17)	(-2.55)	(-2.59)
Distraction (t+2)	-0.0262*	-0.0352*	-0.0216**	-0.0218**
	(-1.74)	(-1.80)	(-2.01)	(-2.04)
Distraction (t+3)	-0.0153	-0.0177	-0.0123	-0.0122
	(-0.95)	(-1.05)	(-1.21)	(-1.20)
Stocks on watchlist (log)	0.0213***	0.0117*	0.0087	0.0162
	(4.87)	(1.68)	(1.27)	(1.57)
Trade volume manager (t-12,t-1) (log)	0.0171***	0.0207***	0.0122***	0.0124***
	(6.35)	(5.07)	(4.52)	(4.49)
Trade number (t-12,t-1)	0.0155***	0.0137***	0.0158***	0.0158***
	(18.73)	(9.51)	(8.51)	(8.76)
Assets under Management (log)		0.0046		-0.0092
		(1.06)		(-1.42)
Change in AuM (%)		-0.0123		-0.0019
		(-0.77)		(-0.28)
Number of Observations	49,403,007	15,303,187	37,332,037	37,202,249
Adjusted-R^2	0.34	0.38	0.49	0.49
Stock×Week fixed effects	Yes	Yes	Yes	Yes
Manager×Stock fixed effects	Yes	Yes	Yes	Yes