Sell-Side Analyst Herding:

Confidence, Limited Attention,

Selective Attention and Distraction.

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Keywords: Behavioral finance, sell-side analysts,

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ABSTRACT

The propensity of groups of sell-side financial analysts to herd (or "disperse") is a function of their bounded cognitive capacity and confidence. When returns are negative, selective attention - a static measure of analysts' endogenous attention at a particular point of time - has a positive association with herding. Limited attention - a relatively involuntary dynamic process of exogenous attentional shift driven by external changes in the market over time - reduces the propensity to herd. Distracted analysts tend to herd when returns are falling. There is a negative association with confidence and, or, social interaction, and herding.

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"Many animals live in communities – herds and packs, flocks and swarms, gaggles of geese and troops of monkeys. The reason they do so varies. Gazelles on the open plains of Africa congregate in herds because it is safer that way. Lions live in prides and wolves in packs because their success in hunting depends on them working together. And pigeons may gather in flocks for no more complicated reason than that a great quantity of food is frequently to be had in a relatively small area" (Attenborough, 1990, p. 211).

1. Introduction

The reasons animals herd can be rationalized, and hence might be thought of as rational, but their propensity to herd is visceral. Humans also tend to herd because herding is motivated by our need for physical and social safety (Prechter, 2001). We join groups to protect ourselves from danger. Safety is a rational reason for herding. "Herding is an unconscious social behavior originating from the primitive portion of our brain" (Durand, Limkriangkrai and Fung, 2014, p. 176). Herding is consistent with rationality but its underlying determinants are behavioral.[1]

1 We will outline a number of herding analyses based on "rational" economics below. To our minds, however, finding that herding is consistent with rational motives obscures our understanding of the underlying determinants of the phenomenon of herding. It is indubitably rational for gazelles to gather in herds for their safety, especially when lions are nearby. It is a logical fallacy to conclude that their herding is a function of their rational cognitive processes.

This paper examines the behavior of groups of sell-side analysts. We demonstrate how their innate propensity to herd, or to "anti-herd" (or "disperse" as we will refer to it in this paper), is determined by unconscious influences.[2] Sell-side analysts' attention can be captured by headlines. Such headlines can make them focus on particular firms. These same headlines can also distract them from following others. Choices must be made about where they put their attention. The analysis in this paper shows that herding and dispersing are functions of selective and limited attention, distraction and confidence and, or, social interaction.

The concept of "selective attention" is well known in Psychology but, to the best of our knowledge, it has not been utilized in Behavioral Finance. We discuss Broadbent's (1958) model of selective attention in Section 2. We cannot observe analysts' attention directly in study such as this: we rely on a large database of historical information and cannot directly observe analysts as we would if we were conducting a study in Psychology. We therefore require proxies for the cognitive processes of interest to this study. We introduce and test a range of intuitive and readily measurable proxies for selective and limited attention in Section 3 of this paper. These proxies are well-known to empirical asset pricing and it may be the case that our analyses inform consideration of the relationship of asset pricing and behavioral finance.

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[2] Sell-side analysts are employed by investment companies to provide firm-level analysis for clients. In contrast to the buy-side analysts who provide analysis for the companies for whom they work (see, for example, Asquith, Mikhail and Au, 2005, for a discussion of sell-side analysts' activities), sell-side analysts' work is provided to clients and, as such, is public.

Analysts herd by providing forecasts that are close to the prevailing consensus forecast.[3] That is, they herd by issuing forecasts that are close to those of other analysts. There is evidence that it is economically rational for analysts to herd (Scharfstein and Stein, 1990; Hong, Kubik and Solomon 2000) and this is consistent with Prechter (2001). Agreeing with the consensus leaves an analyst less open to criticism, especially when her forecast is inaccurate. To be truly economically rational, however, a risk-averse analyst should engage in behavior which will maximize her expected wealth: herding does not provide new information to the market and there is evidence that *not* herding (that is, providing new, or different, information to the market) is profitable (Loh and Stulz, 2011). Herding might be rational in that it is the consequence of rules, and not the product of haphazard mental processing, but, to the extent it is not wealth maximizing, is quasi-rational behavior. As such, herding is a natural subject for study in Behavioral Finance. Behavioral explanations of herding, however, are relatively rare. Durand, Limkriangkrai and Fung (2014) provide a recent behavioral analysis of herding. They use confidence and meta-cognition to model individual analysts' herding towards, or away from, the prevailing consensus. In contrast to Durand et al.'s study of individuals, we focus on the cohort of analysts following a particular firm and find that their herding towards a consensus, or diverging away from consensus, has a statistically significant relationship with behavioral phenomena.

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[3] Clement and Tse (2005) and Jegadeesh and Kim (2009) provide empirical support that sell-side analysts herd. Bernhardt, Campbello and Kutsoati (2006) provide empirical support for "anti-herding". Our empirical design, discussed below in section 3, allows for both herding and anti-herding and seeks to explain both behaviors. Rather than "anti-herding", we choose to use "dispersing" to denote the opposite of herding.

Herding implies agreement rather than disagreement. In Section 3 we also introduce an easy to measure construct for herding which, we believe, to be intuitive: if analysts herd, the differences between their forecasts will fall. If their forecasts diverge, the differences between them will increase. Our analysis of herding is presented in Section 4 and we find that the proxies for limitations in analysts' cognitive capacity have significant associations with our herding construct. Proxies for selective attention have positive associations with herding but the effect is found only for firms with negative returns. Limited attention reduces the propensity to herd and this effect is most pronounced for cohorts following companies which are experiencing negative returns. Distraction has a positive association with herding propensity but this effect is most pronounced, again, for firms with negative returns. Analysts appear to devote greater cognitive resources to firms whose price is falling. Confidence and social interaction are related, as we discuss below, and our proxy is unable to clearly delineate between these effects. However, as confidence/social interaction increases, herding decreases, and *vice versa.*

We stress that the psychology of selection applies to individuals. We cannot directly observe the cognitive processes of the subjects we study: as is typical in Behavioral Finance, we use archival data with a large number of potential subjects over a considerable time span. Furthermore, following the usual methodology in Behavioral Finance, we aggregate individual behavior to the behavior of the group. We write about groups as if they were dominated by individuals with particular cognitive processes. We discuss the psychological phenomena of interest to our study and the operationalization of our proxies for these phenomena in Section 3 of this paper and, in Section 4, find that they have a statistically significant relationship to herding.

2. Attention

Broadbent (1958) proposed a two-stage model of selective filter theory of attention. This model posited that, unlike the processing of the basic physical properties of stimuli (e.g. pitch, color, and loudness), semantic processing of stimuli, because of its complexity, is subject to severe capacity limitation. As our cognitive system has limited information processing capacity, a selective filter is necessary to screen out irrelevant or unimportant stimuli, and we only attend to a particular channel of limited information for complex semantic processing.

Under this selective filter system, all stimuli that arrives our sensory system will be initially processed based on some preliminary features necessary for the segregation of channels in the first stage. Conscious attention will only be allocated to stimuli that has passed through this selective filter for semantic processing in the second stage. The resulting information will then be used for the formulation of appropriate decisions and responses. Stimuli being screened out by the selective filter will not be allocated conscious attention and will receive no further processing beyond the first stage.

Broadbent (1958) proposed that, the filtering of stimuli is guided by both exogenous, stimulus-driven bottom-up influences (e.g. intensity of the preliminary physical properties of the stimuli) and endogenous, goal-driven top-down influences (e.g. personal goals, motivation, and preferences).

2.1 Bottom-Up Stimulus-Driven Exogenous Attentional Shift

Exogenous attention describes attentional processing driven by the properties of the external objects themselves. These external factors, such as the intensity of the preliminary features (e.g. bright color, loud noises, highly valenced information), will capture one's attention in a non-volitional way. For example, highly arousing photographs were found to capture greater attention.[4] Participants looked at these photos longer than neutral ones (Lang et al., 1998). These photos also elicited enhanced cortical slow waves in electroencephalographic recording, which reflect increased attentional processing to the arousing photographs presented. Furthermore, abrupt onset of stimuli will also attract attention involuntarily (Yantis & Jonides, 1984). Therefore, a loud and unexpected noise will automatically capture attention. Similarly, abrupt changes with great intensity in the market will capture our attention, and our focus will shift to these events involuntarily.

However, research evidence has shown that, it was the intensity of preliminary features, but not the semantic features, of external stimuli that captures one's attention automatically. By using the partial report paradigm (Sperling, 1960), after being presented a large array of stimuli very briefly (e.g.

[4] In Finance, Barber and Odean (2008) find that individual investors are net buyers of "attention-grabbing stocks. The behavior they document is consistent with limited attention. Their paper, which is now a very influential work in Behavioural Finance, does not seek to differentiate the cognitive processes which we explore in this paper.

letters in a matrix), participants were asked to recall a particular subset of items based of certain features (e.g. recall the letter in color red; recall the letters in a particular location). Subsequent research has found that the participants can recall items based on physical cues such as color (Banks & Barer, 1977), but not by semantic features such as alphanumeric category (letter versus number; Sperling, 1960). Similar results were found in studies using the visual search paradigm, in which the participants managed to find items defined by simple physical features within an array of stimuli very quickly, but not so it the items were defined by semantic feature. Automatic attention shift in response to intense and abrupt changes in the market, does not necessarily involve careful processing of available information.

2.2 Top-Down Goal-Driven Endogenous Attention Capturing

Attention can be driven by top-down influences such as motivation, long-term memory, and expectations. Endogenous attention is the orientation of attentional resources to a pre-determined area according to the person's goals, desires and motivation.

Beck and colleagues (1976; Beck, Emery & Greenberg, 1985; Beck, Rush, Shaw, & Emery, 1979) proposed the concept of "schema", which is a prototypical representation in the long-term memory. It is a mental template that processes specific types of information and diverts attention towards schema-congruent information, resulting in bias in attention towards stimuli relevant to the schema. Experimental studies in cognitive psychology showing that both emotional motivational states and motivation in general of individuals are associated with selective attention biased toward encoding interest-relevant information. For example, with the use of various experimental paradigms, considerable research evidence has shown that anxiety and phobias were associated with heightened attention towards the relevant threat-related information. For example, when compared to non-anxious controls, anxious individuals were found to shift their attention towards the spatial location occupied by threat-related stimuli (e.g. MacLeod et al., 1986; Mogg et al., 1995). Patients with spider phobia have biased attention towards photographs of phobia (e.g. Lavy & van den Hout, 1993), and social phobia patients directed their attention towards threatening social cues (Mogg, Philippot, & Bradley, 2004) Apart from emotional motivational states such as anxiety, other studies have also found attentional biases associated with motivational states in general. For instance, subjects were found to demonstrate greater attention towards hobby-related (Dalgleish, 1995) and personally relevant information (Rieman & McNally, 1995). When compared to non-fasting subjects, subjects who had fasted also showed greater attention in processing hunger-related stimuli (Channon & Hayward, 1990; Lavy & van den Hout, 1993; Mogg et al., 1998). Carving in substance abuse is also associated with attentional bias for substance-related stimuli (see meta-analysis Field, Munafò, & Franken, 2009). Similarly, as analysts are mainly driven by the goal of maximising the gain and the chance of success, their attention will be endogenously driven by this motivation and their personal beliefs and expertise. Hence, they will be more focused on covering firms with characteristics resembling their internal “schema”, or mental template representing an archetypal successful firm.

The present study examines both types of attentional processes, namely, *Limited Attention*, representing the dynamic process of exogenous attentional shift driven by external changes in the market over time, which changes analysts' attention in a relatively involuntary manner. On the other hand, the variable *Selective Attention* is a static measure of analysts' attention at a particular point of time, representing firms that generally capture coverage of the majority of analysts in the market.

3. Data and Variable Definition

Herding implies agreement rather than disagreement. As analysts herd, their forecasts become closer. In contrast, dispersion (or "anti-herding") implies forecasts disperse. Key to our study is the operationalization of a variable which captures herding. Unlike a variable such as "return", which can be measured without much controversy, there is no consensus on a metric for herding (Spyrou, 2013). The measure introduced in this paper is intuitive, simple and easy to measure. If analysts herd, the differences between their forecasts will fall; that is, agreement will increase. If their forecasts diverge (i.e. "anti-herd"), the differences between them will increase. Our herding measure, ${}^{D_1}/{}_{D_2}$, operationalizes this intuition. We take a group of analysts making forecasts for firm i at time t and measure the difference between the most optimistic and most pessimist "live" earnings-per-share (EPS) forecast at the end of April.[5] We then

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5 Our preliminary analysis did not suggest that our results were sensitive to choosing this April cut-off period rather than March. Our decision to use April in our calculation of D_1 was driven by conservatism.

repeat this at the end of October.[6] If the second measure is smaller than the first, there is less disagreement. We take this as herding. Alternatively, if the second ratio is greater than the first, we interpret this as forecast dispersion (anti-herding).[7,8] Our sample is limited to firms with fiscal year-ends in December which are followed by at least five analysts in the period over which we calculate

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6 The cut-off period, i.e. end of October, is selected so that it is close to the end of forecasting period, but far enough to allow a sufficient number of forecasts to calculate the dispersion.

7 Analogous measures of herding taken from the distribution of forecasts at a particular time are not the focus of this study. When we consider the distribution of forecasts, the second moment, standard deviation, is analogous to the dispersion metric studied in this paper and, if the distribution is symmetric, potentially correlated with it. Standard deviations must be estimated and our analysis would require consideration of the effect of using a generated dependent variable. Such an analysis would not be problematic, however, if the regression error terms are uncorrelated with the exogenous variables. It is likely that this will *not* be the case in this study.

When considering the distribution of forecasts, it would be reasonable to assume that the fourth moment, kurtosis, is also a proxy for herding: as analysts' forecasts converge, they should cluster around the mean leading to a more peaked distribution (that is, higher kurtosis). Given that the fourth moment may be thought of as the error with which the second moment is estimated, and that the fourth moment will also be estimated, the generated variable issues associated with these potential measures of herding are, at a minimum, econometrically daunting.

8 Clearly, acceptance of the construct validity of ${}^{D_1}\!/_{D_2}$ as a measure of herding is a key to readers' acceptance of any conclusions drawn by this article. One issue we explored was whether taking the most optimistic and least pessimistic forecast is appropriate for this measure. We might, for example, exclude these forecasts and choose the second-most optimistic and second-least pessimistic forecast for our analysis. Furthermore, if any concern about using the most optimistic and least pessimistic forecast is driven by the potential influence of unusually divergent opinions, there is no guarantee that excluding these observations will leave more representative opinions. The forecasts we issue are "live" in that they are made after the beginning of the fiscal year and therefore exclude stale forecasts that might be lurking in the database. As such, we assume the conscious decisions of professional analysts are representative of opinions in the market.

$^{D_1}/_{D_2}$ (that is, April to October). $^{D_1}/_{D_2}$ focusses on change and, as such, our definition differs from studies such as Jegadeesh and Kim (2009) and Durand, Limkriangkrai and Fung (2014) which analyse herding *at* a point of time. In focussing on a dynamic definition where we examine change, our herding metric is consistent with the notion that herding may be associated with information cascades (Bickhandani, Hirshleifer and Welch, 1992).

To provide some intuition for $^{D_1}/_{D_2}$, we plot the full-year earnings forecasts for Alcoa (ticker AA), which has a December fiscal year end, in 2000. Figure 1 shows that the dispersion of analysts' forecasts of Alcoa's full-year EPS falls as the date approaches the actual announcement date. Indeed, as the announcement date of January 8th 2001 approaches, analysts' differences become negligible. The pattern depicted in Figure 1 is what might expected when analysts herd: as time progresses, agreement increases. As the fiscal year unfolds, more information will be known about firms and a pattern such as that depicted in Figure 1 in the normal course of events.[9] The summary statistics discussed below reveal that this is not the case; while not as common as herding, dispersal of agreement (anti-herding) is common.

[FIGURE 1 ABOUT HERE]

[9] Of course, information might contain noise, be controversial, contain uncertainty, be misleading or even duplicitous and, or, simply be hard to analyze. If this is the case, we might expect opinions to diverge.

We employ the details file containing full-year EPS forecasts and actual reported earnings from the IBES Earnings Forecast database to calculate ${D_1}/{D_2}$. We also limit our sample to US firms with December fiscal year ends. Ensuring that the firms in our sample have the same fiscal-year end ensures that our sample are following approximately similar timetables in their production of formal accounting information to investors. *W*e utilize "live" forecasts at to calculate both D_1 and D_2. Analyst A's forecast is considered live if she issued it on or after January 1st of the fiscal year and has not revised it; her latest revision *after* her initial forecast is then considered the live forecast. D_1 is the range of "live" forecasts at the end of each April (t_1) in each year of our sample period.[10] The end of April is an appropriate time to begin consideration of herding as inspection of Figure 2 suggests that there are, on average, a sufficient number of analysts to make inferences about any difference of opinion or any consensus. Furthermore, inspection of Figure 3 suggests that most firms issue the results for their previous fiscal year before the end of April; our results are unlikely to be confounded by noise associated with the end-of-year announcements. D_2 is range of "live" forecasts at the end of October (t_2). To reiterate, the ratio of D_1 to D_2 captures herding of analysts' forecasts but allows for "dispersing" of analysts' views. A value of ${D_1}/{D_2}$ that is greater than 1 indicates herding and a value less than 1 indicates dispersion. In the case of herding, higher values of ${D_1}/{D_2}$ indicate

[10] Literature on analyst forecast dispersion has used share price to scale measures the dispersion of analysts' earnings per share forecasts (Lundholm and Lang, 1996; Hope, 2003). Such scaling is not needed in this study as our dependent variable is a ratio.

that the herding is more pronounced. In the case of dispersion, lower values of D_1/D_2 indicate greater dispersion.

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

A degree of herding might be expected as more information becomes available for a firm simply through the passage of time and, as the date earnings are announced approaches, disagreement may be negligible. There are 29,682 observations in our sample[11] and summary statistics for D_1/D_2 and the other variables utilized in this study are presented in Table 1 and their pairwise correlations are presented in Table 2 (with significant estimates in bold typeface). The summary statistics for D_1/D_2 indicate that, on average, analysts herd: the mean is 1.594 and the median 1.143. Of the 29,682 observations, approximately 56% are instances where D_1/D_2 is greater than 1 (that is, cases where we observe herding). 41% are instances where analysts' forecasts disperse (that is, where D_1/D_2 is less than 1). Approximately 3% are cases where analysts neither herd nor disperse. The information being produced by firms and

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[11] We trim at the 99% and 1% levels to remove *prima facie* extreme observations and also exclude observations where data are unavailable for all of the explanatory variables used in equation.

uncovered by analysts increases during the reporting cycle but it does not lead to greater certainty. Herding is does not appear to be a function of the passage of time.

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

To analyze the determinants of herding, we utilize unbalanced fixed effects panel regression to estimate equation 1:

$$
\begin{aligned}
ln\left(\frac{D_1}{D_2}\right)_{i,t} \quad &= \alpha + \beta_1 ln\left\{\frac{1}{n}\left(\sum_{a=1}^{n} NoF_{i,a}\right)\right\} \qquad (1) \\
&+ \beta_2 ln\left\{\frac{1}{n}\left(\sum_{f=1,f\neq i}^{m}\sum_{a=1}^{n} NoF_{f,a}\right)\right\} + \beta_3 Return_{i,(t_1,t_2)} + \beta_4 \ln\left(Size_{t_1}\right) \\
&+ \beta_5 ln\left(book\ to\ market_{i,t_1}\right) + \beta_6 \ln\left(Price_{i,t_1}\right) \\
&+ \beta_7 ln\left(Trading\_Acitivity_{i,(t_1,t_2)}\right) + \varepsilon_{i,t}
\end{aligned}
$$

We transform all but $return_{i,(t_1,t_2)}$ to natural logarithms to facilitate the estimae. We utilize a dummy variable taking the value of 1 when returns are positive, and zero otherwise, when extending the analysis of the above equation; *not* transforming facilitates the ready interpretation of our results. The transformation of ${D_1}/{D_2}$ addresses concerns about the use of a ratio as a dependent variable. The transformation results in a distribution which has a recognizable bell shape although tests (not reported) reject the null hypothesis that the data conform to a normal distribution. Firm fixed effects control for firm-specific influences. Year fixed effects provide controls for systematic influences on the market and herding in the calendar year the forecasts are being made.

The first explanatory variable in equation (1), $\left\{\frac{1}{n}\left(\sum_{a=1}^{n} NoF_{i,a}\right)\right\}$, measures the average number of forecasts made by analysts covering firm *i* where *n* is the number of analysts and $NOF_{i,a}$ is the number of full-year forecasts analyst *a* makes for firm *i* between the end of April and end of October (the times when D_1 and D_2 are calculated). We refer to this variable as *forecasts for firm i* in our subsequent analyses. The average number of forecast for each firm is 3.677 (median 3.450) (Table 1). We find a statistically significant positive univariate correlation with *herding* ($^{D_1}/_{D_2}$) although the correlation coefficient reported in Table 2 is relatively small (0.04). Durand, Limkriangkrai and Fung (2014) analyze individual analysts and use the number of forecasts made by an analyst as a proxy for the analyst's confidence. Therefore, this variable might be interpreted as the level of aggregate confidence of the cohort of analysts following firm *i*. The evidence we present shortly (when we discuss Table 3) is supportive of this interpretation.

A second interpretation of *forecasts for firm i* is that it captures analysts' social interaction. We might think of a conversation as a series of statements conveying information and, or, responses to information provided by others. The discussion observed in this variable is captured by the number of EPS forecasts. Confidence and social interaction are related constructs. As social interaction increases, cognitive dissonance can be reduced leading to increased confidence. According to Festinger's (1957) cognitive dissonance theory, the perception of an inconsistency between one's cognitions will generate an aversive psychological state, called dissonance. For example, an analyst may experience cognitive dissonance when he/she is aware of that conflicting forecast direction for a particular stock are equally likely. This negative psychological state will motivate a person to seek and implement a dissonance reduction strategy, such as changing or justifying the conflicting behavior or cognition, or by introducing a consonant cognition. Social support plays an important role in cognitive dissonance reduction. Previous studies found the knowledge that other people have behaved the same manner acts as a consonant cognition that helped reducing cognitive dissonance (Lepper, Zanna, & Abelson, 1970; Stroebe & Diehl, 1981). Furthermore, from the perspective of social identity theory (e.g. Tajfel, 1978; Tajfel & Turner, 1979), the behavior of other people is relevant to the self only when he or she feels that they share an in-group membership together. McKimmie and colleagues (2003) confirmed this notion in an experiment. The participants in their experiment demonstrated a reduction in cognitive dissonance when there was behavioral support from others, and an increase in dissonance when there was no behavioral support, *only* when the in-group membership with these comparison others was emphasized. Herding behavior is therefore a form of social interaction through which the analysts seek for a consonant cognition from an in-group they identify with. Consistent forecasts from other analysts (an in-group) act as a confirmatory consonant cognition that reduce one's cognitive dissonance and increase one's confidence of a particular forecast direction. As such, this interpretation of *forecasts of firm i* is in harmony with it proxying for aggregate confidence.

A third interpretation *forecasts for firm i* is that this variable might capture limited attention but we will reject this and are left with the first two interpretations. We examine whether *forecasts for firm i* – the variable $\left\{\frac{1}{n}\left(\sum_{a=1}^{n} NoF_{i,a}\right)\right\}$ - can be considered as a proxy for analysts' limited attention in Table 3. Limited attention is characterized by increased attention being paid to something; it involves attention changing. Customers in a restaurant may only be peripherally aware of a waitress but all eyes will turn to her if she drops some plates. If a variable captures limited attention, it will have a positive relationship the number of analysts joining the cohort following a firm. A proxy for limited attention will therefore have a positive association with the change in the number of analysts following a firm. The analysis of the variable *forecasts for firm i* in Table 3 (in the first, third and sixth columns) finds that the relationship is negative and statistically significant and, to reiterate, we expected a positive relationship for the variable to be considered a proxy for limited attention. Therefore, we are left with the first two interpretations for this variable: that is, it either proxies for aggregate confidence and social interaction which, as we have outlined in the preceding paragraphs are related concepts.

[TABLE 3 ABOUT HERE]

Analysts follow more than one firm and herding is more pronounced when people are distracted (Kiesler and Mathog, 1968). We capture the attention that the analysts following firm *i* pay to *all* the other firms they analyze through the variable $\frac{1}{n}\left(\sum_{f=1,f\neq i}^{m}\sum_{a=1}^{n} NoF_{f,a}\right)$, the second term in equation 1, which is the average number of forecasts made by analysts following firm *i* for all of the other firms they cover (denoted by the subscript *f*). In the regression analyses, we utilize the natural logarithm of this variable and refer to it as *forecasts for other firms.* The summary statistics reported in Table 1 show that the average number of *forecasts for other firms* is 49.056 and the median 42.60. The correlation between *forecasts for firm i* and *forecasts for other firms* reported in Table 2 is 0.40. We also consider if *forecasts for other firms* might be a proxy for limited attention but the results reported in columns two, three and six in Table 3 indicate that the variable is statistically significant and negative (and, to reiterate the point we have made previously, this is the opposite sign to what we should observe if the variable captured limited attention). The interpretation of *forecasts for other firms* is clear: the more analysts focus on *other* firms, the less they can focus on a particular firm. *Forecasts for other firms* captures distraction.

We also control for the return of firm *i* between times D_1 and D_2 using variable $Return_{i,(t_1,2_2)}$ in equation (1).[12] We utilize CRSP monthly return data to

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12 Fama and Franch (1993, 1996) and Carhart (1997) present the seminal articles establishing the generally accept model for the determinants of firms' returns. For firm *i,* $R_{i,t} = R_{f,t} + \hat{b}_i\left(R_m - R_f\right)_t + \hat{s}_i(SMB)_t + \hat{h}_i(HML)_t + \hat{m}_i(UMD)_t + \varepsilon_{i,t}$ where where $R_{i,t}$ is the return for firm *i* in month *t*, $R_{f,t}$ is the risk-free rate at time *t*, R_m is the return of the market, *SMB* represents the size-premium, *HML* is the value-premium, *UMD* is the momentum

calculate returns and, given the six month gap between t_1 and t_2 we aggregate the return over this period; where $R_{i,t}$ is the return of firm i in month t, $Return_{i,(t_1,2_2)} = \prod_{t=1}^{n} 1 + R_{i,t} - 1$. $Return_{i,(t_1,2_2)}$ is associated with limited attention. The analyses in columns four, five and six of Table 3 reveal positive and statistically significant relationship of $return_{i,(t_1,2_2)}$to the change in the number of analysts. The univariate correlations reported in Table 2 point to a negative relationship between $return_{i,(t_1,2_2)}$ and both measures of analyst activity (*forecasts for firm i* and *forecasts for other firms*). We also note that there is a small but statistically significant positive correlation between and *herding* reported in Table 2.

In addition to returns, a firm's market capitalization (its size) and the ratio of the book value of its assets to its market value have been shown to be priced in the market (Fama and French, 1993). Size_{i,t_1} and $\text{book to market}_{i,t_1}$ are the respective market capitalization and book to market ratio for each firm at the end of April. Given that these variables are measured at a precise point in time, it is inappropriate to consider them as proxies for limited attention which deal with changes over a period. If these variables are related to the number of analysts covering a firm at the time they are derived, they reflect the preferences of these analysts. In other words, they capture what determines analysts' selective attention. We consider if size_{t_1} and $\text{book to market}_{i,t_1}$ are related to

premium. Therefore, given this standard asset pricing framework, $Return_{i,t}$ is exogenous in equation 1.

the number of analysts following each firm in Table 4[13] and find both have statistically significant relationships with the number of analysts following each firm at the end of April. Size_{t_1} has a positive relationship with analyst coverage (models 1 and 4).

[TABLE 4 ABOUT HERE]

Examination of Table 4 also shows that book to market_{i,t_1} is statistically significant in both the equation where it is the only explanatory variable (model 2) and also where it is included with the other candidate proxies for selective attention (model 4). It takes a different sign in each of these equations suggesting that at least one equation is subject to bias induced by misspecification of the model. The Adjusted R^2 and AIC indicate that model 4, where book to market is found to have a negative is the preferred model but the change in sign is worth further consideration. Hong, Lim and Stein (2000) find that "…that although a number of other variables are significantly related to analyst coverage, firm size is by far the dominant factor [determining analyst coverage" (p. 273). Given this finding for the relationship of size and analyst coverage, we orthogonalized *book to market* to *size* and *price* (the othogonalizing regression is reported in Table A.2 of the Appendix and we discuss *price* in the following paragraph). Using orthogonalized *book to market* (reported in the fifth column of Table 4) we find results consistent with those in model 4: after market capitalization is accounted

13 The explanatory variables used in Table 4 have been transformed to logs and these transformed variables exhibit much higher correlations than those reported in Table 2. These correlations are reported in Table A.1 in the Appendix to this paper).

for, it appears that analysts are less likely to cover "glamour" (or "growth") firms rather than "value" firms.[14]

It may also be the case that lower priced stocks attract less attention (Arbel and Strebel, 1982; Arbel, Carvell and Strebel, 1983; Beard and Sias, 1997). and may, therefore, reflect selective attention. We consider if the price of a firm's stock at the end of April, $price_{i,t_1}$, is related to the number of analysts following each firm in models 3 and 4 of Table 4 and find a statistically significant positive relationship but, as with $Book\ to\ market_{i,t_1}$ we find that the sign of the coefficient of is sensitive to model specification and, also as with $Book\ to\ market_{i,t_1}$ the Adjusted R^2 and AIC suggest that model 4 is to be preferred. As with *book-to-market*, we orthogonalized *price* to *size* and *book-to-market* (again, the othogonalizing regression is reported in Table A.2 of the Appendix). Using orthogonalized price (reported in the fifth column of Table 4) we find results consistent with those in model 4. After size is accounted for, it appears that analysts are less likely to cover firms with higher prices per share.

$Trading\_Activity_{i,(t_1,2_2)}$ measures the level of trading for each firm between t_1 and t_2, which is captured by the number of shares traded in the period. We also considered two alternate measures: the dollar value of shares traded each month and the between t_1 and t_2 (*dollar volume*) and a measure of share turnover where the average number of shares traded between the end of April and end of October is divided by the number of shares outstanding at the

14 High book-to-market ratios represent "value" stocks and low book-to-market ratios represent "glamour" (or "growth") stocks.

end of April. The differences between $trading_activity_{i,(t_1,2_2)}$and these two alternative measures are trivial and subsequently are not reported. In Table 3 we consider whether trading activity might proxy for limited attention and, as was the case with $return_{i,(t_1,2_2)}$, we also find a positive and statistically significant relationship of $trading_activity_{i,(t_1,2_2)}$and the change in the number of analysts. Therefore, $trading_activity_{i,(t_1,2_2)}$also captures limited attention.

4. The Determinants of Herding

Many of the variables discussed in the previous section are familiar to students of asset pricing (*return*, *size*, *book-to-market*, *price* and *number of shares traded*); they are priced by investors and reflect aspects of the market which determines their behavior. The analysis in the previous section has argued that they are proxies for limited attention (*return* and *trading activity*) and selective attention (*size*, *book-to-market* and *price*). In addition *forecasts for firm i* captures the aggregate confidence of the cohort of analysts following a firm and *forecasts for other firms* captures their distraction. These variables are utilized to model the convergence of analysts' forecasts using the variable *herding* which is captured by the variable ${}^{D_1}/{}_{D_2}$. As defined previously, if this variable takes a value greater than 1, analysts are herding, and if it takes a value less than 1, analysts are dispersing. Therefore, explanatory variables with positive values suggest a variable increases analysts' propensity to herd. Those with negative values militate against herding. The anlaysis reported in Table 1, where equation 1 is estimated, indicates that confidence, distraction, limited and selective attention all influence sell-side analysts propensity to herd. We report the estimated coefficients for equation 1 in column 1 of Table 5. Our preliminary analysis suggests that the effects we find are asymmetrically related to returns. Therefore, we include a dummy variable taking a value of 1 when returns are positive (and zero otherwise) and incorporate interaction terms in equation 2 in column 2. Given the asymmetry in effects, and also the fact that both adjusted R^2 and AIC suggest that equation 2 is a better model, our discussion will focus on equation 2. In addition, when interaction terms are reported, we introduce a third column in Table 5 to consider the net effect of the sum of each of the coefficients and then report a Wald test (a χ^2 statistic) that this sum is equal to zero. This analysis features in all of the subsequent tests we present (save for our consideration of potential effects from endogeneity reported in Table 6). Consideration of the significance of the interaction term alone is not enough in our analysis.

[TABLE 5 ABOUT HERE]

Forecasts for firm i is negative and statistically significant in equation 2 in Table 5. That is, as analysts make more forecasts about a firm, the dispersion of their forecasts increases. In introducing this variable, we noted that Durand, Limkriangkrai and Fung (2014) find that the number of forecasts made by an individual analyst is a proxy for the analyst's confidence. The analysis presented above, when we discussed Table 3, suggested that this variable might proxy for analysts' aggregate confidence about a firm. Increased confidence is associated with dispersing and, accordingly, reduced confidence is associated with herding.

If our interpretation of *forecasts for firm i* as a proxy for confidence is correct, it is intuitively appealing that reduced confidence should be associated with herding, which is consistent with Prechter, 2001, who sees herding as a strategy enhancing psychological safety.

The effect of *forecasts for firm i* is found only for firms experiencing negative returns. When we interact *forecasts for firm i* with the *positive return dummy* (which takes a value of 1 when the returns for firm *i* are positive) we find that the coefficient of this interactive term, 0.0209; the net effect of *forecasts for firm i* when markets are falling (that is, the sum of *forecasts for firm i* and *positive return dummy*) is -0.0643. The estimate of the value of χ^2 test is reported in the third column of Table 5 beneath the estimated joint effect and, in this case, the value of χ^2, 2.576, indicates that the null hypothesis that the sum of the coefficients is jointly equal to zero cannot be rejected within the standard confidence levels.

Distraction, proxied by *forecasts for other firms*, is found to have a positive and statistically significant association with herding. Distracted analysts tend to herd when returns are falling. The net effect of interaction effect between the *positive return dummy* and *forecasts for other firms* remains positive and statistically significant in equation 2 (the model before the interaction of *size* and *price* is included) and equation 3 in Table 5: distracted analysts still herd when prices are rising but to a lesser extent than they do when prices fall.

In contrast to positive relationship of distraction to herding, limited attention reduces the propensity to herd. *Return*, a proxy for limited attention, is also positive (0.8901) and statistically significant in Table 5. Remember that the base case is for the analysis in equation 2 is herding behavior when returns are negative. Therefore, the product of the positive coefficient with negative returns indicates that analysts disperse when prices fall. Falling prices would appear to have a similar effect on analysts. If so, the analogy of falling plates is perhaps misleading as the crash of a plate is momentary.Analysts' attention is caught by falling prices and, as prices fall, they devote a greater share of their cognitive resources to analyzing firms. We explore this notion further below when we focus on the years associated with the recent period currently referred to as the Global Financial Crisis (GFC).

The analysis in equation 2 of Table 5, our preferred model, shows no role for *trading volume*, another proxy for limited attention.[15] We do not consider this variable further as it is not significant in our subsequent analyses.

Equation 2 in Table 5 indicates that two of the proxies for selective attention – *size* and *price* are significantly related to analysts' propensity to herd (the coefficients are 0.0934 and -0.1193 respectively). *Book-to-market*, the other proxy for selective attention, is not statistically significant. When the sum of the coefficients for *size* and *price* are interacted with the positive return dummy,

[15] We find, however, that the coefficient of *number of shares traded* is negative in equation 1 (that is, when we conduct the analysis without considering the interactions of the variables with the *positive return dummy*).

however, the joint effect (0.16 for *size* and -0.1789 for *price*) the Wald tests of the null hypotheses that each joint effect is cannot reject the null hypothesis that each is insignificantly different from zero. Therefore, the analysis in equation 2 suggests that the effect of selective attention on herding appears limited to companies which are experiencing negative returns. When returns are falling, the positive coefficient of *size* indicates that analysts are more likely to herd for larger firms (and, accordingly, less likely to herd for smaller firms). Again this finding reminds us of Prechter (2001) as it seems safer to agree with firms who are garnering more attention. The analyses presented in Table 4 indicate that larger firms are likely to have more analyst coverage (and therefore be the objects of greater selective attention). The negative coefficient for *price* indicates that dispersal of the consensus (anti-herding) is more likely for firms with higher share prices and the propensity to herd is increased for firms with lower prices. Bearing in mind that the analysis presented in model 4 of Table 4 indicates that there negative association of *price* and analyst following, after *size* is accounted for, the negative coefficient suggests that herding is more pronounced in firms associated with greater selective attention. Therefore, both proxies for selective attention have a positive association with herding**.**

Might the analyses presented in Table 5 be influenced by endogeneity? *Return* is exogenous: the generally accepted model for returns does not include analysts' forecasts.[16] Given that return is exogenous, the *positive return dummy*, which is determined by the direction of a firm's return, is also exogenous to our

[16] See footnote 12 for our outline of this model.

herding/dispersing dependent variable, ${}^{D_1}/_{D_2}$. *Size*, *book-to-market* and *price* are also exogenous: they are measured before ${}^{D_1}/_{D_2}$ is calculated. Our proxy for confidence, *forecasts for firm i*, are a function of the underlying psychology of the cohort of analysts and has a biological basis (Fung and Durand, 2014, pp. 104-105) and, given this biological basis, this variable is also exogenous. Distraction, *forecasts for other firms*, is simply the flipside of limited and selective attention and is also exogenous by construction. Only *trading volume* is left as a candidate for endogeneity. It does not follow that the analyst tails wags the volume dog: trading can, and does, exist for firms which do not have analyst coverage. Our principal concern about endogeneity is that it may bias estimates and lead to incorrect inferences about the variables being examined. Accordingly, the simplest way of considering if *trading volume* is problematic is simply to exclude it from the analysis and we repeat the analyses in Table 5 *excluding trading volume* and report the results in Table 6. For both equations 1 and 2, the Wald tests of the null hypothesis that *all* of the coefficients reported in Table 6 are equal to *all* those reported in Table 5 are statistically significant (the value of the χ^2 statistic for equation 1 is 28.263 and, for equation 2, is 3,850.9). However, we also test the restriction that *each* of the coefficients reported in Table 6 is equal to its counterpart in Table 5; the χ^2 statistics are to the right of the estimated coefficient. For example, the coefficient for *forecasts for firm i* is -0.0755 in equation 2 in Table 6 and -0.0852 in equation 2 in Table 5. The χ^2 statistic of 0.0851 reported in the fourth column of Table 6, immediately to the right of the coefficient -0.0755. In almost all cases, we cannot reject the null hypotheses that the coefficients reported in Table 6 are equal to those reported in Table 5. In the few cases where the null hypothesis can be rejected, the sign and magnitude of the coefficient reported in Table 6 is consistent with the value reported in Table 5. We can conclude that there are no issues relating to endogeneity.

[TABLE 6 ABOUT HERE]

Durand, Limkriangkrai and Fung (2014) argue that analysts' confidence and its relationship to herding is associated with the difficulty that analysts face issuing forecasts for the firm. In particular, they find that the herding of the individual analysts they study is more pronounced for firms which are harder to analyze. They explain this behavior using the link between metacognition, the ability to reflect on tasks, skill and confidence (Kruger and Dunning, 1999) and conclude the analysts they study are "…unskilled, unaware of it and working on Wall Street" (Durand, Limkriangkrai and Fung, 2014,p 189). On a more general level, behavioral biases become more pronounced when tasks become more difficult Durand et al. argue that task difficulty is reflected in the consensus forecast error; the higher the error, the more difficult it is to analyze the firm. We follow Durand et al. and divide our sample by forecasting difficulty. We divide our sample based on the difference between the consensus forecast and t2 and the actual earnings announced for that fiscal year and report the results for the firms that fall within the group with the lowest absolute values of forecast errors (the "easy" firms) (that is, the bottom 30% of our sample when ranked by the absolute value of forecast error) and the firms with the highest absolute values of forecast errors (the "hard" firms – that is, those in the top 30% of firms) in Table 7.

[TABLE 7 ABOUT HERE]

Given our expectations for our proxy for confidence given Durand, et al. (2014), it is perhaps surprising *that forecasts for firm i* is not statistically significant in both of the regressions reported in Table 7. We find, however, that both of the proxies for selective attention that were significant in Table 5, *size* and *price* are significant for the *hard* sub-sample and not the *easy* sub-sample. Furthermore, the Wald test of the null hypothesis that the coefficient for *price* reported in the *hard* sub-sample, -0.2438, is equal to that reported for *price* in the *easy* sub-sample, -0.0061 is 15.906 and is significant at the 1% level. The Wald test that the coefficients for *size* in the *hard* and *easy* sub-groups is 3.278 and has a *p*-value of approximately 0.07. When discussing our main results in Table 5, we noted that both of these proxies for selective attention have a positive association with herding. Here, we find the effect is most pronounced for firms which are the hardest to analyze

The coefficients for *return* and the coefficients for interaction of *return* with the *positive return dummy* are significant in both *easy* and *hard* sub-samples and the differences between these estimates are insignificantly different from zero. *Return*, a proxy for limited attention, is important for herding and this confirms the inferences we made on the basis of the analyses presented in Table 5. To risk labouring our example of crashing plates, it is perhaps when the market is at its ”extreme” that we might see the effects of limited attention with the most clarity. Therefore, we examine herding in two separate years, 2007 and 2008, which are the most “extreme” of those which are included in the period that is currently referred to as the Global Financial Crisis (GFC).[17] The analyses for each year may be found in Table 8 and they confirm our conclusions for the important role of *return* when returns are both falling and rising in both 2007 and 2008. Additionally, in 2007, *forecasts for other firms*, a proxy for distraction, is found to be positive and statistically significant: analysts tend to herd as they become more distracted. Unlike previous analyses in this paper *book-to-market*, a proxy for selective attention is found to be statistically significant and negative in both 2007 and 2008. In our analysis of candidate proxies for selective attention presented in Table 4, we found that, after market capitalization is accounted for, it appears that analysts are less likely to cover “glamour” firms rather than “value” firms. Therefore, the analyses of 2007 and 2008 indicate herding is greater for those firms which analysts are less likely to select to cover when the returns of those firms are negative.

[TABLE 8 ABOUT HERE]

5. Conclusion

Our paper examines the behavior of groups of sell-side analysts. We demonstrate how their innate propensity to herd, and to disperse (“anti-herd”) is determined by unconscious influences.

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17 The period over which ${D_1}/{D_2}$ is calculated, April to October, spans the critical events in both years.

In order to study sell-side analyst herding behavior, this study introduced an intuitive, simple and easy to measure metric. For firms with fiscal year-ends in December, we take a group of analysts making forecasts for firm *i* at time *t* and measure the difference between the most optimistic and most pessimist "live" EPS forecast at the end of April. We then repeat this at the end of October. If the second measure is smaller than the first, there is less disagreement (that is, herding). If it is bigger, there is dispersion.

We explicitly utilize specific psychology concepts and the aforementioned metrics which capture these aspects which appear to not have been used in the Behavioral Finance literature. That is, we introduce proxies for *limited attention*, *selective attention*, confidence/social interaction and distraction. Our proxies for these psychological phenomena capture aspects of sell-side analyst herding behavior. The effects we find are most pronounced for firms experiencing negative returns over the period we measure herding. For firms with negative returns between the end of April and end of October, we find that increased confidence is associated with dispersing and, accordingly, reduced confidence is associated with herding. Distracted analysts tend to herd when returns are falling. In contrast to positive relationship of distraction to herding, limited attention reduces the propensity to herd; this effect is most pronounced when prices are falling (but it is still present when prices are rising).

Sell-side analysts are, we believe, probably highly motivated and intelligent individuals. Financial markets are large, complex and fast moving. The challenge of analysing these markets is daunting. Despite their commitment and work ethic, sell-side analysts' time is limited, and their cognitive capacity is bounded. It is, to us, clear that nature, rather than nurture, plays an important role in determining responses to pressure and complexity. The propensity to herd is visceral and our study has demonstrated how the psychological influences on our behavior drive analysts' herding instinct. Our study highlights the important influence of limited cognitive capacity on key participants in financial markets.

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Table 1

Summary Statistics

$^{D_1}/_{D_2}$ measures herding/dispersing. D_1 is the range of live full-year forecasts at the end of each April in each year of our sample of firms with December fiscal year ends for the period 1993 to 2012. D_2 is the range of live forecasts at the end of October. Forecasts for firm *i* is $\left\{\frac{1}{n}\left(\sum_{a=1}^{n} \mathrm{NoF}_{i,a}\right)\right\}$, the natural logarithm of the the average number of forecasts made by analysts covering firm *i* where n is the number of analysts and $NOF_{i,a}$ is the number of full-year forecasts analyst a makes for firm *i*. Forecasts for other firms is $\ln\left\{\frac{1}{n}\left(\sum_{f=1,f\neq i}^{m} \sum_{a=1}^{n} \mathrm{NoF}_{f,a}\right)\right\}$, the average number of forecasts made by analysts following firm i for all of the other firms they cover. *lnSize$_i$* is the market capitalization of firm *i* on the last trading day in April. *Book_to_market* is the ratio of the book value of assets reported by firm i for the previous fiscal year divided by the market capitalization of firm i on the last trading day in April (i.e., Size). *Price* is the f firm firm i on the last trading day in April. *Trading_Activity* is the sum the dollar value of shares traded each month between, and including, May and October.

	$^{D_1}/_{D_2}$	Forecasts for firm *i*	Forecasts for other firms	Return	Size	Book to market	Price	Number of shares traded
Mean	1.594	3.677	49.056	0.013	5,685,172	1.019	51.710	1,656,886
Median	1.143	3.450	42.600	0.000	1,171,124	0.492	25.500	459,525
St. Dev.	1.502	1.359	26.735	0.368	18,984,227	15.219	1,468.182	8,096,323
Skewness	2.31	1.21	1.36	2.38	10.46	84.61	76.33	52.71
Kurtosis	9.96	5.57	5.43	26.60	165.85	8644.92	6046.39	4100.91

Table 2

Correlations

These table reports estimates of correlations between variables (defined in Table 1). Estimates of correlations with *p*-values less than or equal to 0.05 are in bold.

	$^{D_1}/_{D_2}$	Forecasts for firm *i*	Forecasts for other firms	Return of firm_i	Size	BTM	Price
Forecasts for firm *i*	**0.04**						
Forecasts for other firms	0.00	**0.40**					
Return of firm_i	**0.05**	**-0.08**	**-0.01**				
Size	0.00	**0.11**	0.04	**-0.01**			
BTM	-0.01	0.00	-0.02	0.01	-0.01		
Price	0.00	0.00	0.01	0.00	**0.08**	0.00	
Number of shares traded	0.01	**0.14**	0.04	**-0.01**	0.33	0.00	0.00

Table 3

Analyses of Candidate Proxies for Limited Attention

This table reports analyses of candidate proxies for analysts' limited attention. Limited attention is characterized by increased attention being paid to something; it involves attention changing. Therefore, the dependent variable *Δ analyst coverage* is the change in analyst coverage from the end of April to the end of October. The explanatory variables are defined in the text accompanying Table 1 and have been converted to natural logarithms for the analyses presented in this table. Coefficients are estimated as an unbalance panel with firm and year fixed effect and standard errors have been corrected for heteroscedasticity. The *t*-statistics associated with each coefficient are reported under each coefficient in brackets. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.

	(1) Δ analyst coverage	(2) Δ analyst coverage	(3) Δ analyst coverage	(4) Δ analyst coverage	(5) Δ analyst coverage	(6) Δ analyst coverage	(7) Δ analyst coverage
Intercept	1.6264	1.7145	1.7862	1.3557	1.1711	1.1438	1.3577
(*t*-statistic)	(76.215)**	(28.777)**	(29.89)**	(426.7)**	(13.821)**	(13.502)**	(13.279)**
Forecasts for firm *i*	-0.2180		-0.2061				-0.2187
(*t*-statistic)	(-13.3)**		(-12.055)**				(-12.468)**
Forecasts for other firms		-0.0954	-0.0465				-0.0468
(*t*-statistic)		(-6.037)**	(-2.82)**				(-2.834)**
Return of $firm_i$				0.0500		0.0523	0.0399
(*t*-statistic)				(4.339)**		(4.528)**	(3.459)**
Number of shares traded					0.0142	0.0162	0.0341
(*t*-statistic)					(2.189)*	(2.504)**	(5.137)**
R^2	0.3046	0.2995	0.3049	0.2988	0.2984	0.2990	0.3062
Adjusted R^2	0.1454	0.1391	0.1457	0.1382	0.1377	0.1385	0.1472
AIC	1.7897	1.7970	1.7893	1.7980	1.7987	1.7978	1.7876

Table 4

Analyses of Candidate Proxies for Selective Attention

This table reports analyses of candidate proxies for analysts' selective attention. The dependent variable *analysts for firm i* is the number of analysts covering a firm at the end of April. The explanatory variables are defined in the text accompanying Table 1 and have been converted to natural logarithms. Coefficients are estimated as an unbalance panel with firm and year fixed effect and standard errors have been corrected for heteroscedasticity. The *t*-statistics associated with each coefficient are reported under each coefficient in brackets. The regressions in which the orthogonalized values of *book-to-market and price* are estimated may be found in the appendix to this paper. AIC stands for Akaike's Information Criterion.

** and * denotes significance at the 1% and 5% levels respectively.

	Analysts for firm *i*	Analysts for firm *i*	Analysts for firm *i*	Analysts for firm *i*	Analysts for firm *i*
Intercept	-18.5562	8.5358	5.7550	-30.3508	-18.5562
(*t*-statistic)	(-26.61)**	(192.1)**	(31.977)**	(-33.219)**	(-27.762)**
Size	1.9346			3.1183	1.9346
(*t*-statistic)	(39.132)**			(39.971)**	(40.81)**
Book-to-Market		-0.2511		0.8453	
(*t*-statistic)		(-4.756)**		(13.801)**	
Price			0.9448	-1.3570	
(*t*-statistic)			(16.673)**	(-16.04)**	
Book-to-Market orthogonalized to Size and Price					1.0113
(*t*-statistic)					(16.316)**
Price orthogonalized to Size and Book-to-Market					-1.5551
(*t*-statistic)					(-18.163)**
R^2	0.7592	0.7324	0.7366	0.7679	0.7679
Adjusted R^2	0.7040	0.6711	0.6763	0.7148	0.7148
AIC	5.4319	5.5374	5.5214	5.3949	5.3949

Table 5

The Determinants of Herding and Dispersing

This table presents estimates of
$ln\left(\left(\frac{D_1}{D_2}\right)_{i,t_1}\right) = \alpha + \beta_1 ln\left\{\frac{1}{n}\left(\sum_{a=1}^{n} NoF_{i,a}\right)\right\} + \beta_2 ln\left\{\frac{1}{n}\left(\sum_{f=1,f\neq i}^{m}\sum_{a=1}^{n} NoF_{f,a}\right)\right\} + \beta_3 Return_{i,(t_1,2_2)} + \beta_4 \ln\left(Size_{t_1}\right) + \beta_5 ln\left(book\ to\ market_{i,t_1}\right) + \beta_6 \ln\left(Price_{i,t_1}\right) + \beta_7 ln\left(Trading\_Acitivity_{i,(t_1,2_{2)}}\right)$. The variables have been defined in Table 1. Coefficients are estimated as an unbalance panel and standard errors have been corrected for heteroscedasticity. The third column of this table reports the net effect (the sum of the coefficient for variable *x* in equation 2 and the interaction of variable *x* with the *positive return dummy variable*) and the number in parentheses beneath each effect is a Wald test (reported using a χ^2-statistic) of the null hypothesis that this net effect is equal to zero. Wald tests are reported in square brackets under the estimate of the net effect. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.

	(1)	(2)
Intercept	-1.1084	-1.0760
(*t*-statistic)	(-5.263)**	(-4.858)**
Forecasts for firm *i*	-0.1206	-0.0852
(*t*-statistic)	(-4.404)**	(-2.496)*
Forecasts for other firms	0.1318	0.1587
(*t*-statistic)	(5.052)**	(5.423)**
Return	0.1442	0.8901
(*t*-statistic)	(6.333)**	(15.09)**
Size	0.1800	0.0934
(*t*-statistic)	(9.043)**	(4.233)**
Book-to-market	0.0334	0.0056
(*t*-statistic)	(2.366)*	(0.367)
Price	-0.1613	-0.1193
(*t*-statistic)	(-7.876)**	(-5.027)**
Number of shares traded	-0.0897	-0.0120
(*t*-statistic)	(-6.878)**	(-0.783)
Positive return dummy		0.3116
(*t*-statistic)		(2.164)

Interaction of positive return with:			Net effect:
* forecasts for firm *i*		0.0209	-0.0643
(*t*-statistic).[χ^2-statistic]		(0.528)	[2.576]
* forecasts for other firms		-0.0711	0.0876
(*t*-statistic).[χ^2-statistic]		(-2.884)**	[24.79]**
* return		-1.0552	-0.1651
(*t*-statistic).[χ^2-statistic]		(-15.609)**	[251.186]**
* size		0.0666	0.1600
(*t*-statistic).[χ^2-statistic]		(3.666)**	[0.618]
* book-to-market		0.0164	0.0221
(*t*-statistic).[χ^2-statistic]		(1.048)	[0.172]
* price		-0.0596	-0.1789
(*t*-statistic).[χ^2-statistic]		(-2.408)*	[1.995]
* number of shares traded		-0.0618	-0.0738
(*t*-statistic).[χ^2-statistic]		(-3.997)**	[3.481]
Number of observations	29,682	29,682	
R^2	0.274	0.285	
Adjusted R^2	0.108	0.121	
AIC	2.792	2.778	

Table 6

Analyses of the Determinants of Herding and Dispersing Excluding Liquidity

This table presents re-estimates the analyses presented in Table 5 *excluding* the variable *trading_activity*. The variables have been defined in Table 1. Coefficients are estimated as an unbalance panel and standard errors have been corrected for heteroscedasticity. For both equations, Wald tests ($\chi 2$ statistics) of the null hypothesis that all of the coefficients reported in Table 6 are reported beneath each equation. A test of the restrictions that each of the coefficients reported in this 6 is equal to its counterpart in Table 5 is immediately to the right of the coefficient in question. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.

		Wald tests (χ^2)		Wald tests (χ^2)
Intercept	-1.3182		-1.1069	
(*t*-statistic)	(-6.322)**		(-5.042)**	
Forecasts for firm *i*	-0.1613	2.2797	-0.0755	0.0851
(*t*-statistic)	(-5.982)**		(-2.271)*	
Forecasts for other firms	0.1389	0.0735	0.1533	0.0341
(*t*-statistic)	(5.324)**		(5.255)**	
Return	0.1349	0.1634	0.8775	0.0481
(*t*-statistic)	(5.867)**		(15.294)**	
Size	0.1009	23.7498**	0.0853	0.2298
(*t*-statistic)	(6.219)**		(5.054)**	
Book-to-market	0.0343	0.0039	0.0024	0.0425
(*t*-statistic)	(2.422)*		(0.159)	
Price	-0.1043	9.5268**	-0.1215	0.0106
(*t*-statistic)	(-5.654)**		(-5.798)**	
Positive return dummy			0.1832	0.8246
(*t*-statistic)			(1.296)	
Interaction of positive return with:				
* forecasts for firm *i*			-0.0388	2.6184
(*t*-statistic)			(-1.052)	
* forecasts for other firms			-0.0538	0.5055
(*t*-statistic)			(-2.215)*	
* return			-1.0787	0.1262
(*t*-statistic)			(-16.3))**	
* size			0.0065	35.6802**
(*t*-statistic)			(0.643)	
* book-to-market			0.0228	0.1702
(*t*-statistic)			(1.463)	
* price			0.0024	9.5685**
(*t*-statistic)			(0.121)	
Wald tests (χ^2)		28.263**		3850.9**
R^2	0.273		0.284	
Adjusted R^2	0.106		0.120	
AIC	2.794		2.779	

Table 7

Task Difficulty and the Determinants of Herding and Dispersing

This table presents re-estimates the analyses presented in Table 5 the subsets of firms which are the easiest and hardest to forecast. We divide our sample based on the difference between the consensus forecast and t2 and the actual earnings announced for that fiscal year. The firms that fall within the group with the lowest absolute values of forecast errors are the "easy" firms (that is, the bottom 30% of our sample when ranked by the absolute value of forecast error). The firms with the highest absolute values of forecast errors are the the "hard" firms (that is, those in the top 30% of firms). The variables have been defined in Table 1. Coefficients are estimated as an unbalance panel and standard errors have been corrected for heteroscedasticity. The third column of this table reports the net effect (the sum of the coefficient for variable *x* in equation 2 and the interaction of variable *x* with the *positive return dummy variable*) and the number in parentheses beneath each effect is a Wald test (reported using a χ^2-statistic) of the null hypothesis that this net effect is equal to zero. Wald tests are reported in square brackets under the estimate of the net effect. In addition, in the rightmost column of this table, we report the difference between the estimated coefficients for the hard and easy firms (hard – easy) and report a Wald test that each of these estimates is equal to zero (reported in square brackets beneath the reported difference. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.
[a]: the p-value associated with this estimate is 0.07.

	Easy		Hard		Hard - easy
Intercept	-0.1380		-1.2932		
(*t*-statistic)	(-0.285)		(-2.208)*		
Forecasts for firm *i*	0.0027		0.1128		0.1102
(*t*-statistic).[χ^2-statistic]	(0.038)		(1.364)		[1.771]
Forecasts for other firms	0.0809		0.0698		-0.0111
(*t*-statistic).[χ^2-statistic]	(1.293)		(1.047)		[0.028]
Return	0.9426		0.9524		0.0098
(*t*-statistic).[χ^2-statistic]	(6.552)**		(7.932)**		[0.007]
Size	0.0108		0.1169		0.1061
(*t*-statistic).[χ^2-statistic]	(0.237)		(1.995)*		[3.278][a]
Book-to-market	-0.0166		0.0045		0.0210
(*t*-statistic).[χ^2-statistic]	(-0.467)		(0.126)		[0.352]
Price	-0.0061		-0.2438		-0.2377
(*t*-statistic).[χ^2-statistic]	(-0.12)		(-4.091)**		[15.906]**
Number of shares traded	0.0024		0.0022		-0.0002
(*t*-statistic).[χ^2-statistic]	(0.068)		(0.063)		[0.000]
Positive return dummy	0.0825		0.2757		0.1932
(*t*-statistic).[χ^2-statistic]	(0.272)		(0.743)		[0.271]
Interaction of positive return with:		Net effect:		Net effect:	
* forecasts for firm *i*	0.0095	0.0122	-0.1226	-0.0097	-0.1321
(*t*-statistic).[χ^2-statistic]	(0.12)	[0.003]	(-1.143)	[2.024]	[1.516]
* forecasts for other firms	0.0019	0.0828	-0.0436	0.0262	-0.0455
(*t*-statistic).[χ^2-statistic]	(0.035)	[0.643]	(-0.747)	[1.214]	[.607]
* return	-1.0379	-0.0953	-1.0657	-0.1132	-0.0277
(*t*-statistic).[χ^2-statistic]	(-5.9)**	[41.579]**	(-7.84)**	[65.778]**	[0.042]
* size	0.0256	0.0364	0.0932	0.2101	0.0676
(*t*-statistic).[χ^2-statistic]	(0.684)	[0.045]	(1.89)	[0.07]	[1.881]
* book-to-market	0.0227	0.0061	0.0555	0.0599	0.0328
(*t*-statistic).[χ^2-statistic]	(0.671)	[0.459]	(1.472)	[0.695]	[0.756]
* price	-0.0201	-0.0263	-0.0653	-0.3091	-0.0451
(*t*-statistic).[χ^2-statistic]	(-0.372)	[0.023]	(-1.1)	[3.08]	[0.58]
* number of shares traded	-0.0276	-0.0252	-0.0811	-0.0788	-0.0534
(*t*-statistic).[χ^2-statistic]	(-0.802)	[0.243]	(-2.143)*	[1.774]	[1.997]
Number of observations	9,107		8,395		
R^2	0.425		0.531		
Adjusted R^2	0.134		0.173		
AIC	2.624		3.038		

Table 8

Herding, Dispersing and the Global Financial Crisis.

This table presents re-estimates the analyses presented in Table 5 for 2007 and 2008. The variables have been defined in Table 1. Standard errors have been corrected for heteroscedasticity. For both equations, Wald tests (χ2 statistics) of the null hypothesis that all of the coefficients reported in Table 6 are reported beneath each equation. . The third column of this table reports the net effect (the sum of the coefficient for variable *x* in equation 2 and the interaction of variable *x* with the *positive return dummy variable*) and the number in parentheses beneath each effect is a Wald test (reported using a χ^2-statistic) of the null hypothesis that this net effect is equal to zero. Wald tests are reported in square brackets under the estimate of the net effect. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.

	2007		2008	
Intercept	-0.2329		-0.1939	
(*t*-statistic)	(-0.577)		(-0.733)	
Forecasts for firm *i*	0.1090		0.1614	
(*t*-statistic)	(0.971)		(1.893)	
Forecasts for other firms	0.2268		0.0229	
(*t*-statistic)	(3.224)**		(0.526)	
Return	1.1488		0.6723	
(*t*-statistic)	(4.724)**		(5.751)**	
Size	-0.0362		-0.0068	
(*t*-statistic)	(-0.645)		(-0.183)	
Book-to-market	-0.0950		-0.0703	
(*t*-statistic)	(-2.714)**		(-2.671)**	
Price	-0.0239		-0.0596	
(*t*-statistic)	(-0.33)		(-1.389)	
Number of shares traded	-0.0033		0.0176	
(*t*-statistic)	(-0.072)		(0.555)	
Positive return dummy	0.3459		0.2949	
(*t*-statistic)	(0.648)		(0.38)	
Interaction of positive return with:		Net effect:		Net effect:
* forecasts for firm *i*	0.1164	0.2253	-0.0105	0.1509
(*t*-statistic).[χ^2-statistic]	(0.732)	[0.001]	(-0.043)	[0.368]
* forecasts for other firms	-0.1766	0.0502	0.0940	0.1169
(*t*-statistic).[χ^2-statistic]	(-1.919)	[6.982]**	(0.638)	[0.184]
* return	-1.6513	-0.5025	-0.7129	-0.0406
(*t*-statistic).[χ^2-statistic]	(-6.047)**	[31.113]**	(-3.124)**	[20.613]**
* size	0.0471	0.0109	-0.0827	-0.0895
(*t*-statistic).[χ^2-statistic]	(0.666)	[0.48]	(-0.773)	[0.368]
* book-to-market	-0.0075	-0.1025	0.0614	-0.0088
(*t*-statistic).[χ^2-statistic]	(-0.14)	[1.174]	(0.801)	[2.179]
* price	-0.0595	-0.0833	0.1717	0.1121
(*t*-statistic).[χ^2-statistic]	(-0.621)	[0.051]	(1.45)	[2.738]
* number of shares traded	-0.0228	-0.0261	0.0024	0.0200
(*t*-statistic).[χ^2-statistic]	(-0.366)	[0.037]	(0.028)	[0.023]
Number of observations	1,877		1,851	
R^2	0.045		0.032	
Adjusted R^2	0.037		0.024	
AIC	2.651		2.616	

Figure 1

<u>Forecasts for Alcoa (Ticker: AA).</u>

This figure depicts the full-year earnings forecasts for Alcoa (ticker AA) made by the analysts following this firm in 2000.

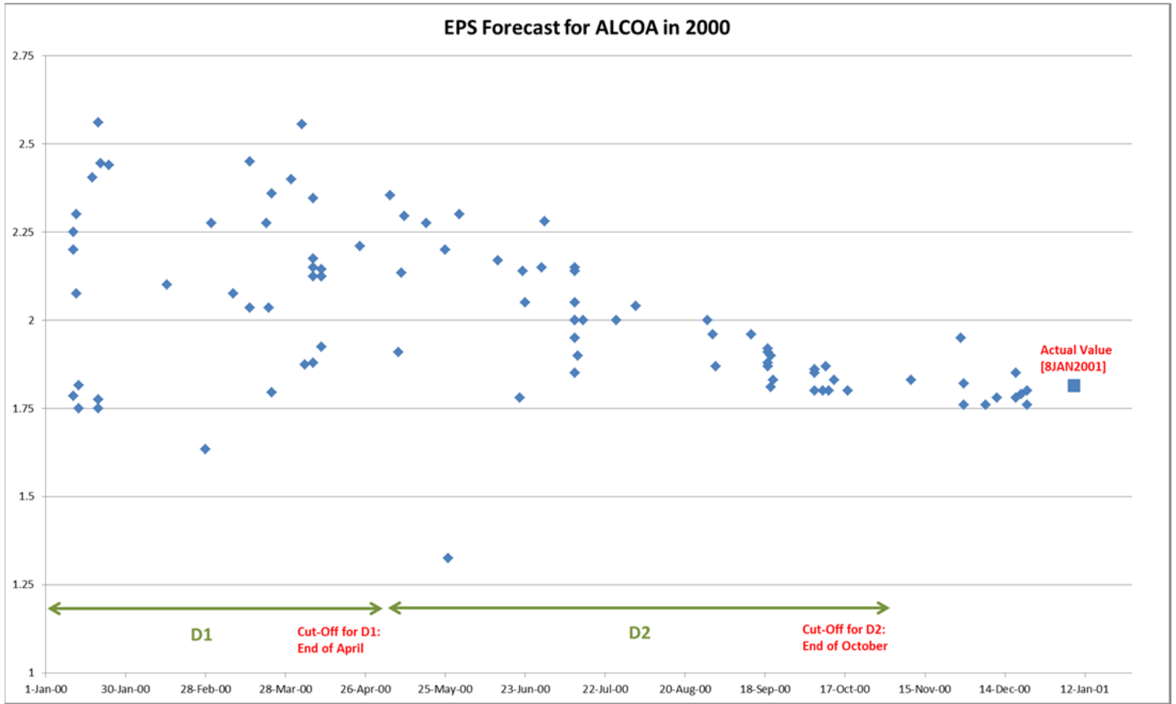


Figure 2

Analysts Initiating Forecasts

This figure depicts the average number of analysts making their first forecasts for a firm (in red) and the average number of analysts with live forecasts at the end of the month (in green).

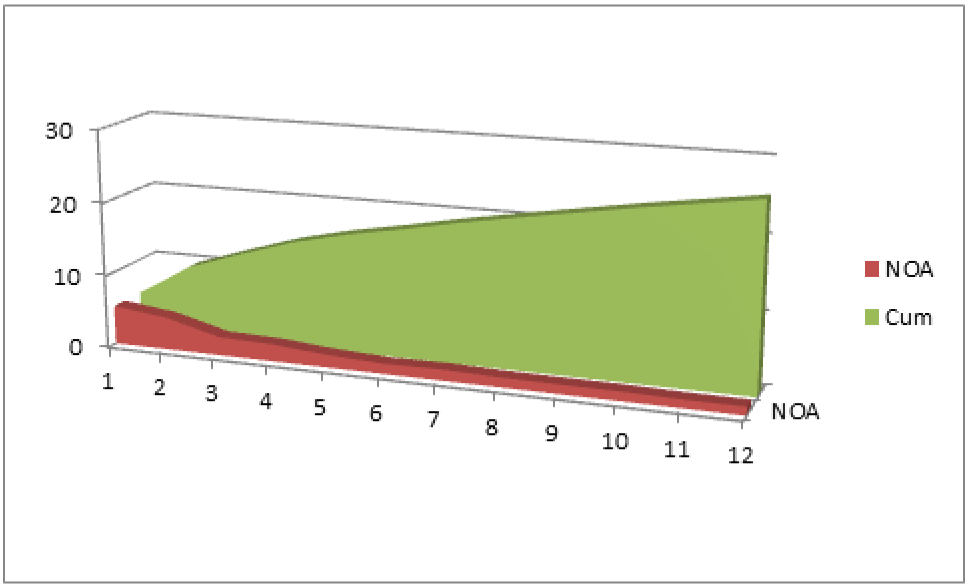
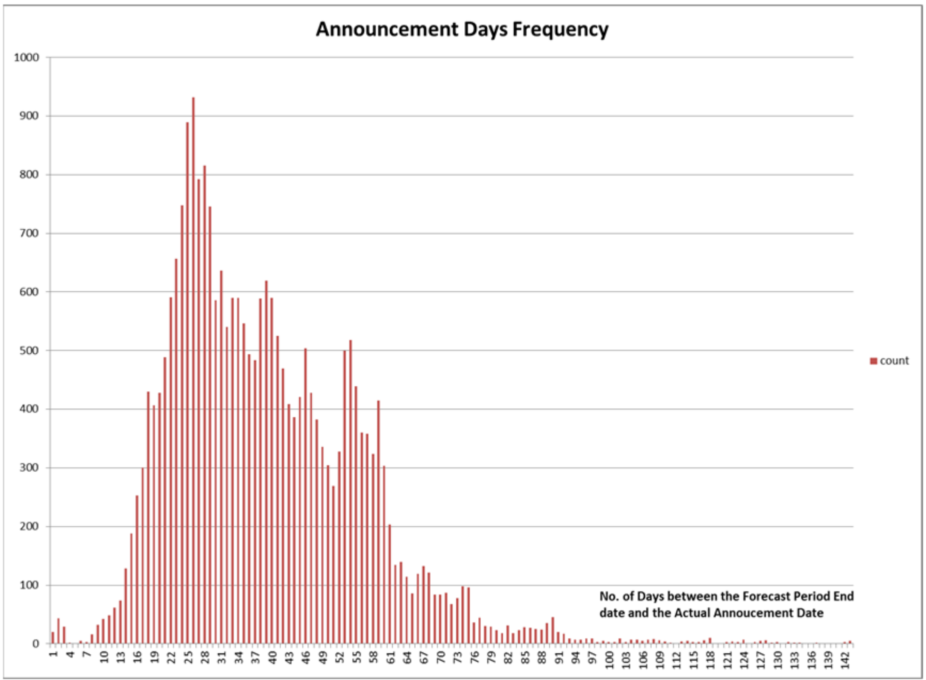


Figure 3

Days from the Last Day of the Fiscal-Year to the Earnings Annoucment.

The firms in this study all have December fiscal-year ends. This figure depicts the days it takes for the firms in our sample to announce their earnings after the last day in the fiscal year.



Appendix

When analyzing proxies for selective attention in Table 4, we presented an analysis of *book-to-market* to *size* and *price* where both these variables were orthogonalized. The orthoganalizing regressions are presented in Table A.2 of this appendix. We also discussed the linear correlations of the logs of variables (correlations of untransformed variables are reported in Table 2 in the paper; we present those correlations in Table A.1 of this appendix.

Table A1. Correlations

This table reports estimates of correlations of *analysts for firm i* (defined in the text accompanying Table 4) and size, *book—to*-market and price (defined in the text accompanying Table 1). Estimates of correlations with *p*-values less than or equal to 0.05 are in bold.

	Analysts for firm *i*	Size	Book-to-market
Size	**0.60**		
BTM	**-0.11**	**-0.21**	
Book-to-market	**0.29**	**0.64**	**-0.19**

Table A2. Orthogonalizing Equations

This table presents te analyses used to obtain the orthogonalized estimates of *bool-to-market* and *price* used to estimate equation 5 in Table 4. The variables have been defined in Table 1 and converted to logarithms. Coefficients are estimated as an unbalance panel and standard errors have been corrected for heteroscedasticity. AIC stands for Akaike's Information Criterion.
** and * denotes significance at the 1% and 5% levels respectively.

	Book-to-Market	Price
Intercept	4.0791	-4.9319
(*t*-statistic)	(23.949)**	(-47.549)**
Size	-0.2987	0.5669
(*t*-statistic)	(-20.278)**	(75.827)**
Book-to-Market		-0.1068
(*t*-statistic)		
Price	-0.1958	
(*t*-statistic)	(-12.69)**	
R^2	0.7862	0.8691
Adjusted R^2	0.7373	0.8390
AIC	1.4249	0.8184