ANALYST HERDING, SHAREHOLDER INVESTMENT HORIZON, AND MANAGEMENT EARNINGS GUIDANCE

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ABSTRACT

This dissertation examines the characterization of transient investors by financial analysts. Transient investors have been portrayed in the literature as either 1) informed investors or 2) poor monitors. No research to date, however, has examined how financial analysts, who are important information intermediaries, characterize transient investors. A view of transient investors through the lens of a financial analyst is obtained through examining how the presence of transient owners in a firm affects financial analysts' decision making. Specifically, this study examines how transient ownership affects both the propensity of analysts to herd when issuing earnings forecasts for a given firm as well as the incidence with which analysts revise their forecasts when the firm issues earnings guidance. Empirical tests show that financial analysts exhibit a greater propensity to herd when there are transient investors present. The proposed reason for this effect is analysts are herding due to reputational concerns. Further testing, however, does not show that the relation between transient ownership and analyst herding is owed to poor monitoring behavior of transient-owned firms. In contrast, evidence is consistent with the hypothesis that the firm information environment of transient-owned firms is an important cause of analyst herding. In summary, evidence is consistent with the informed investor portrayal of transient investors and there is no evidence indicating financial analysts view transient owners as poor monitors. Finally, when the decision of analysts to issue revised forecasts is examined, it is found that having a higher percentage of the firm owned by dedicated

or long-term investors increased the propensity of analysts to issue a revised forecast. Thus, while my analysis is inconsistent with a poor monitoring portrayal of transient investors, results suggest that a dedicated investor base can enhance the perceived credibility of firm disclosures.

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1. INTRODUCTION

This research examines the effects of short-term (transient) investors on the propensity of analysts to herd in issuing earnings forecasts for a given company. The potential implications of this investigation are significant as the contribution should help to characterize how analysts view transient investors and the effect they have on firm earnings disclosures. Transient investors have been depicted in the literature in one of two ways. First, transient investors have been portrayed as poor monitors whose myopic short-term focus causes management to make suboptimal decisions. Extant research demonstrates this characterization of transient institutions by investors (Gaspar et al. 2005) as well as firm management (Dikolli et al. 2009). A second way transient investors have been portrayed is as informed investors who profit from superior information (Ke and Petroni 2004; Yan and Zhang 2009). No research to date, however, has examined how analysts, who are important information intermediaries, characterize transient investors. This study explores this issue and attempts to fill this gap in the literature. Understanding how analysts view the effects of a transient investor base and the potential implications for firm disclosure should provide important insight into the debate regarding the relative advantages or disadvantages associated with the presence of this category of institutional investor, as well as their effects on firm earnings disclosures.

The financial analyst characterization of transient investors and their effect on disclosure is assessed by examining the degree to which analysts exhibit herding behavior when making earnings forecasts for companies with a substantial transient investor base. Herding is defined as the tendency for rational decision-makers to change their interpretation of their private information in order to be closer to some consensus belief held by colleagues (Mensah and Yang 2008). The objective of this study is not simply to document the existence of an effect on analyst herding caused by short-term investors, but also to analyze specific reasons for this effect. One possible reason relates to the credibility of firm disclosures. If the impact of transient investors on analyst herding is found to be due to the credibility of company disclosures, then this is consistent with analysts' view of transient investors as poor monitors. An alternative explanation is the impact of transient investors on analyst herding is due merely to a correlation between the information environment of firms in which transient investors hold shares and in which analysts herd in their forecasts. Consistent with this interpretation, Yan and Zhang (2009) find transient investors to be informed and analyst herding could be impacted by the opportunity to acquire private information.

To supplement the initial tests related to analyst herding, I implement an analysis designed to gauge how the reaction of analysts to voluntary firm disclosures differs when transient investors are present. This analysis is performed by examining the degree to which analysts revise their forecasts in the event of management earnings guidance, conditional on shareholder investment horizon. Utilizing results from tests using different vantage points, a robust characterization should be possible regarding transient investors and their perceived effects on firm disclosures.

Results indicate there is indeed an effect on the propensity of analysts to herd associated with the shareholder investment horizon. More specifically, the results show the percentage of transient institutional owners in a stock is positively associated with a greater degree of analyst herding in issuing earnings forecasts. Documenting an increased incidence of analyst herding supports the hypothesis that security analysts are less willing to assume the risks associated with deviating from the consensus and being wrong when there are more transient investors present. This is consistent with the conjecture that the dominant effect in the relation between analyst herding and transient owners is the impact on the analyst's incentive to protect their reputation by trading off accuracy for safety by conforming.

After documenting a positive association between transient ownership and analyst herding, the next set of tests seek to determine the aspect of transient ownership that causes the association. The results of these tests examining the reason for the positive association between transient investors and financial analyst herding are consistent with the hypothesis that the firm information environment in transient-owned firms is an important cause of financial analyst herding. Results, however, are not consistent with the hypothesis that financial analysts herd in transient-owned firms due to the poor monitoring of these investors. Using a two-stage regression procedure, I find utilizing a prediction of transient ownership on the basis of how informed investors are demonstrates greater strength in explaining analyst herding than when a prediction of transient ownership based on the degree of accounting discretion is employed. Therefore, my analysis does not indicate financial analyst herding in the presence of transient-owned firms results from concerns about the credibility of firm disclosures. Furthermore, my results demonstrate the poor monitoring portrayal of transient investors may be misguided. In fact, transient ownership is shown to be associated with a diminished incidence of small positive earnings surprises. Further testing is needed to more thoroughly address the important research question of how shareholder investment horizon affects management decision making. Overall, the results of my study are consistent with the view that transient investors are informed investors and there is little evidence to support the view that financial analysts characterize these shareholders as poor monitors.

A second set of results examines the effect of shareholder investment horizon on analysts' reaction to management guidance. A significant positive relationship is found between the degree of analyst revisions and the percentage of dedicated or long-term holdings in the stock, although the results are not consistent with a significant effect of transient holdings on analysts' reaction. This is consistent with the credibility of management disclosures being enhanced by the presence of dedicated owners in the stock.

This paper contributes to the literature by being the first to analyze how analysts view transient investors. It represents a significant contribution to the debate concerning whether transient investors are a) informed investors who profit from superior information or b) bad monitors who cause management disclosures to be less believable. The results in this analysis support the characterization of transient investors as informed investors who utilize private information to trade profitably. While I do find analyst herding is affected by the type of investor in the firm, this is likely due to a correlation between transient ownership and analyst herding caused by the firm's information environment. Therefore, there is little evidence in my analysis consistent with the view that transient investors are poor monitors who exacerbate the agency problem between management and shareholders. Rather, evidence is consistent with the more neutral view of transient investors as informed investors who can acquire and skillfully process private information.

With respect to analyst behavior, this study contributes to research by showing financial analysts herd when they believe other analysts are better informed. An analyst is incentivized to run with the pack in firms where private information exists and he is not in possession of it. While it is difficult to distinguish between reasons for herding, such as herding due to an information cascade versus herding due to protecting one's reputation, the results in this study indicate that reputational concerns represent a major reason for analyst herding. Analysts appear to herd in transient owned firms due to their desire to protect their reputation against better informed market participants. This represents an important contribution to research as it provides insight into the black box of the analyst decision making process. The results of my analysis extend the institutional investor, analyst behavior, and firm disclosure streams of literature and should be of interest to academics, company managers, and regulators alike.

The remainder of the paper is structured as follows. Section II reviews the relevant literature on analyst herding and shareholder investment horizon. Section III develops the hypotheses to be tested in the study. Section IV describes the methodology used to test the hypotheses. Section V details the sample used in the tests of the hypotheses. Section VI presents results. Section VII presents a robustness test. Section VIII details interesting extensions to this study and Section IX concludes the research.

2. LITERATURE REVIEW

2.1 Analyst Herding

Herding behavior refers to the tendency for rational decision-makers to change their interpretation of their private information in order to be closer to some consensus belief held by colleagues (Mensah and Yang 2008). Analyst herding specifically refers to the tendency of security analysts to issue an earnings forecast that is not without influence from a tendency to conform to the prevailing consensus. One of the early papers to investigate the propensity of analysts to herd is Trueman (1994). He conjectures that under certain circumstances an analyst prefers to release a forecast that is closer to prior earnings expectations and the likelihood that an analyst releases a conforming forecast is greater than could be justified by his prior information.

Several studies empirically examine the tendency of analysts to herd in issuing their earnings forecasts. Krishnan et al. (2006) document pervasive herding at the analyst level and results demonstrate that herding is positively related to forecast horizon and analyst coverage but negatively related to analysts' general experience and brokerage size. They find that approximately 75% of analysts tend to exhibit herding behavior. Naujoks et al. (2008) examine analyst herding among German analysts. Their results contrast those of Krishnan et al. (2006) as they find analysts anti-herd or exhibit a tendency to issue forecasts that are further away from the consensus. Furthermore, they show this behavior is more intense among analysts that are in high competition. Welch (2000), on the other hand, examines herding in the domain of analyst buy-sell recommendations and finds analyst revisions influence the following two analyst recommendations. These findings are supported by a more recent study done by Jegadeesh and Kim (2010) which also documents herding behavior in analysts' buy-sell recommendations. Further, the results in their analysis show the market reaction to recommendation revisions is stronger when the recommendation is away from the consensus, suggesting that the market weights revisions more heavily when they are bold.

Two different models exist in the literature which can be utilized to describe analyst herding behavior. The first model describes herding which occurs through information cascades. An individual is said to be in an information cascade if, based upon his observation of others, his selected action does not depend on his private information signal (Hirshleifer and Teoh 2003). Arya et al. (2005) incorporate the information cascade model to analyze the effect of Reg FD on analyst herding. In their model, they hypothesize that public firm disclosure will cause an analyst following the firm to ignore their private signal and instead follow the company's lead by issuing a report in line with the firm's disclosure. An information cascade then arises as a subsequent analyst following the firm is persuaded by the report of the first analyst and chooses to mimic that report, ignoring his own private information signal. The authors conjecture that one potential negative externality of Reg FD is herding by security analysts who will cascade on public firm disclosure. There are a few factors which can influence the propensity of an information cascade occurring. One factor concerns the possession of private information. Hirshleifer and Teoh (2003) indicate that the arrival of an individual with deviant information or preferences can dislodge a cascade. Clement and Tse (2005) show analysts who issue a bold forecast can be more likely to possess private information. This means analysts who possess private information can be less likely to cascade. A second factor which can affect the likelihood of a cascade occurring is the quality of the public signal, or in this case, the quality of the firm's public disclosure. Lang and Lundholm (1996) show companies with a more informative disclosure policy have more accurate earnings forecasts, less dispersion in forecasts, and less volatility in forecast revisions. When public firm disclosure is of higher quality, an information cascade can occur as analysts should be more apt to ignore their private signal and follow the lead of the firm. Understanding the information cascade model as it relates to analyst herding is important as the presence of transient investors can affect the likelihood that analysts cascade on the firm's public disclosure.

The second model which attempts to describe analyst herding is the reputational herding model. When circumstances make it more difficult to issue an accurate forecast, analysts will opt to herd in order to preserve their reputation. An early study by Scharfstein and Stein (1990) hypothesizes agents will herd due to the negative reputational consequences associated with maintaining a contrarian view and ultimately being wrong. Their research shows under certain circumstances a manager may mimic the decisions of others and ignore private information. They show that while this behavior may be inefficient, it can be rational. Kadous et al. (2009) demonstrate a similar phenomenon with analysts, finding analyst reputation is harmed more when analysts issue poor forecasts that diverge from the consensus versus poor forecasts in line with extant expectations. In addition, analyst reputation is enhanced more when accurate forecasts are bold forecasts than when they conform to the consensus. This implies there is a risk-reward trade-off in deciding whether or not to "run with the pack". Analysts can enhance their reputation to a greater extent by providing bold forecasts, but this comes with the substantial potential price of deviating and being wrong, resulting in a significant loss in reputation. Analysts must balance the costs and benefits of standing out with the importance of providing accurate forecasts. Hong, Kubik, and Solomon (2000) find those analysts who were historically less accurate were the most likely to be terminated and the least likely to be promoted. Thus, analysts need to be accurate but must weigh the potential effect of issuing a forecast that deviates from the consensus. Understanding that reputational incentives can cause increased herding is important as scenarios exist where transient investors increase the incentive to issue a conforming forecast and therefore would be associated with greater analyst herding behavior.

2. 2 Shareholder Investment Horizon

Shareholder investment horizon describes the length of time which a certain investor class normally holds a given investment before selling. Bushee (1998) classifies institutional investors into three different categories of transient, quasi-indexer, and dedicated investors. To perform this classification, Bushee (1998) starts with a large number of variables utilized in the literature to describe trading behavior and portfolio characteristics. Principal factor analysis is then used to generate a small number of common factors that explain the overall variance of the factors. Finally, institutions are classified into groups using k-means cluster analysis in the factor scores. The result is a classification grouping institutions on 1) how well diversified their portfolio is and 2) how quickly they turn it over (shareholder investment horizon).[1] Transient investors develop investment portfolios that are well-diversified and they turn these portfolios over relatively fast. Quasi-indexing institutions hold portfolios that are relatively diverse but do not turn over their portfolios as fast as transient investors. Dedicated institutions, on the other hand, hold concentrated portfolios and maintain a longer investment horizon relative to transient institutions. Accounting research has examined the implications of having shareholders fall into one of the three classes with the short-term or transient investor class representing the most scrutinized class of institutional investors. In the

[1] I would like to acknowledge Brian Bushee for making his institutional investor classifications available for research purposes.

literature, transient investors are portrayed as being either informed investors who profit from superior information (Ke and Petroni 2004; Yan and Zhang 2009) or as poor monitors of management whose actions cause management to focus solely on the short-term (Gaspar et al. 2005; Dikolli et al. 2009).

The informed investor portrayal of transient investors describes their ability to trade on private information obtained from management. Ke and Petroni (2004) show that transient investors can predict a break in hitting earnings benchmarks at least one quarter in advance of the event. In a follow-up study, they show this prediction ability of transient investors has diminished in the post-Reg FD environment (Ke et al. 2008). This suggests the superior predictive ability was accomplished via the acquisition of selective disclosure from management. Yan and Zhang (2009) also portray transient investors as being relatively more informed and find that the ability of institutional investor trading to predict future returns (documented by Gompers and Metrik 2001) is completely driven by the trading behavior of transient institutions. Yan and Zhang (2009) also attribute this superior ability to be the result of management disclosures. More recently, Hu et al. (2009), show that transient institutions sell in the event of a small negative earnings surprise and this type of investor selling is informative as it is predictive of the following three month abnormal return on the security. These findings again reinforce the portrayal of transient institutions as informed investors, trading on superior information.

The second portrayal of transient investors found in the literature is as shareholders solely focused on the short-term which cause company management to make suboptimal decisions in an attempt to cater to these investors. Bushee (1998) finds companies are more likely to cut research and development spending to meet earnings estimates when there are more transient shareholders present. Dikolli et al. (2009) find companies take into account the presence of transient shareholders when designing executive compensation packages. They show companies are less likely to give importance to meeting short-term earnings in compensation when there are more transient investors in the stock indicating that companies understand the implicit pressure to focus on the short-term when transient investors are present. Finally, Gaspar et al. (2005) demonstrate target firms with short-term shareholders are more likely to receive an acquisition bid but get lower premiums and attribute this to the fact that short-term shareholders are poor monitors of management. The authors hypothesize this poor monitoring allows managers to broker a deal for themselves that does not necessarily take into consideration the best interests of shareholders. The characterization of institutional investors as poor monitors, however, does not apply to long-term institutions. Chen and Li (2007) show long-term institutions are more likely to engage in monitoring and they gain financially from these monitoring activities.

In summary, financial analysts will herd less due to a disruption of the information cascade and will herd more when concerns to protect the analyst's reputation are greater. Transient investors have two distinct portrayals as a) informed investors and b) bad monitors. Either characteristic can play a role in the cascading of information or reputational herding and would thus affect the degree of analyst herding present in the security. These interactions form the basis for my hypotheses which are described in the next section.

3. HYPOTHESIS DEVELOPMENT

There are two distinct models which have been utilized to describe financial analyst herding. The first model, referred to as the information cascade model, depicts analyst herding as operating through the cascading of information. The second model, referred to as the reputational herding model, illustrates herding due to concerns to protect the analyst's reputation. This model concerns the reputational impact on analysts' incentive to issue a bold versus conforming forecast. The two principal characteristics of transient-owned firms established by the literature are 1) the availability of private information and 2) the poor monitoring of firm management. As will be developed in more detail below, it is hypothesized that the presence of transient investors can impede the cascading of information but may result in an increase in the propensity to herd due to reputational concerns. Because of the conflicting directions of these effects, an understanding of which model is shown to be more representative will be necessary in order to determine whether the presence of transient investors results in greater or diminished financial analyst herding.

The first model of financial analyst herding relates to the effect of an information cascade. This occurs when an analyst observes the signal available through the firm's public disclosure and chooses to ignore his own private signal, instead mimicking that of the firm. If a second analyst follows suit by mimicking the signal of the first analyst, then an information cascade has occurred. It is hypothesized that the presence of transient investors results in a decreased chance of an information cascade. This diminished chance of an information cascade could be caused either by the availability of private information or by the poor monitoring of management by transient investors.

With respect to the availability of private information, Hirshleifer and Teoh (2003) propose an individual with deviant information can disrupt an information cascade. Transient investors have been shown to acquire superior private information. Analysts also will be able to acquire this available private information with varying degrees of success. Therefore, in transient-owned firms, it should be more likely an analyst possesses deviant information which would disrupt the information cascade. This conjecture appears to be supported by the study by Clement and Tse (2005) who infer bold forecasts are more likely to have arisen from the possession of private information. Thus, an analyst possessing private information is more likely to disrupt an information cascade.

An alternative result of the information cascade model is the cascade is disrupted as a result of the poor monitoring of transient investors. The effect of poor monitoring on management can cause credibility concerns surrounding the firm's disclosure. A firm possesses a private signal and a public signal. The private signal represents management's true belief regarding the firm's state. This belief is conveyed to third parties via the public signal as represented in the public disclosure. If the investor base, however, is known to be poor monitors, then it is less likely the firm's private and public signal are the same. Management may instead be using the public signal as a means to engage in deceptive behavior. If analysts indeed recognize a monitoring problem and question the credibility of the firm's public signal, then they are less apt to mimic the signal and this would diminish the chance of an information cascade occurring. In a transient-owned firm, herding due to an information cascade would be reduced due to credibility problems associated with the firm's public signal.

The second model of financial analyst herding, reputational herding, depicts herding to protect the analyst's reputation in the presence of transient investors. Analysts have an incentive to herd when they do not want to risk the negative reputational consequences associated with deviating from the pack and ultimately being wrong. I propose here that the propensity of analysts to herd and protect their reputation will increase in the presence of transient investors. The factors which are conjectured to cause this reputational herding relate to the availability of private information and the poor monitoring of management. With respect to the availability of private information, it is presumed when private information exists, some analysts will possess this information while others will not. The analyst who does not possess the information perceives his chance of issuing an accurate forecast is diminished relative to his peers. This analyst will be incentivized to run with the pack as there is safety in numbers. Furthermore, there exists the possibility the private information is contained in the consensus forecast. Therefore, when some analysts possess superior information, there exists within the uninformed analyst, an incentive to herd. The analyst will be less accurate than the more informed analysts, but it is preferable to be wrong with others due to reputational concerns.

The second manner with which the presence of transient investors may result in an increased incidence of analysts herding to preserve their reputation relates to the poor monitoring by transient investors. Analysts must balance the need for accuracy with the risk of issuing a bold forecast. If an analyst has serious concerns about their own ability to issue an accurate forecast for a given company, then it is more likely they will issue a conforming forecast and at least preserve their reputation. When management is more poorly monitored, it is more likely they will engage in behavior which may mislead third parties such as analysts. This would make it more difficult for analysts to discern the true state of the company and subsequently lead them to question their ability to issue an accurate forecast. In this case, it is preferable for an analyst to seek safety in conforming and thereby protect their reputation.[2] Pursuing accuracy when the true state of the firm is more difficult to ascertain could severely damage the reputation of the analyst via a forecast that is both bold and incorrect. Therefore, since transient investors are known to be poor monitors, it is hypothesized that financial analysts will seek safety in herding due to a diminished chance of being accurate.

Two different models of herding which can be utilized to depict financial analysts' behavior in the presence of transient investors have been described, the information cascade model and the reputational herding model. A priori, it is uncertain whether the association between the presence of transient institutional investors and analyst herding will be positive or negative because it is uncertain which will be dominant, i.e. the effect of a disruption in the cascading of information or the increased incentive for the analyst to protect their reputation through herding. It is clear, however, that the effect of having dedicated investors will be opposite that of having transient shareholders. This is true because unlike transient investors, dedicated investors have not been found to invest in companies where they acquire private information[3] (Yan and Zhang 2009) and they are good monitors of management (Chen and Li 2007). Finally, it

[2] This conjecture is also discussed in Ramnath et al. (2008) where it is posited that uncertainty with respect to firms' earnings could be the underlying cause of herding behavior.
[3] Yan and Zhang (2009), Ke and Petroni (2004), and Hu et al. (2009) fail to find evidence consistent with dedicated investors possessing private information. While Bushee and Goodman (2007) find evidence consistent with dedicated investors trading on private information, evidence is scarce. Furthermore, research has criticized the adequacy of the methodologies employed in the Bushee and Goodman (2007) study (see Chen 2007).

has been shown that both the information environment of transient-owned firms and the poor monitoring of firm management can cause either a reduced chance of an information cascade or increased herding due to reputational concerns. Therefore, this leads to my first two non-directional hypotheses stated as follows:

> H1: Shareholder investment horizon is associated with analysts' propensity to herd with respect to a particular firm's earnings forecast.
>
> H2a: The availability of private information associated with a transient investor base will have an impact on analysts' propensity to herd with respect to a particular firm's earnings forecast.
>
> H2b: The poor monitoring behavior associated with a transient investor base will have an impact on the propensity of analysts to herd with respect to a particular firm's earnings forecast.

In summary, H1-H2b relate to the characterization of transient investors by financial analysts as exhibited through their propensity to herd in issuing earnings forecasts. The hypotheses describe how the availability of private information and the poor monitoring of transient investors can affect either the cascading of information or the incentive of the analyst to herd in order to protect their reputation. These possibilities are represented in the following diagram:

[Insert Figure 1]

The next hypothesis examines the reaction of security analysts to company disclosures when there is a large concentration of transient investors present. While transient investors are generally considered poor monitors of firm management, dedicated investors, are generally considered effective monitors of firm management. This is expected to affect the credibility of firm disclosures. Thus, it is likely that the longer the average investment horizon in a given security, the greater weight analysts will give to company disclosures. This conjecture is discussed in Cotter et al. (2006) with respect to the possibility of management using firm guidance to game analysts. It is expected that this type of behavior would be more prevalent in the presence of short-term investors. The third hypothesis is as follows:

> H3: The number of forecast revisions in the event of management earnings guidance will be positively associated with shareholder investment horizon.

The results of examining these three hypotheses should serve to provide a characterization of transient investors from different angles that will contribute to the discourse on the implications of attracting these investors and the effects they may have on disclosure.

4. METHODOLOGY

4.1 Hypothesis 1

My first hypothesis states that shareholder investment horizon will have an impact on the propensity of security analysts to herd. This hypothesis is tested using an OLS regression where the degree of herding is the dependent variable and the main independent variables of interest are percentage of transient institutional holdings and dedicated institutional holdings in the stock. The degree of herding measure is known as the S-statistic developed by Bernardt et al. (2006) and it measures herding using conditional probabilities. More specifically, the S-statistic is based on the concept that the probability a forecast exceeds actual earnings conditional on that forecast being above (or below) the consensus is one-half. If forecasts above the consensus are frequently below actual earnings then it is indicative of analysts who are herding by pulling their forecasts closer to the consensus. If, on the other hand, forecasts above the consensus are frequently above actual earnings then it is indicative of anti-herding as analysts are not pulling their forecasts downward toward the consensus. For example, assume the consensus annual eps forecast for a company at time t is 1.25 and r days later (time t+r), the consensus rises to 1.35. Further, assume actual earnings per share are 1.30. Herding would be evidenced if the forecasts above the consensus (1.25) at time t were consistently below 1.30 while those below the consensus (1.35) at time t+r were consistently above 1.30. If this is the case then the distribution of forecasts around actual earnings is not random as analysts are adjusting their forecasts to be closer to the consensus. Figure 2 provides a diagrammatical presentation of the S-statistic.

The S-statistic is the average of the percentage of forecasts above actual earnings when they are above the consensus and the percentage of forecasts below actual earnings when they are below the consensus. Therefore, an S-statistic of 0 indicates perfect herding while an S-statistic of 1 indicates perfect anti-herding. The following equation adapted from Mensah and Yang (2008) illustrates the calculation of the S-statistic in greater detail:

	Forecast > Consensus	Forecast < Consensus
Forecast > Actual EPS	$\sum\delta+$	$\sum\gamma-$ less $\sum\delta-$
Forecast < Actual EPS	$\sum\gamma+$ less $\sum\delta+$	$\sum\delta-$
Column Total	$\sum\gamma+$	$\sum\gamma-$

δ^+ = 1 if forecast > prior consensus forecast, and forecast > actual earnings; zero otherwise;

δ^- = 1 if forecast < prior consensus forecast, and forecast < actual earnings; zero otherwise;

γ^+ = 1 if forecast > prior consensus forecast; zero otherwise;

γ^- = 1 if forecast < prior consensus forecast; zero otherwise;

$$\text{S-statistic} = 0.5 * \left[\frac{\sum_{i=1}^{N}\delta_i^+}{\sum_{i=1}^{N}\gamma_i^+} + \frac{\sum_{i=1}^{N}\delta_i^-}{\sum_{i=1}^{N}\gamma_i^-}\right] \quad (1)$$

A lower S-statistic indicates a greater incidence of herding behavior;

My first regression model utilizes Equation 1 and calculates the S-statistic using annual earnings forecasts, including all forecasts between the time period starting 150 days prior to the announcement of annual earnings and extending through the announcement date. The general model follows Mensah and Yang (2008) and includes additional variables for shareholder investment horizon. The model is as follows:

$$S_j = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}TRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnaly + \beta_8 RegFD{*}NAnaly + \beta_9 AGE + \beta_{10} HES + \beta_{11} SIZE + \beta_{12} F\_Error + \varepsilon \quad (2)$$

The dependent variable in the regression is the S-statistic for each company as described in Equation 1 above. TRA is the percentage of transient holdings in the firm while DED is the percentage of the firm owned by dedicated institutional investors. I calculate transient holdings and dedicated holdings as of the end of the third fiscal quarter as the third fiscal quarter is generally closest to the beginning of the S-statistic calculation period.[4] The investor classifications of transient and dedicated are adapted from Bushee (1998) as described previously. RegFD is an indicator variable equal to one if the beginning of the observation period occurred after the formal passage of Reg FD and zero otherwise. RegFD is also interacted with each investor classification in order to determine how the effect of each investor class on analyst herding may have changed post-Reg FD. Due to the non-directional hypothesis regarding β_1 and β_2, no prediction is made on the sign of the interaction terms. NObs is the number of forecasts made by analysts in the company's fiscal year. It is expected the coefficient on this variable will be positive since greater forecasts will cause analysts to try to differentiate themselves. NAnaly is equal to the number of analysts following the firm. It is expected that this variable will be positive since the greater number of analysts will lead to lesser herding due to increased incentive to stand out from the crowd (Lin and McNichols 1998). An interaction of NAnaly and RegFD allows for the coefficient on NAnaly to vary in the post-Reg FD environment. No prediction is made regarding the sign of this variable. AGE is the average age of the forecasts utilized in the observation period. Forecast age is calculated as the time in days between forecast issue date and earnings announcement date to which that forecast pertains. It is expected the sign on this variable will be

[4] See Section 7 for my robustness check which uses an S-stat calculation window of 120 days instead of 150 days.

positive because older forecasts should be more greatly dispersed, whereas newer forecasts should appear closer together. HES is the historical earnings stability measured as the standard deviation of quarterly earnings over the past 5 years. The predicted sign of this variable is unknown due to the conflicting effects of an uncertain environment which could lead to more or less herding. SIZE is the natural log of firm market capitalization where market capitalization is measured as the beginning of the quarter firm stock price times the number of common shares outstanding. No prediction is made with respect to the sign of this variable. Finally, F_Error is the absolute value of the difference between actual earnings and the last consensus forecast issued before the earnings announcement. It is expected that the sign on this variable will be positive as a smaller forecast error is indicative of newer forecasts and consequently less forecast dispersion.

Hypothesis 1 will be tested by analyzing the sign and significance of the variables representing the percentage of transient investors (TRA) and the percentage of dedicated investors (DED). Since a lower S-statistic is indicative of greater analyst herding, a significant negative coefficient on either TRA or DED indicates a positive association with analyst herding while a positive coefficient indicates a negative relationship. If TRA is associated with greater analyst herding, this is consistent with the reputational incentives to herd driving the relationship, as described previously. Conversely, if TRA is associated with less analyst herding behavior, then the disruption in the information cascade is driving the relationship. Any effect of DED should be opposite that of TRA.

4.2 Hypothesis 2

My second hypothesis attempts to more closely examine the reason for any relation between analyst herding and shareholder investment horizon. As described earlier, the two potential reasons relate to: 1) the firm's information environment, and 2) poor monitoring by transient shareholders. A two-stage regression procedure is utilized to examine these two possible reasons for analyst herding. For each two-stage regression, a prediction of transient owners (PredTRA) in a particular stock is made in a first stage regression and then utilized in Equation 3. Equation 3 is the generalized second stage of the regression and can be represented as follows:

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*PredTRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnaly + \beta_8 RegFD*NAnaly + \beta_9 AGE + \beta_{10} HES + \beta_{11} SIZE + \beta_{12} F\_Error + \varepsilon \quad (3)$$

PredTRA is the predicted value of transient holdings calculated using various first stage regressions (Equations 4, 5, 6 explained in detail below). All other variables are the same as in Equation 2. The parameters used to calculate PredTRA (Eq. 4 – Eq. 6) are obtained using two distinct datasets. The first dataset (hereafter "Original sample") includes only the original observations utilized in testing H1. Thus, the factors utilized to explain transient ownership are calculated using only those original observations. As a verification of the generalizability of my findings, I also calculate PredTRA on a second dataset (hereafter "Full sample") using all data available on the CRSP/Compustat Universe. In this Full sample, the factors utilized to explain transient ownership are calculated using all available data. This should help provide evidence indicating whether my results are unique to the original data sample.

The first specification of the first stage regression includes control variables that have been shown in the literature to be associated with transient ownership, and uses neither future returns to proxy for the firm's information environment nor accounting discretion variables to proxy for accounting discretion. This benchmark specification follows Yan and Zhang (2009) and is utilized to determine the preferences of short-term institutional investors. This specification provides a standard against which to evaluate the strength of the results obtained with alternative specifications. The basic model is as follows:

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \varepsilon \quad (4)$$

The predicted variable in the regression (TRA) is the percentage of transient investors in a particular stock. MktCap is equal to the natural log of the firm's market capitalization with a coefficient expected to be positive because institutions exhibit a preference for larger firms. AGE is the number of months the firm has appeared in the CRSP database. The anticipated sign of this variable is negative as short-term investors have been shown to have a preference for younger firms (YZ 2009). DP is equal to the company's dividend yield. The coefficient expected on DP is negative as short-term investors have been shown to prefer firms with lower dividend yields (YZ 2009). BM is calculated as the firm's book-to-market value.[5] It is expected that this coefficient is positive as institutions have been found to target firms with higher book values. PRC is the firm's share price. Due to the institutional preference for larger firms, it is expected that this coefficient will be positive. TURN is equal to the average monthly turnover over the

[5] Following YZ (2009), firm book-to-market and dividend yield are winsorized at the 1rst and 99th percentile.

previous quarter. The expected coefficient on TURN is positive as short-term institutions have been found to exhibit a strong preference for stocks with high turnover (YZ 2009). VOL is equal to the monthly volatility of the stock over the past two years. It is expected that the coefficient on VOL will be positive as it has been found that short-term investors invest in volatile stocks (YZ 2009). SP500 is an indicator variable equal to 1 if the firm was a member of the S&P 500 Index. It is unclear what the direction of this coefficient will be as transient investors have not been shown to exhibit a preference for S&P 500 stocks. Utilizing this control specification will help to determine the incremental effect on analyst herding acquired by including either a proxy for the firm information environment (future return variables) or a proxy for poor monitoring (accounting discretion variables). This should help to more accurately identify potential reasons for any association between analyst herding and transient ownership.

The main purpose for using a two-stage regression is to capture the aspect of transient investors causing analysts to herd. Hypothesis 2a essentially asserts it is the firm information environment in which transient shareholders invest which causes an association between analyst herding and shareholder investment horizon. This is tested using a regression predicting transient institutional holdings on the basis of how informed they are. The degree to which transient investors are informed is operationalized by including variables for the 3-month and 12-month cumulative returns of the security. This first stage regression is represented as follows:

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 RET3 + \beta_{10} RET12 + \varepsilon \quad (5a)$$

A second specification of the above model is also tested which includes the lagged 3-month and 12-month returns. Including lagged returns should further improve the ability of the regression to yield a prediction of transient ownership associated with available private information because transient investors have been found to be momentum traders. Including variables for prior returns will control for the portion of future returns earned using momentum trading strategies. Controlling for momentum trading returns should better isolate the returns transient investors earn from being informed and should give a better prediction of transient ownership associated with private information. Therefore, the second specification includes prior as well as future returns and can be represented as follows:

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 RET3 + \beta_{10} RET12 + \beta_{11} LAGRET3 + \beta_{12} LAGRET12 + \varepsilon \quad (5b)$$

The control variables ($\beta_1 - \beta_8$) are as defined previously. RET3 and RET12 are equal to the cumulative 3-month and 12-month returns for the stock, respectively.[6] Due to the informed nature of transient investors, it is expected the coefficients on both variables will be positive. LAGRET3 and LAGRET12 are equal to the cumulative 3-month and 12-month lagged returns for the stock, respectively. Because of the nature of momentum trading strategies, it is expected the coefficients on both variables will be positive. The predicted values for TRA from Equation 5a and 5b are then inserted into Equation 3. This procedure permits a test of whether analyst herding is due to the information environment surrounding companies which affords transient investors the

[6] Following Yan and Zhang (2009), the cumulative 3-month return (RET3) is defined as the cumulative return from month t+1 through month t+3. The cumulative 12-month return (RET12) is defined as the cumulative return from month t+4 through month t+12. A similar procedure is used for the lagged returns (LAGRET3 and LAGRET12).

opportunity to acquire private information. Obtaining a significant coefficient on the predicted value of TRA from Equation 3 is consistent with the type of firm information environment causing a correlation between analyst herding and the presence of transient investors.

To test H2b regarding transient investors as poor monitors, a two-stage regression approach is also utilized. First, a prediction of transient investor holdings using accounting discretion variables is developed using a model adapted from Bowen et al. (2008). In their study, three measures of accounting discretion are identified. Equation 6 predicts TRA on the basis of those measures of accounting discretion and is represented as follows:

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 ABNACC + \beta_{10} SMOOTH + \beta_{11} SMP + \varepsilon \quad (6a)$$

A specification of the same model using leading accounting discretion variables in place of current accounting discretion variables is also utilized in an attempt to differentiate between analysts reaction to the current accounting discretion transient owners may cause versus accounting discretion these owners may cause in the future. The concept is that analysts may herd as a reaction to the current level of transient ownership even though they believe the poor monitoring effects which result from this current level of transient ownership will not manifest until the next period. This second specification with leading variables is as follows:

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 LEADABNACC + \beta_{10} LEADSMOOTH + \beta_{11} LEADSMP + \varepsilon \quad (6b)$$

Similar to Equations 5a and 5b, the predicted variable is the percentage of transient investors (TRA). Furthermore, β_1 through β_8 for Equations 6a and 6b are the same as those defined in the previous stage one regression and their predicted coefficient signs remain the same. ABNACC is the average absolute value of quarterly abnormal accruals (see Dechow, Sloan, and Sweeney 1995) taken over the prior three year period. SMOOTH is a measure of earnings smoothing calculated as the standard deviation of operating cash flows divided by the standard deviation of earnings measured over the prior three years. Finally, SMP is a measure of the incidence of small positive earnings surprises[7] and is calculated as the fraction of the prior 12 quarterly earnings surprises that were small positives. The "lead" transformations of each accounting discretion variable (LEADABNACC, LEADSMOOTH, and LEADSMP) are equal to the value of the variable in year t+1. The predicted sign of the coefficients on all three of the current and leading accounting discretion variables is positive due to the poor monitoring behavior of transient investors. Predicting TRA using these measures of accounting discretion permits a test of whether analyst herding is due to the perceived poor monitoring of transient investors that allows management to exercise excess discretion and consequently makes firm disclosures less credible. Hypothesis H2b is supported by finding a significant coefficient on the predicted value of TRA (PredTRA).

4.3 Hypothesis 3

Hypothesis 3 states that analysts will give more weight to management earnings guidance when the shareholder investment horizon is longer. This implies having more transient investors will cause analysts to weight guidance less while having more

[7] A small positive surprise occurs when the change in seasonally lagged quarterly earnings after tax (E_q-E_{q-4}) scaled by total assets at the end of quarter q-5 falls within the range of (0.00 to 0.0025).

dedicated investors will cause analysts to weight guidance more. This is tested by calculating the percentage of analysts that revise their forecasts surrounding the issuance of management earnings guidance. The model is adapted from Cotter et al. (2006) and is as follow:

$$FRAC = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 AnalystOptimism + \beta_4 AnalystDispersion + \beta_5 ROA + \beta_6 LOSS + \beta_7 POINT + \beta_8 RANGE + \beta_9 LessThan + \beta_{10} GreaterThan + \beta_{11} TimeTrend + \beta_{12} NumFCast + \beta_{13} PostFD + \beta_{14} SIZE + \varepsilon \quad (7)$$

The dependent variable FRAC is measured as the percentage of analysts who revise their forecast within five days of the issuance of management guidance. TRA and DED are as defined previously. AnalystOptimism is the difference between the beginning of period consensus analyst forecast and actual earnings, scaled by the absolute value of earnings. It is expected that the sign on AnalystOptimism will be positive because analysts will weight guidance more when it is relatively pessimistic. AnalystDispersion is the standard deviation of analysts' earnings per share forecasts as of the beginning of the quarter, scaled by the absolute value of earnings. It is anticipated that the sign on this variable will be positive because when dispersion is high, it is more likely management will issue meaningful guidance to correct the mistaken consensus. ROA is analysts' consensus quarterly earnings forecast at the beginning of the fiscal quarter, scaled by the lagged value of assets. LOSS is an indicator variable that equals 1 if analysts' consensus quarterly earnings forecast at the beginning of the quarter is a loss and 0 otherwise. No prediction is made with respect to ROA or LOSS. Indicator variables representing the form of management guidance are included as it has been shown this can influence the reaction to guidance (Pownall 1993). POINT is an indicator variable that equals 1 if the forecast is a point forecast. RANGE is an indicator variable that equals 1 if the management earnings forecast is a range. It is anticipated the coefficient on both POINT and RANGE will be positive as both types of forecasts are more precise than open-ended forecasts. LessThan is an indicator variable equal to 1 if management provides "less than" guidance. The coefficient on LessThan is expected to be positive as it has been found that analysts are more likely to react to bad news (Williams 1996). GreaterThan is an indicator variable equal to 1 if management provides "greater than" guidance. No prediction is made with respect to the sign of GreaterThan. TimeTrend is equal to 1 in the first quarter of the sample. NumFCast is equal to the number of analysts appearing in the consensus forecast. PostFD is an indicator variable equal to one if the beginning of the consensus period occurs after October 31, 2001. SIZE is equal to the natural log of the firm's market capitalization calculated as the firm's stock price times the number of common shares outstanding at the beginning of the quarter. No predictions are made with respect to the sign of TimeTrend, NumFcast, PostFD, and SIZE. Hypothesis 3 will be supported if either the coefficient on TRA is negative and significant or, alternatively, that on DED is positive and significant. Either of these two possibilities will demonstrate that analyst forecast revision is positively associated with shareholder investment horizon.

5. SAMPLE SELECTION

The sample for my analyses contains data from CRSP, Compustat, Thompson-Reuters, and First Call databases while the time period examines the years 1998-2007. Bushee (1998) classifications are utilized to categorize institutional holdings data, as described previously. Institutional holdings data for the transient (TRA) and dedicated (DED) variables were gathered from the 13f filings on the Thomson-Reuters database. Analysts' forecasts for the calculation of the S-statistic described in Equation 1 to assess the impact of shareholder horizon on analyst herding were obtained from the I/B/E/S database.[8] Control variables for the model to test analyst herding, including forecast error and analyst following, are also calculated using data from I/B/E/S. To calculate historical earnings stability and company size, data is obtained from the Compustat database.

The stage one regressions are conducted using data from the CRSP and Compustat databases. As discussed in Section 6, each stage one regression is run on two different data samples. The first sample (Original sample) uses only data available from the original test of H1 to calculate predicted transient ownership. The second data sample (Full sample), however, uses all data available on the CRSP/Compustat Universe when performing the first stage regressions.

The test of analyst forecast revisions utilizes data from the First Call databases between the years of 1998-2007. The sample contains all firms that issued guidance during the observation period. Management guidance data was obtained from the First Call Company Issued Guidance database. Information surrounding analyst revisions and the consensus forecast were calculated using data from the First Call Analyst Estimate database. Finally, actual amounts for earnings announcements were obtained from the First Call Actuals database and necessary data regarding company size were obtained from the Compustat database.

[8] Firms must have at least two analyst forecasts in the 150 day S-statistic calculation period preceding the announcement of earnings to be included.

6. RESULTS

6.1 Shareholder Horizon and Analyst Herding

This section describes the empirical analyses that have been completed to provide some insight into analysts' characterization of transient investors and their effects on company disclosure. A summary table of all the results from the tests performed in this study is included in Appendix B. The first hypothesis tests the effect of shareholder investment horizon on the propensity of analysts to herd in issuing earnings forecasts. The model utilized in this test is adapted from Mensah and Yang (2008) and is conducted using Equation (2) which regresses the herding measure (the S-statistic) on a number of variables where the main variables of interest are the percentage of transient (TRA) and dedicated (DED) holdings in the firm's stock. Descriptive statistics for all variables in the regression are presented in Table 1.[9] The mean of the S-statistic is 0.626 is very similar to the mean S-statistic (0.63) found in the samples of Mensah and Yang (2008). This demonstrates a high degree of consistency in the calculation of the herding measure. Overall, the descriptive statistics appear to be generally in line with their study.

[Insert Table 1 Here]

Table 2 presents the results for examining H1, which is a test of shareholder investment horizon and analyst herding behavior. The main variables of interest are TRA and DED which represent the percentage of transient and dedicated investor holdings, respectively. The prediction of H1 was nondirectional as, a priori, it is not clear whether the effect of shareholder investment horizon on the cascading of information or on herding due to reputational concerns would dominate. The results indicate the coefficient on TRA is highly significant (-0.1142; p<.001). Since a lower S-statistic is indicative of

[9] Five outlying data points with an HES greater than 100 were removed from my sample. Including those data points causes the standard deviation of HES to go from around 1 to 362. All of my results, however, are robust to the inclusion of those data points.

greater analyst herding, this supports H1 and implies having more transient shareholders is associated with a greater degree of analyst herding in issuing forecasts. While it is difficult to ascribe economic significance to the coefficient value, relevant inferences can be made. For example, the coefficient of -0.1142 means, ceteris paribus, a firm with the median amount of analyst herding (S-stat = 0.567) and no transient ownership would experience a move to the top quartile of firms experiencing analyst herding behavior (S-stat = 0.500) if ownership completely shifted to transient investors. Thus, the more transient ownership a stock has, the more likely an analyst is to exhibit herding behavior and issue a conforming forecast. These results are consistent with the effect on the analyst's incentive to preserve their reputation through herding dominating. They support the hypothesis analysts are herding to a greater extent in transient-owned companies because there is less of an incentive to trade-off safety for accuracy. The variable DED is insignificant which means that the percentage of dedicated institutional ownership does not cause a change in the firm's S-statistic. With respect to the interactions between institutional ownership and RegFD, it is found that both interactions are significant. The coefficient on TRA*REGFD is 0.0575 (p-val=.075) while that on DED*RegFD is 0.0789 (p-val=.034). These results concur with those of Mensah and Yang (2008) and demonstrate that overall RegFD has diminished the propensity of financial analysts to herd in their forecasts.

[Insert Table 2 Here]

With regards to my control variables, I find the sign on F_Error is negative and significant and therefore is associated with a greater degree of herding. AGE is not found to be significantly related to analyst herding. These primary results are consistent with those of Mensah and Yang (2008), as well as the majority of results for the control variables. Minor differences in control variables are found with respect to variables utilizing RegFD. These discrepancies involving the RegFD indicator variable could be due to the differential in the time periods examined. The sample examined in this proposal is dominated by the post RegFD period while that of MY (2008) is predominantly pre-RegFD. Overall, the results are consistent with the conjecture that reputational concerns dominate the effect on analyst herding behavior caused by the investment horizon of shareholders. The next phase of my analyses tests the second set of hypotheses which will examine whether this effect is due to the company information environment of firms in which transient institutions invest or whether it is the result of poor monitoring by transient investors which causes company disclosures to be less credible.

6.2 Predicting Transient Ownership

The second phase of my analysis is the test of H2 which attempts to identify the reason for the positive association between transient investors and financial analyst herding. H2a indicates the reason for the association between transient investors and analyst herding has to do with the availability of private information in transient-owned firms. In contrast, H2b indicates the reason for the association is due to the poor monitoring behavior associated with a transient investor base. To test these hypotheses, a two-stage regression procedure is utilized, as described in Section IV. This two-stage regression procedure is performed on two different data samples. The first sample uses only data from the original test of H1. The second sample, however, uses all available data in the CRSP/Compustat universe in the first-stage regression. Using this larger dataset serves as an additional test of H2 and will examine whether the results are unique to the Original data sample.

Table 3 presents descriptive statistics for both the Original sample as well as the Full sample of data. Included in this table are the two future return variables (RET3 and RET12), the accounting discretion variables, and all the relevant control variables used in the first stage regressions. As discussed in Section IV, the accounting discretion variables are those found in Bowen et al. (2008). Generally, the values for my accounting discretion variables line up very well with those in the Bowen et al. (2008) study with the exception of the discretionary accruals variable (ABNACC). The mean and median of SMOOTH and SMP are very close to the statistics presented in Bowen et al. (2008), but the mean and median of ABNACC are significantly higher for both of my data samples. The median for my samples is around 0.15 while the median value for ABNACC in their study is 0.036. This difference may be due to the differing time periods used. The sample period used in Bowen et al. (2008) is from 1992-1995 while my sample contains data from 1998-2007. This increase in ABNACC suggests the average amount of abnormal accruals in a firm has increased significantly over time.

[Insert Table 3 Here]

Comparing the Original dataset to the Full dataset yields several interesting differences. First of all, the Original dataset has a higher average transient ownership per firm. The mean transient ownership on the Original dataset is 0.187 while the mean transient ownership in the Full sample is only 0.142. This could be due to the fact that firms in the Original dataset have a higher average analyst following, as firms followed by analysts tend to have larger transient ownership. Another feature of the firms in the

Original dataset is they are generally older firms with an average company age of 278.02 months on CRSP (compared to an average age of 194.19 months in the Full dataset). Additionally, the firms in the Original datasets have larger values for RET3. In the Original dataset, the mean for RET3 is 0.080. For the Full dataset, however, the means for RET3 is only 0.063. The values for RET12, however, are very similar. Along with greater transient ownership, the higher returns in RET3 could also be due to an association with higher analyst following. Finally, the book-to-market ratio of firms in the Original dataset (0.477) is lower than the firms in the Full sample (0.623).

Comparing the descriptive statistics of my Full dataset with those of Yan and Zhang (2009) also yields interesting differences. The most striking contrast between my Full dataset and YZ (2009) is the average dividend yield on my Full dataset (0.006) is far lower than that of YZ (0.021) (2009). It is clear, however, that the reason for this difference is the fact that Yan and Zhang (2009) only include dividend paying firms, as evidenced by a minimum amount on dividend yield which is greater than zero, while in my sample some firm observations have cash dividends equal to zero.[10] Another difference between my dataset and that of Yan and Zhang (2009) is the average book-to-market ratio of my firms (0.623) is a bit lower than that of Yan and Zhang (0.74). A final difference is the average turnover of the firms used in my sample (0.136) is a bit higher than that used in YZ (2009) (0.078). Other than the differences described here, the descriptive statistics of my Full dataset line up well with those of Yan and Zhang (2009).

The first test of my results utilizes the Original dataset to obtain parameters to predict transient ownership. Panel A of Table 4 shows the results of the first stage regressions using this Original sample. The first specification of my regression (Eq. 5a)

[10] Missing cash dividend amounts were set to zero.

uses future returns as a proxy for the informed nature of transient investors. Yan and Zhang (2009) find greater short-term institutional ownership is generally associated with positive future returns. Unfortunately, it is not possible to draw clear conclusions regarding future returns and transient ownership in my analysis. Of the 10 years in my sample, RET3 is positive and significant[11] in only 1 year and also shown to be negative and significant in 1 other year. RET12 is positive and significant in 2 years but is also negative and significant in 2 other years. Unlike prior research, results using the Original dataset do not indicate that transient ownership is unequivocally associated with greater future returns. This lack of significance could be due to the lower power associated with the smaller size of the Original sample. When lagged returns are added to the regression (Eq. 5b), there are similar results providing mixed evidence as to whether RET3 or RET12 are associated with greater future returns. One interesting finding, however, is that both LAGRET3 and LAGRET12 appear to be positive and significant. LAGRET3 is found to be positive and significant in 4 of the 10 years sampled while LAGRET12 is found to be positive and significant in 6 of the 10 years sampled. These results with respect to lagged return variables are consistent with momentum trading by transient institutions. This characterization of short-term institutions as momentum traders is consistent with the results of YZ (2009) and it underscores the need to control for a momentum trading effect when trying to tease out the degree to which transient institutions are informed. In summary, I find mixed results in my Original sample regarding the association between transient ownership and future returns, but document a strong positive association between transient ownership and lagged returns.

[11] A variable is deemed to be "significant" in a year if the coefficient on the variable contains a p-value less than .05.

[Insert Table 4 Here]

The next test predicts transient ownership (TRA) using accounting discretion (Eq. 6a) in the Original sample. These results are presented in Panel B of Table 4. Accounting discretion is utilized as a proxy for the poor monitoring of transient investors. The three variables of interest are ABNACC, SMOOTH, and SMP which capture abnormal accruals, earnings smoothing, and the incidence of small positive earnings surprise. The first test uses current year accounting discretion variables. With respect to ABNACC, it does not appear that greater transient ownership is associated with higher abnormal accruals. ABNACC is not found to be significant in any of the 10 sample years. Regarding earnings smoothing, results show that SMOOTH is positively and significantly associated with transient ownership in 2 of the 10 years of the sample. This finding could indicate transient owners are associated with greater accounting discretion but the effect is not robust as the variable is significant in only 2 years. The results for small positive earnings (SMP) demonstrate an effect opposite of what was anticipated. In 3 of the 10 years sampled, the coefficient on SMP is negative and significant. This implies transient ownership is associated with a diminished incidence of small positive earnings. This result is consistent with prior research which finds transient owners to be informed investors who are only influenced by the failure to meet earnings benchmarks when it is indicative of future performance (Hu et al. 2009). Thus, merely manipulating earnings to beat the amount of the prior year may not persuade transient investors. The results are similar when leading accounting discretion variables are used in place of current accounting discretion variables (Eq. 6b). LEADABNACC is statistically significant in explaining transient ownership in only 1 year of the sample while

LEADSMOOTH is found to be significant and positive in 4 out of 10 years. Finally, the association between transient ownership and LEADSMP is found to be negative. The coefficient on this variable is negative and significant in 4 years of my sample. Overall, there does not appear to be strong support indicating transient ownership is associated with greater use of accounting discretion by management.

With respect to the control variables used to predict transient ownership, the variables in my Original sample line up well with those of Yan and Zhang (2009) (results presented in Panel B of Table 4). Similar to their analysis, I find transient investors prefer firms that have lower dividend yields and higher turnover. Yan and Zhang (2009), however, find short-term institutions prefer firms that are larger, younger, and have a higher book-to-market ratio. While short-term institutional ownership is not found to be associated with larger or younger firms in this dataset, both of these variables are positive and significant in the Full dataset. However, with respect to book-to-market ratios, I find results opposite from those of YZ (2009). The coefficient on BM is negative and significant in 5 years of my sample and is not found to be positive and significant in any of the years sampled. This contrasts the results of YZ (2009), which find short-term institutional ownership to be associated with higher book-to-market firms.

After using the Original sample to test H1, I rerun the regressions using the Full sample of data available in the CRSP/Compustat universe. This gives a prediction of TRA using all data available and provides a good generalization of the results. Findings are presented in Table 5. In the first specification, using only future returns (RET3 and RET12), the coefficient on RET3 is positive and significant in 4 of the 10 years sampled and is not found to be negative and significant in any of the years sampled (results presented in Panel A of Table 5). This is consistent with prior research that shows transient ownership to be associated with positive future annual returns. Results on the coefficient of RET12 are mixed, however, and thus a significant association between transient ownership and future annual returns is not found. The next specification incorporates the lagged three month and twelve month returns (LAGRET3 and LAGRET12). When the lagged returns are included in the regression, RET3 maintains significance in only 2 years of the sample. Furthermore, RET12 continues to be insignificant. With respect to lagged returns, LAGRET3 is negative and significant in 4 years of the sample while a positive and significant coefficient is not documented in any of the years. This may suggest transient owners prefer to invest in stocks they believe have been undervalued in the short-term. Ultimately, this serves to underscore the short-term nature of this category of investors. Interestingly, however, opposite results are found for LAGRET12. The coefficient is shown to be negative and significant for only 1 year while it is positive and significant for 4 of the 10 sample years. This finding is consistent with transient investors employing momentum trading strategies. In summary, in the Full sample, the analysis of transient ownership and firm stock returns demonstrates transient ownership is both associated with positive short-term future returns and is strongly association with lagged or prior returns.

Next, results for the first-stage regression utilizing accounting discretion variables for the full data sample are examined. The findings are presented in Panel B of Table 5. When current accounting discretion variables are employed (Eq. 6a), I fail to find evidence consistent with the conjecture that transient investors are associated with greater accounting discretion. In fact, results indicate an opposite effect. While the coefficient on ABNACC is positive and significant in 1 year of the sample, it is negative and significant for 3 of the 10 years sampled. Furthermore, a strong negative association is found between transient ownership and the incidence of small positive earnings. The coefficient on SMP is negative and significant in 6 years of the sample and is not found to be positive and significant in any of the years sampled. Regarding earnings smoothing, no conclusive evidence is found supporting either a positive or a negative association between transient ownership and earnings smoothing, as the coefficient on SMOOTH is significant in only 1 year sampled. Results are similar when leading accounting discretion variables are used in place of current discretion variables. Transient ownership is significantly associated with negative abnormal accruals (LEADABNACC) in 2 of the 10 years in my sample while a positive and significant association between abnormal accruals and transient ownership is not documented in any of the years sampled. Similar to the specification using current accounting discretion variables, a strong negative association between small positive reported earnings and transient ownership is exhibited. The coefficient on LEADSMP is found to be negative and significant in 5 of the 10 years studied. Finally, there is again no conclusive evidence that transient ownership is related to more or less earnings smoothing as the coefficient on LEADSMOOTH is insignificant in all 10 years sampled. As with the Original sample, tests using the Full sample fail to document a positive association between transient ownership and greater accounting discretion.

Results for the control variables in the Full dataset are also similar to the Original dataset in that they match up well with the results of YZ (2009) (results presented in Panel B of Table 5). These results indicate transient owners prefer firms that are larger, younger and have lower dividend yields and higher turnover. As in the Original sample, however, transient ownership is found to be associated with firms that have a lower book-to-market ratio. Therefore, the results of the analysis predicting transient ownership are all consistent with the findings of Yan and Zhang (2009) with firm book-to-market being the one exception.

[Insert Table 5 Here]

Overall, the results of this analysis are consistent with prior research which shows transient investors are informed, but inconsistent with the poor monitoring characterization of transient owners. With respect to the informed nature of transient owners, the Original dataset does not provide conclusive evidence regarding the relation between transient owners and future returns. When the Full dataset is utilized, however, it is shown transient ownership is generally associated with positive short-term returns. Furthermore, the results support the characterization of transient investors as momentum traders. Lagged 3-month and 12-month returns are found to be even more significant than future returns in explaining transient ownership. This indicates it is important to control for momentum when attempting to capture the informed nature of transient investors. With regards to the poor monitoring characterization of transient investors, evidence supporting the conjecture that transient owners are associated with greater accounting discretion is not found. There does exist slight evidence that transient ownership may be associated with greater earnings smoothing but no results are found to indicate transient owners are associated with either greater abnormal accruals or an increased incidence of small earnings surprises. In fact, the analyses point to the opposite relation, particularly in the case of small positive earnings surprises. In summary, the findings documented are inconsistent with the poor monitoring characterization of transient investors. It does not appear that the results are sufficient to support the conjecture that transient owners are associated with enhanced monitoring. Further testing, such as that described in Section 8, is needed to more completely address this research question.

6.3 Analyzing the Reason for Analyst Herding

The next phase of my analysis is to perform the second stage of the two-stage regressions using the prediction obtained for TRA (PredTRA). The model utilized is depicted in Equation 3. This two-stage regression is performed to provide additional insight into whether analysts are herding due to the informed nature of transient investors or the poor monitoring associated with these owners. This is first performed using the Original dataset with results presented in Tables 6A, 6B, and 6C. The first specification of PredTRA uses neither return variables to proxy for the firm's information environment nor accounting discretion variables to proxy for the poor monitoring of transient investors but includes only a vector of control variables known to be association with transient ownership. This specification serves as a benchmark for the evaluation of my succeeding tests (results presented in Table 6A). Since I do not include proxies for the availability of private information or accounting discretion, this specification is used to gauge the degree to which adding those proxies strengths my results. In this benchmark specification, the coefficient on PredTRA is found to be very significant (-.1885; p-value=.004). This demonstrates the finding of analyst herding in the presence of transient ownership is robust to using a predicted value for transient shareholdings. The tests which follow will help to differentiate between the informed investor and poor monitoring hypotheses.

[Insert Table 6A]

The next two specifications utilize return variables as proxies for the firm information environment (results presented in Table 6B). Using only future return variables (RET3 and RET12) yields a coefficient of -0.1886 (p-value=.004) for PredTRA. This suggests there is a strong association between the prediction of TRA obtained by using return variables and analyst herding. Furthermore, the coefficient on DED*RegFD is also positive and significant (.0905; p-value=.036). This shows the effect Reg FD had on diminishing analyst herding is robust to using a predicted value of TRA. While the results of using future return variables to predict TRA yield a strong association with analyst herding, the prediction of TRA which includes lagged return variables is even stronger (Table 6B). When lagged return variables are included in the regression (LAGRET3 and LAGRET12), the coefficient on PredTRA increases to -0.2495 (p-value <.0001). This coefficient (-0.2495) far exceeds the coefficient obtained using the benchmark specification containing only control variables (-0.1885). In fact, this is the strongest coefficient of all the specifications utilized and it demonstrates controlling for momentum trading is an important component of predicting transient ownership on the basis of the informed nature of these investors. The strength of this coefficient is consistent with the conjecture that analyst herding is increasing due to some aspect of the information environment of transient-owned firms.

[Insert Table 6B]

The specification utilizing accounting discretion variables (ABNACC, SMOOTH, and SMP) yields significantly weaker results than the specification using return variables (presented in Table 6C). The prediction of TRA that utilizes current accounting discretion variables gives a coefficient of -0.1625 (p-value=.021) on PredTRA. When leading accounting discretion variables are employed in place of current discretion variables, the coefficient on PredTRA is further weakened (-0.1455; p-value=.046). This suggests financial analysts are reacting to the current accounting discretion caused by transient owners in a greater way than to accounting discretion these investors may cause in the future. Overall, the results of using PredTRA from accounting discretion variables are significantly weaker than those using return variables. Furthermore, both specifications utilizing accounting discretion variables give significantly weaker results than those obtained using the benchmark specification (-0.1625 and -0.1455 versus -0.1885). This demonstrates that including proxies for accounting discretion does not improve the ability of transient ownership to explain analyst herding. This finding is inconsistent with the hypothesis that analysts are herding in the presence of transient owners due to the belief that transient owners are poor monitors.

[Insert Table 6C]

As a verification of the robustness of the previous findings, the 2nd stage regression is also run on the Full dataset comprised of all available data on the CRSP/Compustat universe. The results are presented in Tables 7A, 7B, and 7C. The first specification of the Full sample of data uses only the control variables for the prediction of transient ownership and uses neither return variables nor accounting discretion variables (results presented in Table 7A). The coefficient on PredTRA using only control variables is both negative and significant (-0.1752; p-value=.022). This result will serve as a benchmark to evaluate the informed investor and poor monitoring hypotheses using the Full dataset.

[Insert Table 7A]

The next specification tested uses only RET3 and RET12 to predict transient ownership (results presented in Table 7B). This test yields a coefficient on PredTRA that is negative and significant (-0.1801; p-value=.02) though not to the same degree as that found in the Original data sample. Furthermore, unlike in the Original sample, adding lagged returns (LAGRET3 and LAGRET12) achieves only a small incremental increase in the magnitude and significance of the coefficient on PredTRA (-0.1810; p-value=.013). Though this increase is not substantial, the strong magnitude and significance of PredTRA in both specifications serves to validate the results found in the Original samples concerning analyst herding due to available private information. Furthermore, the results are greater than the benchmark specification (-0.1801 and -0.1810 versus -0.1752). This indicates that the inclusion of proxies for the firm information environment enhances the relationship exhibited between financial analyst herding and the firm information environment. This is consistent with the hypothesis that it is the informed nature of transient owners which is causing an association with analyst herding.

[Insert Table 7B]

The final specifications on the Full sample utilize predictions of transient ownership containing current accounting discretion variables and future accounting discretion variables, respectively. The association found in these specifications between transient ownership and analyst herding is demonstrably smaller (results presented in

Table 7C). The first specification uses current accounting discretion variables (ABNACC, SMOOTH, and SMP) to examine analyst herding related to the accounting discretion caused by the poor monitoring of transient investors in the forecast period. The coefficient on PredTRA using this specification is negative and marginally significant (-0.1418; p-value=.055). In the next specification, leading accounting discretion variables are used to examine the effect that future expected accounting discretion caused by transient investors could have on financial analyst herding (Table 7B). Using this specification yields a coefficient of a slightly smaller magnitude and diminished significance (-0.1376; p-value=.072). Overall, these results are significantly weaker than those using future return variables. Similar to when the Original data sample is used, the results using accounting discretion variables are weaker than those obtained using only control variables (-0.1418 and -0.1376 versus -0.1752). This provides further support for the conjecture that while there is indeed an association between transient ownership and financial analyst herding, it probably is not due to the poor monitoring of transient owners. However, because of the fact that there does exist some significance when accounting discretion variables are used, it is difficult to rule out with complete certainty the possibility that analyst herding is related to the monitoring characteristics of transient owners.

[Insert Table 7C]

Results are consistent with the hypothesis that the availability of private information in transient-owned firms is one important factor in the decision of financial analysts to herd. This result is shown in both the Original sample and in the expanded sample using all data available in the CRSP/Compustat universe. In both samples, after controlling for momentum trading, transient ownership, based on the degree to which these owners are informed, gives the strongest results. This prediction has a stronger association with analyst herding than a prediction of transient ownership obtained using only control variables. With respect to monitoring characteristics, however, my results do not support analyst herding as arising from the accounting discretion associated with transient owners. This is understandable as analyses conducted in the first-stage regressions were unable to establish a definite link between transient ownership and accounting discretion. Thus, my results are most consistent with analysts maintaining a view of transient investors as informed investors who trade in stocks with available private information. In contrast, there is insufficient evidence to support the hypothesis that analysts characterize these investors as poor monitors.

6.4 Analyst Revisions and Shareholder Horizon

Empirical results have also been completed with respect to H3. The third hypothesis is designed to examine the effect of shareholder investment horizon on the propensity of analysts to revise their forecasts in the event that management issues earnings guidance. The basic model utilized to test H3 is adapted from Cotter et al. (2006). This test is conducted by regressing the percentage of analysts who issue revised forecasts on a standard set of control variables along with the percentage of transient and dedicated ownership in the stock. The descriptive statistics for the second developed dataset are presented in Table 8 and are very much in line with those presented in Cotter et al. (2006). One difference appears to be the percentage of greater than and less than forecasts issued. A "greater than" forecast is a form of guidance where management gives an indication that earnings are expected to be "greater than" some amount while a “less than” forecast is one where management explains that earnings are anticipated to be “less than” a given amount. In my sample, only 8.67% of forecasts are “greater than” forecasts and only 8.46% of forecasts are “less than” forecasts. This differs from the samples used in Cotter et al. (2006) where 7.17% of the forecasts are “greater than” forecasts and 16.58% of the forecasts are “less than” forecasts. This is likely the results of different time periods for the samples. The Cotter et al. (2006) time period was 1995-2001 compared to my current sample (1998-2007).

[Insert Table 8 Here]

The regression results for testing H3 are provided in Table 9. The variable representing transient investors (TRA) does not appear to have a significant effect on the percentage of analysts revising their earnings forecast. Thus, no significant relation is found regarding the propensity of analysts to revise forecasts due to the presence of transient shareholders. In contrast, the coefficient on the variable representing dedicated investors (DED) is both positive and significant (0.2184; $p<.0001$). This finding is consistent with H3 which states that a longer shareholder investment horizon will be positively associated with the propensity of analysts to revise forecasts. These results are consistent with the conjecture that the better monitoring resulting from the dedicated institutional investors increases the degree of credibility associated with management earnings guidance. Analysts are more likely to change their earnings expectations when guidance is issued by firms that have better monitors of management. The coefficient of 0.2184 for DED indicates that there is approximately a 22% increase in the number of analysts who revise their forecasts for firms with dedicated owners compared to firms with no dedicated owners. Concerning the control variables, AnalystOpt, ROA, Range and LessThan are all positively and significantly related to the percentage of analyst revisions. These results are consistent with Cotter et al. (2006). Unlike Cotter et al. (2006), however, I did not find AnalystDis which measures the dispersion of analyst forecasts to be significant and I found Point and GreaterThan to be positive and significant. Finally, while the results of Cotter et al. (2006) do not show RegFD to be significant, my findings demonstrate a marginally significant positive relation between RegFD and Frac. Again, this is likely due to the differing periods used in the sample. Most of the control variables in the model are similar in sign and significance to that of Cotter et al. (2006). One important overall difference relates to the lower R-square of my model (5.86%) compared to the Cotter et al. (2006) model (21.8%). This differential is likely due to the fact that in Equation 5, unlike the Cotter et al. (2006) model, it is not appropriate to include firm fixed effects because my analysis seeks to test differences caused by type of owner. Inclusion of firm fixed effects would substantially raise the overall model R-square, but preclude the type of test I am most interested in conducting. Importantly, the results are consistent with the interpretation that firms with a substantial percentage of shareholders with a longer investment horizon improve the credibility of management disclosures in the view of analysts who, subsequently, are more likely to revise their earnings forecast after receiving management earnings guidance.

[Insert Table 9 Here]

7. **ROBUSTNESS CHECK**

One potential criticism of the methodology employed is the use of company data from the third fiscal quarter with the assumption that this gives me transient holdings as of the beginning of my S-statistic calculation period. Using the third fiscal quarter of company data does tend to place the calculation of transient holdings just inside the 150-day S-stat calculation period. On average, transient holdings are calculated as of day 30 with day 0 being the beginning of the S-stat calculation period. This means transient holdings are given, on average, not 150 days before the earnings announcement date but 120 days before. To alleviate concerns that arise from calculating transient holdings inside the S-stat calculation period, I perform a robustness check by shrinking my S-statistic calculation period to 120 days. This means, on average, transient holdings are calculated as of the beginning of the S-stat calculation period. Using this dataset, tests of H1 and H2 are rerun to determine effects on the results. Performing this robustness check serves to diminish concerns about whether the results are due to calculating transient ownership inside the S-stat calculation period.

Descriptive statistics on the dataset using the shorter S-statistic calculation period are presented in Table 10. The first noteworthy observation regarding the comparison of these descriptive statistics with my original sample is that there are fewer observations. This is understandable because the time period where available data is collected is shorter. The mean and median of the S-statistic, however, are virtually identical to my original sample. This is important as it indicates consistency in my tests. The average number of forecast observations (NObs) is slightly greater. This is also understandable as only firms with more forecast observations will meet the data requirements to be included in the sample when the S-Stat window is shortened. Finally, the AGE variable also decreased from a mean value of 87.27 in my original sample to a mean value of 78.25. The reason for this is obvious as shortening the S-stat period would make the forecasts, on average, closer to the announcement date. Overall, in this sample there are no significant deviations from my original sample other than the diminished average age of the forecasts.

[Insert Table 10]

The results of testing H1 using the shorter S-statistic calculation period demonstrate that the positive association between transient ownership and financial analyst herding is robust to the alteration of the S-statistic calculation window. Results are presented in Table 11. Similar to my original results, the coefficient on TRA is negative and significant (-0.112; p-value=.001). This demonstrates the finding of transient ownership leading to greater financial analyst herding was not merely due to the comingling of the periods in which transient ownership was determined and the S-stat was calculated. Not all of the effects discovered in the original results, however, are shown to be as robust. The interaction effects between institutional ownership and RegFD are not found to be significant when the shorter S-statistic calculation period is used. The interactions between transient and dedicated ownership with RegFD are both significant in the original specification (p-values of .065 and .0344, respectively), but neither interaction maintains significance when the S-stat calculation period was altered. The reason for this loss of significance is unclear. While these variables sustained a decrease in significance, other variables that were not significant in the original specification became significant when the calculation period is shortened. The interaction between NAnalyst and RegFD is found to be negative and significant at the 5 percent level though it was not significant earlier. The negative coefficient on this variable signifies that RegFD increased the effect of financial analyst following on herding. Finally, when the shorter S-stat calculation period is used, AGE is significant at the 1 percent level. This could be due to the diminished variability in the measure which makes the values more meaningful. Overall, the results show that the finding of transient ownership being associated with greater financial analyst herding is robust to altering the period in which herding behavior is analyzed.

[Insert Table 11]

After it has been shown the results of H1 are robust to the shortening of the S-stat calculation period, the next step is to repeat the test of H2. The tests of H2 find that predicting transient ownership using return variables as a proxy for the information environment yields the most significant association with financial analyst herding. Repeating these tests demonstrates the results are robust to the alteration of the S-stat calculation period. Results are presented in Table 12.

The results using only control variables obtain a coefficient that is both negative and significant (-0.1644; p-value=.027) but is of weaker magnitude and significance than when the return variables are included. For the next two specifications of the two-stage regressions using returns and lagged returns, results show the coefficient on PredTRA is negative and significant. The first specification using only current returns yields a coefficient on predicted ownership equal to -0.1654 (p-value=.020). Similar to my original results, including lagged returns increases the size and significance of the coefficient (-0.2175; p-value=.001). These results are consistent with the hypothesis that there exists an association between transient ownership and financial analyst herding due to the information environment of firms in which transient shareholders invest.

Regarding the prediction of transient ownership using accounting discretion variables, I do not find significance using the shorter S-stat window. This shows this finding is not robust to the manipulation of how herding is calculated. It is, however, somewhat understandable that the significance of the prediction employing these variables is weakened when the S-stat window is shortened, due to the fact that these discretion variables are annual variables. Having a shorter S-stat calculation window diminishes the relevance of abnormal accruals, earnings smoothing, and small earnings surprises. These variables are calculated over annual periods and thus should tend to influence behavior throughout the year and not in any one point in time. This may be the reason for the lack of robustness demonstrated by the accounting discretion prediction of transient ownership when the S-stat calculation period is shortened.

When the two-stage regression is performed on the Full data sample, the main tenor of the results is preserved. Using return variables produced the greatest and most significant association between analyst herding and predicted transient ownership. Results are given in Panel B of Table 12. Overall, the results are consistent with the assertion that the firm information environment is an important reason for the association between financial analyst herding and transient ownership. In summary, tests utilizing a shorter S-stat calculation period window find no conclusive evidence supporting the conjecture that financial analysts view transient investors as poor monitors of firm management. Conversely, the evidence is consistent with the portrayal of transient owners as informed investors.

[Insert Table 12]

8. FUTURE RESEARCH EXTENSIONS

One major extension of this study concerns an additional hypothesis which examines whether companies recognize the negative perception of transient investors by analysts. If companies recognize their disclosures are given less weight due to their investor base, then this could diminish the incentive to provide detailed disclosures. This is particularly true in the earnings guidance setting where critics have questioned the motivation of companies who provide such guidance. It is then very feasible that given a shareholder base comprised of more transient investors, management will choose not to issue earnings guidance. My additional hypothesis is then as follows:

H4: The decision to cease issuing earnings guidance is negatively associated with shareholder investment horizon.

Hypothesis 4

My additional hypothesis (H4) examines whether companies are aware of the effect that having a transient investor base can have on the credibility of firm disclosures. Specifically, H4 states that management will be more likely to discontinue issuing earnings guidance if the company has a transient investor base. H4 is tested by analyzing whether shareholder investment horizon affects the propensity of a firm to discontinue management earnings forecasts. The model to test this is adapted from Houston et al. (2008) who examine firm specific factors that contribute to the decision to cease issuing earnings guidance. It uses quarterly firm observations of companies that have continued to issue versus ceased issuing quarterly guidance. The four quarters before the quarter under observation are termed the pre-event period and the quarter of the observation combined with the successive three quarters are termed the post-event period. The model is as follows:

$$\Pr(\text{Stop} = 1) = \alpha_1 + \beta_1\text{TRA} + \beta_2\text{DED} + \beta_3\Delta\text{EPS} + \beta_4\text{MBanalyst} + \beta_5\text{FutureEPS} + \beta_6\text{Loss} + \beta_7\text{Return} + \beta_8\text{Management} + \beta_9\text{IndNo} + \beta_{10}\text{Dispersion} + \beta_{11}\text{FutureVAR} + \beta_{12}\text{Litigation} + \beta_{13}\text{LogMVE} + \beta_{14}\text{Analyst} + \beta_{15}\text{Volatility} + \beta_{16}\text{quarterlydummies} + \varepsilon \quad (8)$$

The dependent variable Stop takes on a value of 1 if the company ceased issuing firm guidance and is zero otherwise. A company is said to have ceased issuing guidance if they do not issue earnings guidance for the entire post-event period after having issued guidance for at least three of the pre-event quarters. TRA and DED are as defined previously. ΔEPS is the average change in diluted EPS of the four pre-event quarters relative to the respective same-quarter-last-year values, deflated by the stock price at the beginning of the pre-event period. MBanalyst is the proportion of quarters in the pre-event period for which the firm meets or beats the most recent analyst consensus compiled before the earnings announcement. FutureEPS will proxy for anticipated performance and is calculated as the average change from pre-event same-quarter values to post-event quarter values, also deflated by beginning stock price. Loss is calculated as the proportion of loss-reporting quarters in the pre-event period. Return is the market-adjusted return during the one-year period before earnings were announced in the quarter preceding the stoppage. ΔEPS, MBanalyst, FutureEPS, and Return are all proxies for performance and are expected to have negative coefficients as firms with superior performance would be expected to continue guidance. Loss is also a proxy for firm performance but the sign of the coefficient is expected to be positive as reporting a loss signals an inability to meet zero earnings which is an important performance benchmark (see Degeorge et al. 1999).

Management is an indicator variable equal to one if the firm had a change in the CEO or CFO. It is expected that a change in management could lead to discontinued guidance and the anticipated coefficient is therefore positive. IndNo is the proportion of companies in the firm's SIC code that did not provide any quarterly guidance in the pre-event period. It is expected that the coefficient on IndNo is positive as firms whose peers do not provide guidance may be more likely to cease issuing guidance. Dispersion is measured as the standard deviation of analysts' forecasts appearing in the last consensus of quarterly EPS. The amount is averaged over the three pre-event quarters. The expected coefficient on this variable is positive as managers who have less precise private information will be less likely to disclose it (Verrecchia 1990). FutureVAR measures managers difficulty in forecasting future earnings and is measured as the degree to which future earnings increasingly deviate from past earnings. It is calculated as taking the average difference between the four post-event quarters and the respective earnings 8 quarters before and comparing that average with the pre-event quarters and the respective earnings 4 quarters before[12]. The expected sign on this coefficient is positive as a greater difficulty in forecasting earnings increases the chance that managers cease to provide earnings estimates. Litigation is the probability of being sued, calculated using a litigation exposure model. The model was developed by Houston et al. (2008) and uses

[12] FutureVars sets the four quarters before the pre-event period as a benchmark period. This means the benchmark period contains quarters at times t-8, t-7, t-6, and t-5. The variable compares the average of the absolute difference between each respective quarter and the post-event period and then subtracts from this the same average performed with the pre-event period instead of the post-event.

firm characteristics such as size, volatility of returns, and industry to predict litigation exposure. The anticipated coefficient is positive as firms with greater liability exposure will be more apt to cease issuing guidance. LogMVE is the natural log of the market value of equity at the beginning of the event quarter. Analyst is the average analyst following for the four pre-event quarters. No predictions are made with respect to LogMVE or Analyst. Finally, Volatility is measured by the standard deviation of daily stock returns in the year ending five days after the earnings announcement in the quarter preceding guidance cessation. It is anticipated that the sign on Volatility is negative as managers tend to see guidance as reducing volatility (Hsieh et al. 2006). Hypothesis 4 will be supported if either the coefficient on TRA is positive and significant or, that on DED is negative and significant. This will demonstrate that stopping earnings guidance is negatively associated with shareholder investment horizon.

Data regarding management's decision to cease issuing earnings guidance will come from the First Call, I/B/E/S, CRSP, and Compustat databases. Information regarding a change in management (CEO or CFO) in the past six months requires a search in Reuters News, as well as *Business Wire, PR Newswire, Associated Press Newswires*, and *Reuters Significant Developments*.

An additional extension of this research concerns adding further proxies for accounting discretion when predicting transient ownership (Eq. 6a and 6b). This represents an interesting extension of the current study because one important part of the analysis is to test whether transient investors truly are poor monitors who cause companies to focus on the short-term. Including additional proxies for accounting discretion would more completely test this poor monitoring hypothesis.

The first additional proxy of accounting discretion which could serve as a valid addition is earnings persistence. Earnings persistence is the degree to which earnings continue into the future and and is considered to be an aspect of earnings quality (Dechow et al. 2010). If transient investors cause management to focus on the short-term then transient ownership should be associated with less persistent earnings. Earnings persistence is one measure of poor monitoring which is especially relevant to analyst herding because less persistent earnings can incentivize analysts to herd. The reason why analysts may be incentivized to herd is that less persistent earnings may make forecasting earnings accurately more difficult (Dechow et al. 2010). Therefore, if transient investors cause earnings to be less persistent, this could be a significant factor in explaining the association between transient ownership and financial analyst herding.

Another useful proxy for accounting discretion concerns asymmetric timeliness. Asymmetric timeliness refers to how quickly losses are captured in the accounting system (Basu 1997). It is an appropriate measure for my research question because it gives an indication of whether transient investors induce management to focus on near-term earnings as suggested by prior research (Bushee 1998; Bushee et al. 2001). Transient investors are sophisticated investors who understand the implications of delaying the reporting of losses. If it is found that transient owners are investing in firms with an asymmetric recognition of losses, then this provides evidence for the characterization of these investors as poor monitors. Therefore, inclusion of asymmetric timeliness would be an interesting addition to this study.

A final metric for accounting discretion which may benefit future analysis is the examination of the distribution of analysts' forecast errors. A kink in the distribution of analyst forecast errors is indicative of earnings management as firms are managing earnings to avoid missing the consensus. It can also be a result of managing the consensus (Matsumoto 2002). This is a good measure because the evidence to support it is more persuasive than evidence supporting earnings management to beat prior earnings or cross the threshold of zero. Furthermore, no other explanation apart from earnings management is given to explain the existence of a kink in the distribution of analysts forecast errors (Dechow et al. 2010). Finally, analyzing the distribution of analysts' forecast errors would be interesting because it has been found transient investors exhibit abnormal selling of a firm's stock when the firm misses their earnings forecast by a marginal amount (Hu et al. 2009). It has not, however, been tested whether the presence of these owners causes firms to manipulate earnings to preclude this event from occurring. For this reason, including an analysis of the distribution of analysts forecast errors, along with measures of earnings persistence and asymmetric timeliness, would be meaningful extensions of the current study. This would go a long way in more completely addressing the important question of whether transient investors are poor monitors of firm management.

9. DISCUSSION AND CONCLUSION

This study examines the effect of shareholder investment horizon on analysts' propensity to herd. The purpose of this investigation is to understand how one set of important information intermediaries, financial analysts, view transient investors. Extant literature has examined how the decisions of investors and management are affected by the presence of transient investors but research is absent regarding how analysts view this class of institutional investors. Empirical results provided in this study show there exists a positive relationship between the amount of transient investors present and the degree of analyst herding. This is consistent with the conjecture that analysts have a diminished incentive to issue a bold forecast in the presence of transient investors. This is also consistent with analysts forgoing potential reputational benefits associated with being more accurate and opting instead for safety in conforming. Additional tests examine whether this effect is due merely to an association between transient investors and the information environments of the firms in which they invest, or whether there exist credibility issues associated with disclosures of companies who are owned to a greater extent by transient investors.

Tests on the reason for the association between transient ownership and financial analyst herding are consistent with the conjecture that firm information environment is an important reason for the herding evidenced. I find that a prediction of transient ownership on the basis of how informed these investors are is very strongly related to financial analyst herding. Results, however, are inconsistent with the conjecture that analysts are herding due to the poor monitoring of transient investors. In fact, when predicting transient ownership, it is found that neither greater current nor future accounting discretion serves as a significant predictor of transient ownership. Thus, my results are inconsistent with the idea that financial analysts characterize transient owners as poor monitors of firm management. Rather, the results are more consistent with the concept that transient owners are informed investors who acquire private information which is likely the cause of the association between transient owners and analyst herding.

The second part of my research uses alternate tests apart from analyst herding to determine whether analysts respond in a greater fashion to disclosures issued by companies with a longer shareholder investment horizon. Results do not show a significant effect caused by transient investors on analysts' propensity to revise forecasts in the event of management guidance. In contrast, results indicate analysts are more likely to revise their forecasts when the concentration of dedicated investors in the stock increases. This is consistent with the viewpoint that analysts view management earnings guidance to be more credible when the stock is owned by shareholders with a relatively longer investment horizon. Further testing described in the extensions section would analyze how having an investor base with a different shareholder horizon may alter the decision to cease issuing earnings guidance. This could provide some insight regarding whether companies recognize a diminished benefit of issuing earnings guidance when shareholders have a shorter investment horizon.

This study is not without limitations. One limitation is no direct evidence is provided regarding the reason for an association between the presence of transient investors and analyst herding but only indirect evidence through a two-stage regression procedure. A further limitation is this study does not effectively take into consideration the presence of individual investors in a stock and how they can alter analyst herding behavior. A final limitation of the study is it does not differentiate between forecasts that are positive or negative. There is no examination of whether transient investors or dedicated investors could cause forecasts to be more positive or negative. These limitations also provide potential opportunities for future extensions of this study. Even with these limitations, the analysis presented here should provide a significant contribution to the literature by introducing a previously neglected viewpoint to the debate on transient investors, namely that of financial analysts.

This research should contribute to the extant literature as it is the first to bring together the analyst herding and shareholder investment horizon literatures. In addition, it is one of the first studies to investigate the effect shareholder investment horizon has on the credibility of a firm's discretionary disclosures. Prior research has characterized transient investors as either a) informed investors who profit off of private information or b) poor monitors who exacerbate the agency problem between management and shareholders. This study analyzes how the decisions of financial analysts are affected by the presence of short-term or transient investors. While the study does contribute to literature by showing analyst behavior is affected by the presence of transient investors, the analysis does not support the idea that financial analysts characterize transient investors as poor monitors of firm management. The tendency to herd is explained more by the future returns these informed investors are able to generate than by the change in management behavior they generate. This calls into question the view in certain streams of research that transient investors exacerbate the agency problem and damage the ability of management to focus on long-term value. The belief that certain benefits accrue from having an investor class with a longer shareholder horizon does, however, find some support in my analysis. Dedicated investors are shown to improve the credibility of management guidance in the view of analysts. This underscores the belief that the actions of management can be seen with less skepticism due to the type of investors holding the company. Thus, while my study is not consistent with a poor monitoring characterization of transient investors, it does demonstrate the potential of investor type in influencing the perception of management behavior in the view of informed market participants such as financial analysts. This is an important area for continued research.

My analysis represents a significant contribution because it documents an important cause of financial analyst herding behavior, shareholder investment horizon, and calls into question the characterization of transient investors in prior research as poor monitors that cause credibility concerns on firm disclosure. The study provides a unique perspective on the complex interactions between institutional investor preferences, firm disclosure environment, and the analyst decision making process.

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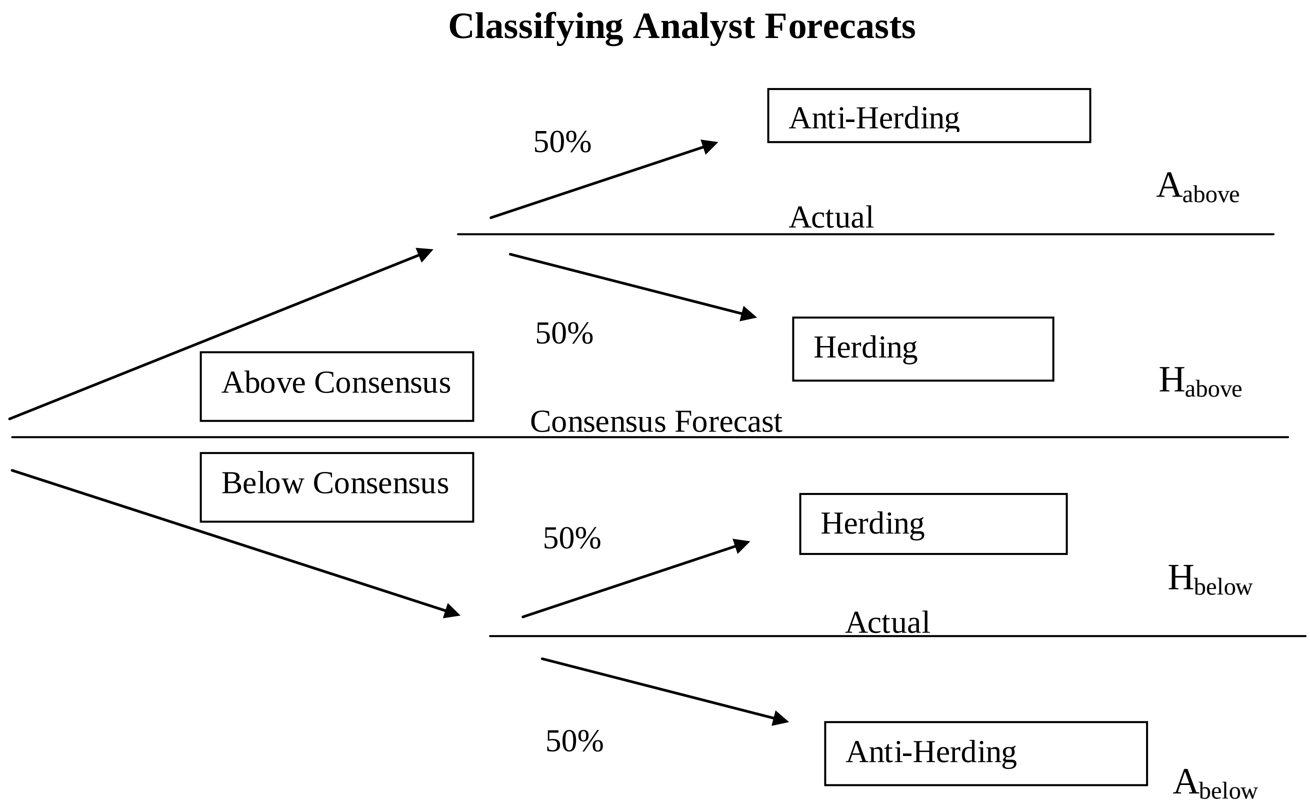
Figure 1 – Hypothesized Effect of Transient Investors on Financial Analyst Herding Behavior

		Model of Herding	
		Information Cascade Model[1]	Reputational Herding Model[1]
Characteristic of Transient-Owned Firm	Availability of Private Information[2]	Analyst possesses deviant information and is more likely to disrupt the information cascade: **Less Herding**	Analysts herd to protect their reputation against better informed analysts: **More Herding**
	Poor monitoring of firm management[3]	Analysts are less likely to follow the company's public signal due to credibility concerns: **Less Herding**	Analysts herd due to a diminished chance of issuing an accurate forecast: **More Herding**

[1] See Hirshleifer and Teoh (2003)
[2] See Ke and Petroni (2004), Yan and Zhang (2009), and Hu et al. (2009)
[3] See Bushee (1998), Gaspar et al. (2005), and Dikolli et al. (2009)

Figure 2 – Diagrammatical Presentation of the S-statistic Measure of Herding



$$\text{S-statistic} = 0.5 * \left[\frac{A_{above}}{(A_{above}+H_{above})} + \frac{A_{below}}{(A_{below}+H_{below})}\right]$$

A lower S-statistic indicates a greater incidence of herding;

The S-statistic is based on the fact that the conditional probability of a forecast being above or below actual earnings when it is above (or below) the consensus is 0.5. A forecast is deemed a herding forecast if it is above the consensus but below actual earnings or if it is below the consensus but above actual earnings. The S-statistic is then the average of the percentage of anti-herding forecasts when the forecast is above the consensus and the percentage of anti-herding forecasts when the forecast is below the consensus. Therefore, an S-statistic of 1 indicates perfect anti-herding behavior while an S-statistic of 0 indicates perfect herding behavior.

Table 1

Descriptive Statistics for Test on Analyst Herding

Variable	N	Mean	Median	Std Dev	1rst Quartile	3rd Quartile
S-Stat	7379	0.626	0.567	0.158	0.500	0.737
TRA	7379	0.182	0.147	0.136	0.080	0.248
DED	7379	0.086	0.059	0.098	0.014	0.123
RegFD	7379	0.662	1.000	0.473	0.000	1.000
NAnalyst	7379	9.925	8.000	7.031	5.000	14.000
NObs	7379	49.659	36.000	45.916	18.000	65.000
AGE	7379	87.268	87.833	16.377	78.000	97.667
HES	7379	5.450	0.281	1.027	0.157	0.547
SIZE	7379	21.348	21.274	1.725	20.124	22.521
FERROR	7379	0.096	0.033	0.298	0.012	0.083

S-Stat is a measure of herding and is calculated as described on p. 18-19. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the stock. **DED** is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share.

Sample Selection

	Companies	Firm Qtrs
Companies with sufficient information on I/B/E/S to calculate S-statistic	5,558	18,264
Companies that do not have information available on Compustat	(2,396)	(6,473)
Companies missing institutional holdings information from 13f filings	(671)	(3,419)
Companies with institutional holdings percentage greater than 1	0	(1)
Companies with other missing information	(64)	(235)
Final Sample	2,427	8,136

Table 1 - Panel B

Pearson Correlations for Test on Analyst Herding (N=8,136)

	S-Stat	TRA	DED	RegFD	NAnaly	NObs	AGE	HES	SIZE	FERROR
S-Stat	1.00	**-0.04**	**0.02**	**0.03**	**0.12**	**0.14**	**-0.03**	**0.06**	**0.10**	**-0.27**
TRA Holdings		1.00	**0.24**	**0.03**	**0.08**	**0.09**	**0.06**	**0.12**	**-0.11**	**-0.08**
DED Holdings			1.00	**-0.11**	**0.08**	**0.08**	**0.13**	**0.05**	**0.04**	**-0.27**
RegFD				1.00	**0.08**	**0.13**	**0.06**	0.02	**0.13**	0.00
NAnaly					**1.00**	**0.93**	**-0.04**	**0.10**	**0.69**	**-0.08**
NObs						1.00	**-0.03**	**0.14**	**0.65**	**-0.03**
AGE							1.00	**-0.03**	**-0.09**	**-0.05**
HES								1.00	**0.12**	**0.28**
SIZE									1.00	**-0.07**
FERROR										1.00

S-Stat is a measure of herding and is calculated as described on p. 14-15. **TRA** is calculated as the percentage of transient (Bushee 1998) investors in the stock. **DED** is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnaly** is equal to the number of analysts who issued forecasts during the S-statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share.

Table 2

Effect of Shareholder Horizon on Degree of Analyst Herding

$$S_j = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}TRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD{*}NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} Size + \beta_{12} F\_Error + \varepsilon \quad (2)$$

Variable	+/-	Est. Coeff.	T-Stat	P-Value
Intercept		0.63483	19.83	<.0001
TRA	?	-0.11423	-4.03	0.001
TRA*RegFD	?	0.05746	1.78	0.075
DED	?	-0.01561	-0.56	0.577
DED*RegFD	?	0.07894	2.12	0.034
RegFD	?	-0.00440	-0.47	0.637
NAnalyst	+	-0.00297	-4.07	<.0001
NAnalyst*RegFD	?	-0.00085	-1.60	0.111
NObs	+	0.00057	7.59	<.0001
AGE	+	-0.00014	-1.15	0.249
HES	?	0.00305	1.70	0.090
SIZE	?	0.00116	0.79	0.430
F_Error	+	-0.05846	-5.18	<.0001
N				8,131
Adj. R-Squared				1.67%

S-Stat is a measure of herding and is calculated as described on p. 18-19. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the stock. **DED** is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 3

Panel A: Original Dataset

Descriptive Statistics for Predicting TRA

Variable	N	Mean	Median	Std Dev	Q1	Q3
TRA	6260	0.187	0.151	0.138	0.084	0.255
RET3	6260	0.080	0.070	0.233	-0.033	0.175
RET12	6260	0.074	0.075	0.382	-0.106	0.253
ABNACC	5423	0.590	0.153	1.711	0.053	0.405
SMOOTH	5423	3.121	1.991	5.861	1.095	3.469
SMP	5423	0.133	0.083	0.165	0.000	0.167
MKTCAP	6260	21.328	21.236	1.718	20.092	22.519
COAGE	6260	278.02	207.50	221.93	109.00	381.00
DP	6260	0.006	0.001	0.008	0.000	0.009
BM	6260	0.477	0.432	0.285	0.272	0.623
PRC	6260	32.82	27.985	31.291	17.132	42.125
TURNOVER	6260	0.160	0.111	0.166	0.065	0.197
RETVOL	6260	0.120	0.102	0.072	0.073	0.147
SP500	6260	0.338	0.000	0.473	0.000	1.000

TRA is the percentage of the firm's stock owned by transient (Bushee 1998) shareholders. **RET3** is the cumulative 3-month return on the stock calculated as the return from month t+1 through month t+3. **RET12** is the cumulative 12-month return on the stock calculated as the return from month t+4 through month t+12. **ABNACC** is abnormal accruals calculated using the modified Jones model (see Kasnick 1999). **SMOOTH** is earnings smoothing calculated as the standard deviation of quarterly cash flows over the standard deviation of earnings. The variable is calculated over the prior three years. **SMP** is the incidince of small positive earnings calculated as the proportion of the prior 12 quarters earnings that were small positives. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the SP500 for the year.

Sample Selection

	Companies	Firm Qtrs
Companies in original sample	2,260	7,607
Companies missing data to calculate control variables or return variables	(265)	(1,347)
Sample used to calculate informed nature of transient investors	**1,995**	**6,260**
Companies with insufficient data to calculate accounting discretion variables	(250)	(837)
Sample used to calculate poor monitoring of transient investors	**1,745**	**5,423**

Table 3

Panel B: Full Dataset

Descriptive Statistics for Predicting TRA

Variable	N	Mean	Median	Std Dev	Q1	Q3
TRA	31283	0.142	0.104	0.291	0.038	0.203
RET3	31283	0.063	0.050	0.287	-0.069	0.173
RET12	31283	0.078	0.069	0.692	-0.148	0.281
ABNACC	27188	0.722	0.193	3.189	0.068	0.490
SMOOTH	27188	2.814	1.801	4.863	0.954	3.243
SMP	27188	0.105	0.083	0.141	0.000	0.167
MKTCAP	31283	19.790	19.693	1.936	18.403	21.022
COAGE	31283	194.19	135.00	176.31	73.00	260.00
DP	31283	0.006	0.000	0.012	0.000	0.008
BM	31283	0.623	0.515	0.487	0.314	0.775
PRC	31283	23.28	17.570	31.637	8.100	30.720
TURNOVER	31283	0.136	0.082	0.213	0.037	0.168
RETVOL	31283	0.137	0.114	0.091	0.077	0.172
SP500	31283	0.111	0.000	0.314	0.000	0.000

TRA is the percentage of the firm's stock owned by transient (Bushee 1998) shareholders. **RET3** is the cumulative 3-month return on the stock calculated as the return from month t+1 through month t+3. **RET12** is the cumulative 12-month return on the stock calculated as the return from month t+4 through month t+12. **ABNACC** is abnormal accruals calculated using the modified Jones model (see Kasnick 1999). **SMOOTH** is earnings smoothing calculated as the standard deviation of quarterly cash flows over the standard deviation of earnings. The variable is calculated over the prior three years. **SMP** is the incidince of small positive earnings calculated as the proportion of the prior 12 quarters earnings that were small positives. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the SP500 for the year.

Sample Selection

	Companies	Firm Qtrs
Companies with sufficient information on institutional holdings from 13f	10,912	53,104
Companies that do not have Compustat data	(1,605)	(3,632)
Companies missing data to calculate control variables or return variables	(2,837)	(18,189)
Sample used to calculate informed nature of transient investors	**6,398**	**31,283**
Companies with insufficient data to calculate accounting discretion variables	(700)	(4,095)
Sample used to calculate poor monitoring of transient investors	**5,698**	**27,188**

Table 4

Predicting Transient Ownership - Original Dataset

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 RET3 + \beta_{10} RET12 + \varepsilon \quad (4a)$$

Panel A: Using Returns as a proxy for the information environment

	Future Return Variables Only		**Including Lag Return Variables**	
	Over 10 Individual Years		Over 10 Individual Years	
Variable	Average Coefficient	[+ Significant, - Significant]	Average Coefficient	[+ Significant, - Significant]
RET3	-0.11994	[1,1]	-0.01012	[1,1]
RET12	-0.00782	[2,2]	0.00048	[2,1]
LAGRET3	-	-	0.01462	[4,1]
LAGRET12	-	-	0.03791	[6,0]
MKTCAP	0.03503	[3,2]	0.00315	[3,2]
COAGE	-0.00012	[0,1]	-0.00001	[0,0]
DP	-0.69803	[0,3]	-0.66100	[0,3]
BM	-0.03563	[0,5]	-0.02538	[0,3]
PRC	0.00017	[3,0]	0.00012	[2,0]
TURN	0.25862	[10,0]	0.25721	[10,0]
RETVOL	0.08024	[1,0]	0.04368	[1,0]
SP500	-0.03623	[0,7]	-0.03326	[0,5]

RET3 is the cumulative 3-month return on the stock calculated as the return from month t+1 through month t+3. **RET12** is the cumulative 12-month return on the stock calculated as the return from month t+4 through month t+12. **LAGRET3** is the 3-month lagged cumulative return calculated as the return from month t-2 through month t. **LAGRET12** is the 12-month lagged cumulative return calculated as the return from month t-11 through month t-3. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the S&P 500 for the year.

Table 4

Predicting Transient Ownership - Original Dataset

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 ABNACC + \beta_{10} SMOOTH + \beta_{11} SMP + \varepsilon \quad (5a)$$

Panel B: Using accounting discretion variables as a proxy for poor monitoring

	Current Discr. Variables		Future Discr. Variables		Control Variables	
	Over 10 Individual Years		Over 10 Individual Years		Over 10 Individual Years	
Variable	Average Coefficient	[+ Significant, - Significant]	Average Coefficient	[+ Significant, - Significant]	Average Coefficient	[+ Significant, - Significant]
ABNACC	-0.00173	[0,0]	-	-	-	
SMOOTH	0.00072	[2,0]	-	-	-	
SMP	-0.03791	[0,3]	-	-	-	
LEADABNACC	-	-	0.00029	[0,1]	-	
LEADSMOOTH	-	-	0.00101	[4,0]	-	
LEADSMP	-	-	-0.03929	[0,4]	-	
MKTCAP	0.00159	[1,2]	0.00133	[1,2]	0.00388	[3,2]
COAGE	-0.00001	[0,0]	-0.00001	[0,0]	-0.00001	[0,0]
DP	-1.55001	[0,6]	-1.51017	[0,5]	-0.66861	[0,3]
BM	-0.03779	[0,5]	-0.03403	[0,5]	-0.03600	[0,5]
PRC	0.00009	[2,0]	0.00010	[2,0]	0.00015	[3,1]
TURN	0.23821	[10,0]	0.24819	[10,0]	0.25199	[10,0]
RETVOL	-0.07254	[0,1]	-0.09484	[0,1]	0.07486	[2,0]
SP500	-0.03982	[0,9]	-0.03925	[0,7]	-0.03699	[0,7]

ABNACC is abnormal accruals calculated using the modified Jones model (see Kasnick 1999). **SMOOTH** is earnings smoothing calculated as the standard deviation of quarterly cash flows over the standard deviation of earnings. The variable is calculated over the prior three years. **SMP** is the incidince of small positive earnings calculated as the proportion of the prior 12 quarters earnings that were small positives. **LEADABNACC** is equal to **ABNACC** at year t+1. **LEADSMOOTH** is equal to **SMOOTH** at year t+1. **LEADSMP** is equal to **SMP** at year t+1. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. Following YZ (2009), firm dividend yield and book-to-market are winsorized at the 1rst and 99th percentile. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the S&P 500 for the year.

Table 5

Predicting Transient Ownership - Full Dataset

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 RET3 + \beta_{10} RET12 + \varepsilon \quad (4a)$$

Panel A: Using Returns as a proxy for the information environment

	Future Return Variables Only			**Including Lag Return Variables**	
	Over 10 Individual Years			Over 10 Individual Years	
Variable	Average Coefficient	[+ Significant, - Significant]		Average Coefficient	[+ Significant, - Significant]
RET3	0.01043	[4,0]		0.00977	[2,0]
RET12	-0.00165	[1,1]		-0.00095	[1,1]
LAGRET3				-0.00501	[0,4]
LAGRET12				0.01013	[4,1]
MKTCAP	0.02198	[10,0]		0.02207	[9,0]
COAGE	0.00005	[0,7]		0.00005	[0,7]
DP	-0.78549	[0,8]		-0.78406	[0,7]
BM	-0.01028	[1,4]		-0.00847	[1,4]
PRC	0.00012	[2,2]		0.0001	[3,2]
TURN	0.23752	[10,0]		0.23888	[10,0]
RETVOL	-0.02506	[1,3]		-0.02773	[2,4]
SP500	-0.05416	[0,9]		-0.05363	[0,9]

RET3 is the cumulative 3-month return on the stock calculated as the return from month t+1 through month t+3. **RET12** is the cumulative 12-month return on the stock calculated as the return from month t+4 through month t+12. **LAGRET3** is the 3-month lagged cumulative return calculated as the return from month t-2 through month t. **LAGRET12** is the 12-month lagged cumulative return calculated as the return from month t-11 through month t-3. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the S&P 500 for the year.

Table 5

Predicting Transient Ownership - Full Dataset

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 ABNACC + \beta_{10} SMOOTH + \beta_{11} SMP + \varepsilon \quad (5a)$$

Panel B: Using accounting discretion variables as a proxy for poor monitoring

	Current Discr. Variables		**Future Discr. Variables**		**Control Variables**	
	Over 10 Individual Years		Over 10 Individual Years		Over 10 Individual Years	
Variable	Average Coefficient	[+ Significant, - Significant]	Average Coefficient	[+ Significant, - Significant]	Average Coefficient	[+ Significant, - Significant]
ABNACC	-0.00178	[1,3]	-	-	-	-
SMOOTH	-0.00016	[0,1]	-	-	-	-
SMP	-0.03581	[0,6]	-	-	-	-
LEADABNACC	-	-	-0.00240	[0,2]	-	-
LEADSMOOTH	-	-	0.00045	[0,0]	-	-
LEADSMP	-	-	-0.03436	[0,5]	-	-
MKTCAP	0.02199	[9,0]	0.02086	[9,0]	0.02263	[9,0]
COAGE	-0.00005	[0,8]	0.00005	[0,8]	-0.00005	[0,8]
DP	-1.52375	[0,9]	-1.57431	[0,9]	-0.78644	[0,8]
BM	-0.01154	[1,4]	-0.01319	[1,3]	-0.00964	[1,4]
PRC	0.00013	[1,0]	0.00014	[1,1]	0.00011	[2,2]
TURN	0.21874	[10,0]	0.22103	[10,0]	0.23210	[10,0]
RETVOL	-0.15906	[0,8]	-0.16537	[0,7]	-0.02828	[1,4]
SP500	-0.06124	[0,9]	-0.05749	[0,9]	-0.05610	[0,9]

ABNACC is abnormal accruals calculated using the modified Jones model (see Kasnick 1999). **SMOOTH** is earnings smoothing calculated as the standard deviation of quarterly cash flows over the standard deviation of earnings. The variable is calculated over the prior three years. **SMP** is the incidince of small positive earnings calculated as the proportion of the prior 12 quarters earnings that were small positives. **LEADABNACC** is equal to ABNACC at year t+1. **LEADSMOOTH** is equal to **SMOOTH** at year t+1. **LEADSMP** is equal to **SMP** at year t+1. **MKTCAP** is the natural log of the firm's market capitalization. **COAGE** is the number of months the firm has been listed in CRSP. **DP** is equal to firm dividend yield calculated as cash dividend divided by share price. **BM** is the firm's book-to-market ratio calculated as common equity divided by market capitalization. Following YZ (2009), firm dividend yield and book-to-market are winsorized at the 1rst and 99th percentile. **PRC** is equal to the price of the firm's stock. **TURN** is equal to the average of the previous three months turnover for the firm's stock. **RETVOL** is equal to the volatility of firm stock taken as the standard deviation of returns calculated over the previous 24 months. **SP500** is an indicator variable equal to 1 if the firm was listed in the SP500 for the year.

Table 6A

Predicted TRA Holdings and Analyst Herding – Original Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*PredTRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD*NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

	Using Only Control Variables			
Variable	+/-	Est. Coeff.	T-Stat	P - Value
Intercept		0.62824	17.25	<.0001
PredTRA	?	-0.18851	-2.88	0.004
PredTRA*RegFD	?	0.10428	1.51	0.132
DED	?	-0.01129	-0.36	0.719
DED*RegFD	?	0.09360	2.27	0.023
RegFD	?	-0.01029	-0.70	0.482
NAnalyst	+	-0.00236	-3.08	0.002
NAnalyst*RegFD	?	-0.00134	-2.28	0.022
NObs	+	0.00057	6.80	<.0001
AGE	+	-0.00003	-0.27	0.784
HES	?	0.00222	1.11	0.268
SIZE	?	0.00155	0.97	0.334
FError	+	-0.06075	-4.11	<.0001
N				6,295
Adj. R-Squared				2.07%

S-Stat is a measure of herding and is calculated as described on p.18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 4. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 6B

Predicted TRA Holdings and Analyst Herding – Original Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}PredTRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD{*}NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

Variable	+/-	Future Returns Only Est. Coeff.	Future Returns Only P – Val	Including Lagged Returns Est. Coeff.	Including Lagged Returns P – Val
Intercept		0.62359	<.0001	0.63521	<.0001
PredTRA	?	-0.18863	0.004	-0.24952	<.0001
PredTRA*RegFD	?	0.10543	0.125	0.16676	0.011
DED	?	-0.01036	0.740	-0.00623	0.842
DED*RegFD	?	0.09046	0.028	0.08610	0.036
RegFD	?	-0.00790	0.589	-0.01797	0.208
NAnalyst	+	-0.00225	0.004	-0.00223	0.004
NAnalyst*RegFD	?	-0.00148	0.012	-0.00150	0.011
NObs	+	0.00057	<.0001	0.00057	<.0001
AGE	+	-0.00003	0.833	-0.00003	0.821
HES	?	0.00225	0.263	0.00226	0.264
SIZE	?	0.00158	0.328	0.00160	0.319
Ferror	+	-0.06273	<.0001	-0.06284	0.000
N		6,256		6,256	
Adj. R-Squared		2.02%		2.14%	

S-Stat is a measure of herding and is calculated as described on p.18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equations 5a and 5b. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 6C

Predicted TRA Holdings and Analyst Herding – Original Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}PredTRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD{*}NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

Variable	+/-	**Current Discretion Vars.** Est. Coeff.	P – Val	**Lead Discretion Var.** Est. Coeff.	P – Val
Intercept		0.63708	<.0001	0.62485	<.0001
PredTRA	?	-0.16247	0.021	-0.14531	0.046
PredTRA*RegFD	?	0.07175	0.330	0.05239	0.491
DED	?	-0.02718	0.401	-0.01802	0.580
DED*RegFD	?	0.10213	0.017	0.09480	0.028
RegFD	?	-0.00490	0.769	0.00130	0.939
NAnalyst	+	-0.00245	0.003	-0.00232	0.004
NAnalyst*RegFD	?	-0.00128	0.038	-0.00132	0.034
NObs	+	0.00060	<.0001	0.00058	<.0001
AGE	+	0.00006	0.648	0.00008	0.576
HES	?	0.00163	0.384	0.00190	0.326
SIZE	?	0.00055	0.750	0.00079	0.648
Ferror	+	-0.05758	0.001	-0.0597	0.0004
N		5,422		5,309	
Adj. R-Squared		2.08%		2.09%	

S-Stat is a measure of herding and is calculated as described on p. 18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 6a and 6b. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 7A

Predicted TRA Holdings and Analyst Herding – Full Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*PredTRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD*NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

	Using Only Control Variables			
Variable	+/-	Est. Coeff.	T-Stat	P - Value
Intercept		0.60156	18.12	<.0001
PredTRA	?	-0.17517	-2.29	0.022
PredTRA*RegFD	?	0.11167	1.41	0.159
DED	?	-0.01378	-0.44	0.659
DED*RegFD	?	0.08384	2.06	0.040
RegFD	?	-0.00902	-0.64	0.520
NAnalyst	+	-0.00240	-3.17	0.002
NAnalyst*RegFD	?	-0.00141	-2.38	0.018
NObs	+	0.00058	6.91	<.0001
AGE	+	-0.00005	-0.38	0.705
HES	?	0.00232	1.15	0.249
SIZE	?	0.00267	1.69	0.090
FError	+	-0.06050	-4.27	<.0001
N				6,473
Adj. R-Squared				1.88%

S-Stat is a measure of herding and is calculated as described on p. 18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 4. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 7B

Predicted TRA Holdings and Analyst Herding – Full Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}PredTRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD{*}NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

Variable	+/-	Future Returns Only Est. Coeff.	Future Returns Only P - Val	Including Lagged Returns Est. Coeff.	Including Lagged Returns P - Val
Intercept		0.60068	<.0001	0.60037	<.0001
PredTRA	?	-0.18011	0.017	-0.18102	0.013
PredTRA*RegFD	?	0.11533	0.139	0.11697	0.123
DED	?	-0.01115	0.721	-0.01027	0.743
DED*RegFD	?	0.07947	0.051	0.07844	0.054
RegFD	?	-0.00697	0.619	-0.00715	0.602
NAnalyst	+	-0.00226	0.006	-0.00226	0.003
NAnalyst*RegFD	?	-0.00155	0.017	-0.00154	0.009
NObs	+	0.00058	<.0001	0.00058	<.0001
AGE	+	-0.00004	0.717	-0.00004	0.733
HES	?	0.00236	0.245	0.00236	0.244
SIZE	?	0.00264	0.096	0.00266	0.091
FError	+	-0.06250	<.0001	-0.06256	<.0001
N		6,432		6,432	
Adj. R-Squared		1.91%		1.91%	

S-Stat is a measure of herding and is calculated as described on p. 18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 5a and 5b. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 7C

Predicted TRA Holdings and Analyst Herding – Full Dataset

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*PredTRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD*NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

Variable	+/-	**Current Discretion Vars.** Est. Coeff.	P - Val	**Lead Discretion Var.** Est. Coeff.	P - Val
Intercept		0.60924	<.0001	0.59790	<.0001
PredTRA	?	-0.14182	0.055	-0.13737	0.072
PredTRA*RegFD	?	0.07816	0.310	0.06682	0.401
DED	?	-0.02781	0.391	-0.01790	0.583
DED*RegFD	?	0.08577	0.043	0.08022	0.060
RegFD	?	-0.00408	0.782	-0.00011	0.994
NAnalyst	+	-0.00254	0.001	-0.00242	0.003
NAnalyst*RegFD	?	-0.00129	0.036	-0.00129	0.038
NObs	+	0.00061	<.0001	0.00059	<.0001
AGE	+	0.00005	0.693	0.00007	0.586
HES	?	0.00187	0.326	0.00200	0.304
SIZE	?	0.00165	0.320	0.00195	0.244
FError	+	-0.05758	<.0001	-0.05927	0.001
N		5,577		5,456	
Adj. R-Squared		1.94%		1.97%	

S-Stat is a measure of herding and is calculated as described on p. 18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 6a and 6b. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 8

Descriptive Statistics for Test on Analyst Revisions

Variable	N	Mean	Median	Std Dev	1rst Quartile	3rd Quartile
FRAC	8539	0.497	0.500	0.409	0.000	1.000
TRA	8539	0.204	0.176	0.142	0.097	0.278
DED	8539	0.067	0.040	0.081	0.001	0.107
AnalystOpt	8539	0.552	0.045	2.596	-0.085	0.500
AnalystDis	8539	0.133	0.061	0.444	0.024	0.135
ROA	8539	0.012	0.012	0.025	-0.005	0.021
POINT	8539	0.281	0.000	0.450	0.000	1.000
RANGE	8539	0.582	1.000	0.493	0.000	1.000
GreaterThan	8539	0.087	0.000	0.281	0.000	0.000
LessThan	8539	0.085	0.000	0.278	0.000	0.000
LOSS	8539	0.102	0.000	0.303	0.000	0.000
NumFCast	8539	4.860	4.000	4.140	2.000	7.000
RegFD	8539	0.733	1.000	0.442	0.000	1.000
T	8539	4.751	4.000	2.516	3.000	7.000
SIZE	8539	20.895	20.746	1.796	19.687	22.011

FRAC is the percentage of analysts who revised their earnings forecasts within five days of the issuance of management earnings guidance. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the security. **DED** is calculated as the number of dedicated investors (Bushee 1998) in the stock. **AnalystDis** is calculated as the standard deviation of the beginning consensus forecast. **AnalystOpt** is calculated as the difference between analyst consensus forecast and actual earnings, scaled by the absolute value of earnings. **ROA** is calculated as the actual amount of earnings, scaled by the lagged value of assets. **POINT** is an indicator variable equal to 1 if management guidance is given as a point estimate. **RANGE** is an indicator variable equal to 1 if management guidance is given in the form of a range. **GreaterThan** is an indicator variable equal to 1 if guidance is "greater than" guidance. **LessThan** is an indicator variable equal to 1 if guidance is "less than" guidance. **LOSS** is an indicator variable equal to 1 if management guidance is a loss. **NumFCast** is equal to the number of forecasts in the consensus. **RegFD** is an indicator variable that is equal to 1 if the beginning of the consensus period occurs after October 31, 2001. **T** is a time trend variable. **SIZE** is the natural log of the firm's market capitalization.

Sample Selection

	Companies	Firm Qtrs
Observations of management issued guidance	3,524	32,643
Companies missing analyst forecasts or actual reported earnings	(1,024)	(22,421)
Companies missing Compustat information for control variables	(113)	(384)
Companies missing institutional holdings information from 13f filings	(264)	(1,214)
Companies with other missing information	0	(85)
Final Sample	2,123	8,539

Table 8 - Panel B

Panel C: Pearson Correlations for Test on Analyst Revisions

	FRAC	TRA	DED	Analy Dis	Analy Opt	ROA	POINT	RANGE	Greater Than	Less Than	LOSS	NFcast	RegFD	T	SIZE
FRAC	1.00	0.02	**0.04**	**0.02**	**0.12**	**0.06**	**-0.08**	**0.14**	**-0.05**	**0.05**	**-0.03**	-0.01	**0.03**	0.01	**-0.08**
TRA		1.00	**0.17**	0.01	-0.01	**0.07**	**0.04**	**-0.03**	0.01	**-0.04**	-0.02	**0.06**	**0.16**	**-0.09**	**-0.04**
DED			1.00	-0.01	-0.02	0.01	0.01	0.00	0.02	-0.01	0.00	**0.05**	**0.14**	**-0.05**	**0.11**
AnalysDis				1.00	**0.42**	**-0.07**	-0.01	**-0.05**	-0.01	**0.07**	**0.06**	0.00	**-0.03**	**-0.05**	**-0.07**
AnalystOpt					1.00	**0.03**	**-0.01**	**-0.04**	**-0.04**	**0.12**	**-0.09**	**-0.03**	**-0.07**	**-0.08**	**-0.10**
ROA						1.00	**0.03**	**0.04**	**-0.04**	**-0.07**	**-0.56**	**0.09**	**0.03**	**0.11**	**0.26**
POINT							1.00	**-0.74**	**0.15**	**0.00**	**-0.05**	**-0.02**	**-0.12**	**-0.12**	**0.08**
RANGE								1.00	**-0.29**	**-0.28**	**-0.02**	**0.05**	**0.25**	**0.30**	**-0.03**
GreaterThan									1.00	**-0.09**	0.02	**-0.03**	**-0.08**	**-0.09**	-0.02
LessThan										1.00	**0.08**	-0.02	**-0.13**	**-0.16**	**-0.06**
Loss											1.00	-0.03	0.02	-0.06	-0.26
NumForecast												1.00	0.22	**0.25**	**0.49**
RegFD													1.00	**0.71**	**0.16**
T														1.00	**0.21**
SIZE															1.00

*Correlations significant at $p < .05$ in bold

FRAC is the percentage of analysts who revised their earnings forecasts within five days of the issuance of management earnings guidance. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the security. **DED** is calculated as the number of dedicated investors (Bushee 1998) in the stock. **AnalystDis** is calculated as the standard deviation of the beginning consensus forecast. **AnalystOpt** is calculated as the difference between analyst consensus forecast and actual earnings, scaled by the absolute value of earnings. **ROA** is calculated as the actual amount of earnings, scaled by the lagged value of assets. **POINT** is an indicator variable equal to 1 if management guidance is given as a point estimate. **RANGE** is an indicator variable equal to 1 if management guidance is given in the form of a range. **GreaterThan** is an indicator variable equal to 1 if guidance is "greater than" guidance. **LessThan** is an indicator variable equal to 1 if guidance is "less than" guidance. **Loss** is an indicator variable equal to 1 if management guidance is a loss. **NumFCast** is equal to the number of forecasts in the consensus. **RegFD** is an indicator variable that is equal to 1 if the beginning of the consensus period occurs after October 31, 2001. **T** is a time trend variable. **SIZE** is the natural log of the firm's market capitalization.

Table 9

Effect of Shareholder Horizon on Degree of Analyst Revisions

$$FRAC = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 AnalystOptimism + \beta_4 AnalystDispersion + \beta_5 ROA + \beta_6 LOSS + \beta_7 POINT + \beta_8 RANGE + \beta_9 LessThan + \beta_{10} GreaterThan + \beta_{11} TimeTrend + \beta_{12} PostFD + \varepsilon \quad (6)$$

Variable	+/-	Est. Coeff.	T-Stat	P - Value
Intercept		0.74251	10.53	<.0001
TRA	-	-0.00345	-0.10	0.9173
DED	+	0.21838	3.90	<.0001
AnalystOpt	+	0.01966	4.61	<.0001
AnalystDis	+	-0.02583	-1.41	0.157
ROA	?	1.20721	4.88	<.0001
POINT	+	0.11306	7.53	<.0001
RANGE	+	0.22473	14.62	<.0001
GreaterThan	?	0.04147	2.51	0.0122
LessThan	+	0.15771	8.70	<.0001
LOSS	?	0.00192	0.11	0.916
NumFCast	?	0.00278	2.41	0.016
RegFD	?	0.02786	1.83	0.067
T	?	-0.00776	-2.90	0.004
SIZE	?	-0.02196	-6.84	<.0001
N				8,539
Adj. R-Squared				5.86%

FRAC is the percentage of analysts who revised their earnings forecasts within five days of the issuance of management earnings guidance. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the security. **DED** is calculated as the number of dedicated investors (Bushee 1998) in the stock. **AnalystDis** is calculated as the standard deviation of the beginning consensus forecast. **AnalystOpt** is calculated as the difference between analyst consensus forecast and actual earnings, scaled by the absolute value of earnings. **ROA** is calculated as the actual amount of earnings, scaled by the lagged value of assets. **POINT** is an indicator variable equal to 1 if management guidance is given as a point estimate. **RANGE** is an indicator variable equal to 1 if management guidance is given in the form of a range. **GreaterThan** is an indicator variable equal to 1 if guidance is "greater than" guidance. **LessThan** is an indicator variable equal to 1 if guidance is "less than" guidance. **LOSS** is an indicator variable equal to 1 if management guidance is a loss. **NumFCast** is equal to the number of forecasts in the consensus. **RegFD** is an indicator variable that is equal to 1 if the beginning of the consensus period occurs after October 31, 2001. **T** is a time trend variable. **SIZE** is the natural log of the firm's market capitalization. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 10

Descriptive Statistics for Short S-Stat

Variable	N	Mean	Median	Std Dev	1rst Quartile	3rd Quartile
S-Stat	6574	0.628	0.559	0.163	0.500	0.750
TRA	6574	0.181	0.147	0.136	0.080	0.247
DED	6574	0.085	0.059	0.098	0.014	0.122
RegFD	6574	0.670	1.000	0.470	0.000	1.000
NAnalyst	6574	9.807	8.000	6.913	4.000	13.000
NObs	6574	51.398	38.000	46.622	19.000	68.000
AGE	6574	78.245	79.250	15.524	69.125	88.500
HES	6574	0.521	0.283	1.002	0.158	0.550
SIZE	6574	21.444	21.389	1.713	20.236	22.629
FERROR	6574	0.090	0.031	0.268	0.012	0.078

S-Stat is a measure of herding and is calculated as described on p. 18-19. **TRA** is calculated as the percentage of transient investors (Bushee 1998) in the stock. **DED** is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnaly** is equal to the number of analysts who issued forecasts during the S-statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share.

Table 11

Effect of Shareholder Horizon on Degree of Analyst Herding – Shorter S-Stat Calculation Period

$$S_j = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*TRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD*NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} Size + \beta_{12} F\_Error + \varepsilon \quad (2)$$

Variable	+/-	Coefficient Estimate	T-Stat	P - Value
Intercept		0.66690	19.33	<.0001
TRA	?	-0.11082	-3.53	0.001
TRA*RegFD	?	0.04958	1.39	0.165
DED	?	0.00193	0.06	0.950
DED*RegFD	?	0.06673	1.64	0.101
RegFD	?	0.00637	0.62	0.538
NAnalyst	+	-0.00287	-3.79	0.000
NAnalyst*RegFD	?	-0.00141	-2.31	0.021
NObs	+	0.00065	7.80	<.0001
AGE	+	-0.00042	-2.95	0.003
HES	?	0.00365	1.75	0.081
SIZE	?	0.00039	0.24	0.807
FError	+	-0.06990	-5.62	<.0001
N				6,574
Adj. R-Squared				2.42%

S-Stat is a measure of herding and is calculated as described on p. 18-19. **TRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share. All *t*-statistics are calculated utilizing White (1980) robust standard errors.

Table 12

Predicted TRA and Analyst Herding - Shorter S-Stat Calculation Period

$$S_j = \alpha_1 + \beta_1 PredTRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD{*}PredTRA + \beta_5 RegFD{*}DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD{*}NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} F\_Error + \varepsilon \quad (3)$$

Panel A: Original Dataset

	Equation 4		Equation 5a		Equation 5b		Equation 6a		Equation 6b	
Variables	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val
Intercept	0.6647	(<.0001)	0.6631	(<.0001)	0.6720	(<.0001)	0.6717	(<.0001)	0.6638	(<.0001)
PredTRA	-0.1644	(0.023)	-0.1654	(0.020)	-0.2175	(0.001)	-0.1316	(0.093)	-0.1253	(0.123)
PredTRA*RegFD	0.0647	(0.396)	0.0666	(0.377)	0.1181	(0.102)	0.0251	(0.761)	0.0170	(0.841)
DED	0.0063	(0.853)	0.0076	(0.825)	0.0113	(0.739)	0.0026	(0.943)	0.0116	(0.748)
DED*RegFD	0.0805	(0.074)	0.0770	(0.087)	0.0732	(0.104)	0.0778	(0.100)	0.0648	(0.174)
RegFD	0.0062	(0.704)	0.0079	(0.627)	-0.0006	(0.973)	0.0154	(0.409)	0.0221	(0.241)

Panel B: Full Dataset

	Equation 4		Equation 5a		Equation 5b		Equation 6a		Equation 6b	
Variables	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val	Coeff.	P-Val
Intercept	0.6346	(<.0001)	0.6348	(<.0001)	0.6317	(<.0001)	0.6432	(<.0001)	0.6354	(<.0001)
PredTRA	-0.1696	(0.045)	-0.1742	(0.036)	-0.1691	(0.036)	-0.1364	(0.097)	-0.1594	(0.061)
PredTRA*RegFD	0.0936	(0.288)	0.0956	(0.269)	0.0904	(0.283)	0.0623	(0.467)	0.0762	(0.390)
DED	0.0057	(0.867)	0.0087	(0.798)	0.0094	(0.783)	0.0040	(0.912)	0.0156	(0.665)
DED*RegFD	0.0699	(0.115)	0.0655	(0.139)	0.0648	(0.144)	0.0603	(0.194)	0.0479	(0.305)
RegFD	0.0043	(0.785)	0.0062	(0.688)	0.0070	(0.649)	0.0106	(0.521)	0.0134	(0.429)

S-Stat is a measure of herding and is calculated as described on p. 18-19. **PredTRA** is calculated as the predicted value of Transient (Bushee 1998) Investors in the stock taken from Equation 4, 5, or 6. **DED** is calculated as the percentage of dedicated investors in the stock. **RegFD** is an indicator variable equal to 1 if the S-statistic calculation period began after October 31, 2001 and zero otherwise. **NAnalyst** is equal to the number of analysts who issued forecasts during the S-Statistic calculation period. **NObs** is equal to the number of forecasts issued by analysts in the fiscal year. **AGE** is calculated as the average age of the forecasts used to calculate the S-Statistic where age is the number of days before earnings are announced. **HES** is the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years. **SIZE** is the natural log of firm market capitalization. **FERROR** represents the forecast error or surprise and is calculated as the last consensus forecast minus actual announced earnings per share.

Appendix A – Individual Data Descriptions by Model

Model Variables for Equation 2

Effect of Shareholder Horizon on Degree of Analyst Herding

$$S_j = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 RegFD + \beta_4 RegFD*TRA + \beta_5 RegFD*DED + \beta_6 NObs + \beta_7 NAnalyst + \beta_8 RegFD*NAnalyst + \beta_9 AGE + \beta_{10} HES + \beta_{11} Size + \beta_{12} F\_Error + \varepsilon$$

Variable	+/-	Description
S-Stat		S-Stat is a measure of herding and is calculated as described on p. 18-19. It is calculated using forecasts from the I/B/E/S database.
TRA	?	TRA is calculated as the percentage of transient investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
DED	?	DED is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
RegFD	?	RegFD is an indicator variable equal to 1 if the S-statistic calculation peroid began after October 31, 2001 and is zero otherwise.
NAnalyst	+	NAnalyst is equal to the number of analysts who issued forecasts during the S-statistic calculation period. It equals the number of distinct analysts following the firm in I/B/E/S.
NObs	+	NObs is equal to the number of forecasts issed by analysts in the fiscal year. It is calculated as the total number of forecasts in the I/B/E/S database for the firm.
AGE	+	AGE is calculated as the average age of the forecasts used to calculate the S-statistic where age refers to the number of days before earnings are announced. Data is taken from I/B/E/S.
HES	?	HES is equal to the historical earnings volatility calculated as the standard deviation of quarterly earnings over the previous 5 years taken from Compustat.
SIZE	?	SIZE is the natural log of the firm's market capitalization calculated as the number of common shares times the market price at the beginning of quarter. Data is taken from Compustat.
F_ERROR	+	F_Error is equal to the forecast error or earnings surprise calculated as actual Compustat earnings minus the mean of the latest forecast for each analyst in the I/B/E/S database. The absolute value is used.

Model Variables for Equation 5

Informed Nature of Transient Shareholders

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 RET3 + \beta_{10} RET12 + \varepsilon$$

Variable	+/-	Description
TRA		TRA is calculated as the percentage of transient investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
MktCap	+	MktCap is the natural log of firm market capitalization. Market capitalization is calculated as share price times total shares outstanding using data from CRSP.
AGE	–	AGE is the natural log of the number of months the firm's first return has appeared in the CRSP database.
DP	–	DP is the natural log of firm dividend yield where dividend yield is calculated as cash dividend divided by share price. The cash dividend is collected from Compustat while the share price is taken from CRSP.
BM	+	BM is the natural log of the book-to-market ratio, calculated as the book value for the most recent fiscal year ended before June 30, divided by the market capitalization of December 31 of that fiscal year. Data for book value is taken from Compustat.
PRC	+	PRC is the natural log of the share price from CRSP.
TURN	+	TURN is equal to the natural log of the average monthly turnover over the previous quarter. It is calculated from the CRSP database.
VOL	+	VOL is equal to the natural log of volatility calculated as the standard deviation of monthly returns over the previous two years. It is calculated from the CRSP database.
SP500	?	SP500 is a dummy variable for S&P 500 Index membership.
RET3	+	RET3 is equal to the cumulative gross return from month t+1 through month t+3 where month t is the month in which institutional holdings are calculated. It is calculated using data from CRSP.
RET12	+	RET12 is equal to the cumulative gross return from month t+4 through month t+12 where month t is the month in which institutional holdings are calculated. It is calculated using data from CRSP.
LAGRET3	+	LAGRET3 is equal to the cumulative gross return from month t-2 through month t where month t is the month in which institutional holdings are calculated. It is calculated using data from CRSP.
LAGRET12	+	LAGRET12 is equal to the cumulative gross return from month t-11 through month t-3 where month t is the month in which institutional holdings are calculated. It is calculated using data from CRSP.

Model Variables for Equation 6

Accounting Discretion Associated with Transient Shareholders

$$TRA = \alpha_1 + \beta_1 MktCap + \beta_2 AGE + \beta_3 DP + \beta_4 BM + \beta_5 PRC + \beta_6 TURN + \beta_7 VOL + \beta_8 SP500 + \beta_9 ABACC + \beta_{10} SMOOTH + \beta_{11} SMP + \varepsilon$$

Variable	+/-	Description
TRA		TRA is calculated as the percentage of transient investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
MktCap	+	MktCap is the natural log of firm market capitalization. Market capitalization is calculated as share price times total shares outstanding using data from CRSP.
AGE	-	AGE is the natural log of the number of months the firm's first return has appeared in the CRSP database.
DP	-	DP the natural log of firm dividend yield where dividend yield is calculated as cash dividend divided by share price. The cash dividend is collected from Compustat while the share price is taken from CRSP.
BM	+	BM is the natural log of the book-to-market ratio, calculated as the book value for the most recent fiscal year ended before June 30, divided by the market capitalization of December 31 of that fiscal year. Data for book value is taken from Compustat.
PRC	+	PRC is the natural log of the share price from CRSP.
TURN	+	TURN is equal to the natural log of the average monthly turnover over the previous quarter. It is calculated from the CRSP database.
VOL	+	VOL is equal to the natural log of volatility calculated as the standard deviation of montly returns over the previous two years. It is calculated from the CRSP database.
SP500	?	SP500 is a dummy variable for S&P 500 Index membership.
ABNACC	+	ABNACC is the average absolute value of quarterly abnormal accruals taken over the previous three years. This is calculated using the modified Jones (1991) model. It is calculated from the Compustat database.
SMOOTH	+	SMOOTH is a measure of earnings smoothing and is calculated as the standard deviation of operating cash flows divided by the standard deviation of earnings over the prior three years.
SMP	+	FREQ is a measure of the incidence of small positive earnings surprises and is calculated as the fraction of the prior 12 quarterly earnings surprises that were small positives. A small positive surprise occurs when the change in seasonally lagged quarterly earnings after tax (E_q-E_{q-4}) scaled by total assets at the end of quarter q-5 falls within the range of (0.00 to 0.0025). It is calculated from the Compustat database.
LEAD Vars.	+	LEADABNACC, LEADSMOOTH, and LEADSMP are equal to, respectively, ABNACC at year t+1, SMOOTH at year t+1, and SMP at year t+1.

Model Variables for Equation 7		
Effect of Shareholder Horizon on Degree of Analyst Revisions $FRAC = \alpha_1 + \beta_1 TRA + \beta_2 DED + \beta_3 AnalystOptimism + \beta_4 AnalystDispersion + \beta_5 ROA + \beta_6 LOSS + \beta_7 POINT + \beta_8 RANGE + \beta_9 LessThan + \beta_{10} GreaterThan + \beta_{11} TimeTrend + \beta_{12} NumFCast + \beta_{13} PostFD + \beta_{14} SIZE + \varepsilon$		
Variable	+/-	Description
FRAC		The percentage of analysts who revised their earnings forecasts within five days of the issuance of management earnings guidance. Data is taken from First Call database.
TRA	–	TRA is calculated as the percentage of transient investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
DED	+	DED is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
AnalystOpt	+	AnalystOpt is calculated as the difference between analyst consensus forecast and actual earnings, scaled by the absolute value of earnings. Data is taken from the First Call database.
AnalstDis	+	AnalystDis is calculated as the standard deviation of the beginning consensus forecast. Data is taken from First Call database.
ROA	?	ROA is calculated as analysts' consensus quarterly earnings forecast at the beginning of the fiscal quarter, scaled by the lagged value of assets. This is taken from the First Call Estimates Database.
POINT	+	POINT is an indicator variable equal to 1 if management guidance is given as a point estimate. It is taken from the First Call CIG Database.
RANGE	+	RANGE is an indicator variable equal to 1 if management guidance is given in the form of a range. It is taken from the First Call CIG Database.
GreaterThan	?	GreaterThan is an indicator variable equal to 1 if guidance is "greater than" guidance. It is taken from the First Call CIG Database.
LessThan	+	LessThan is an indicator variable equal to 1 if guidance is "less than" guidance. It is taken from the First Call CIG Database.
LOSS	?	LOSS is an indicator variable equal to 1 if management guidance is a loss. It is taken from the First Call CIG Database.
NumFCast	?	NumFCast is equal to the number of forecasts in the consensus. It is taken from the First Call Estimates Database.
RegFD	?	RegFD is an indicator variable that is equal to 1 if the beginning of the consensus period occurs after October 31, 2001.
T	?	T is a time trend variable. T equals 1 for the first quarter in my sample.
SIZE	?	SIZE is the natural log of the firm's market capitalization taken as the number of common shares outstanding times the firm's stock price. It calculated from the Compustat Database.

Model Variables for Equation 8

Effect of Shareholder Investment Horizon on Ceasing Guidance

$$\Pr(\text{Stop} = 1) = \alpha_1 + \beta_1\text{TRA} + \beta_2\text{DED} + \beta_3\Delta\text{EPS} + \beta_4\text{MBanalyst} + \beta_5\text{FutureEPS} + \beta_6\text{Loss} + \beta_7\text{Return} + \beta_8\text{Management} + \beta_9\text{IndNo} + \beta_{10}\text{Dispersion} + \beta_{11}\text{FutureVAR} + \beta_{12}\text{Litigation} + \beta_{13}\text{LogMVE} + \beta_{14}\text{Analyst} + \beta_{15}\text{Volatility} + \beta_{16}\text{quarterlydummies} + \varepsilon$$

Variable	+/-	Description
Stop		Stop is an binary variable that takes on a value of 1 if the company ceased issuing firm guidance and is zero otherwise.
TRA	+	TRA is calculated as the percentage of transient investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
DED	-	DED is calculated as the percentage of dedicated investors (Bushee 1998) in the stock. This data comes from the Thomson Reuters database which contains 13f filings.
ΔEPS	-	ΔEPS is the average change in diluted EPS of the four pre-event quarters relative to the respective same-quarter-last-year values, deflated by beginning stock price. It is calculated using data from Compustat.
MBanalyst	-	MBanalyst is the proportion of quarters in the pre-event period for which the firm meets or beats the most recent analyst consensus compiled before the earnings announcement. Earnings data is collected from Compustat while forecast consensus data comes from I/B/E/S.
FutureEPS	-	FutureEPS is calculated as the average change from the pre-event same-quarter values to post-event quarter values, deflated by stock price. It is calculated using data from the Compustat and CRSP databases.
Loss	+	Loss is calculated as the proportion of loss-reporting quarters in the pre-event period. It uses earnings data from Compustat.
Return	-	Return is the market-adjusted return during the one-year period before earnings were announced in the quarter preceding the stoppage. It is calculated using data from CRSP.
Management	+	Management is an indicator variable equal to1 if the firm had a change in the CEO or CFO.
IndNo	+	IndNO is the proportion of companies in the firm's SIC code that did not provide any quarterly guidance in the pre-event period. It is calculated using data from the First Call Company Issued Guidance Database.
Dispersion	+	Dispersion is measured as the standard deviation of analysts' forecasts in the most recent consensus before earnings are announced. It uses data from I/B/E/S. The amount is the average over the three pre-event quarters.
FutureVar	+	FutureVAR measures difficulty in forecasting earnings and is measured as the degree to which future earnings increasingly deviate from past earnings. Compustat earnings data is used. For a detailed description see footnote 4.
Litigation	+	Litigation is the probability of being sued, calculated using a litigation exposure model. The model is a probit model where the probability of a lawsuit is predicted on the basis of firm size, stock turnover, firm beta, returns, volatility of returns, and firm industry. These variables are obtained from the CRSP and Compustat databases. The dependent variable of lawsuit is obtained from the Stanford Securities Class Action Clearinghouse website.

LogMVE	?	LogMVE is the natural log of the firm's price times the number of common shares outstanding at the beginning of the event quarter. It is calculated using data from Compustat.
Analyst	?	Analyst is the average analyst following for the four pre-event quarters. It is equal to the number of distinct analysts following the firm in I/B/E/S.
Volatility	-	Volatility is measured as the standard deviation of daily stock returns in the year ending five days after the earnings announcement in the quarter preceding guidance cessation. It is calculated using returns data from the CRSP database.
Qtr Dummies	?	These are indicator variables for whether the fiscal quarter is the first, second, third, or fourth.

Appendix B

Full Results for Analyst Herding, Shareholder Horizon, and Management Earnings Guidance

						Original Sample			Full Sample		
Hypothesis	Dep Var.	Table	Method	Measure	Pred.	Actual	T-Stat	Signif.	Actual	T-Stat	Signif.
H1	S-Stat	2	OLS	TRA	+/-	-	-4.03	***	n/a	n/a	n/a
	S-Stat	2	OLS	DED	+/-	-	-0.56	n/s	n/a	n/a	n/a
H2a Stage 1	TRA	4a/5a	OLS	RET3	+	+/-	n/a	n/s	+	n/a	**
	TRA	4a/5a	OLS	RET12	+	+/-	n/a	n/s	+/-	n/a	n/s
	TRA	4a/5a	OLS	LAGRET3	+	+	n/a	*	-	n/a	**
	TRA	4a/5a	OLS	LAGRET12	+	+	n/a	***	+	n/a	*
H2b Stage 1	TRA	4b/5b	OLS	ABNACC	+	+/-	n/a	n/s	-	n/a	*
	TRA	4b/5b	OLS	SMP	+	-	n/a	*	-	n/a	***
	TRA	4b/5b	OLS	SMOOTH	+	+	n/a	*	+/-	n/a	n/s
	TRA	4b/5b	OLS	LEADABNACC	+	+/-	n/a	n/s	-	n/a	*
	TRA	4b/5b	OLS	LEADSMP	+	-	n/a	**	+/-	n/a	n/s
	TRA	4b/5b	OLS	LEADSMOOTH	+	+	n/a	**	-	n/a	**
H2 Stage 2	S-Stat	6a/7a	OLS	CONTROL	-	-	-2.88	***	-	-2.29	**
	S-Stat	6b/7b	OLS	RET	-	-	-2.9	***	-	-2.4	**
	S-Stat	6b/7b	OLS	LAGRET	-	-	-4.06	***	-	-2.48	**
	S-Stat	6c/7c	OLS	ACCDIS	-	-	-2.32	**	-	-1.92	**
	S-Stat	6c/7c	OLS	LEADACCDIS	-	-	-2	**	-	-1.8	**
H3	FRAC	9	OLS	TRA	-	-	-0.10	n/s	n/a	n/a	n/a
	FRAC	9	OLS	DED	+	+	3.9	***	n/a	n/a	n/a

For all hypotheses with the exception of H2-Stage 1, *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels. For H2-Stage 1, significance is based on the number of years (out of 10) the coefficient exhibited the actual sign on the variable (given in column "Actual"). This is compared with the number of years the variable exhibited the opposite sign. Significance for *, **, and *** levels is obtained if the variable exhibited the actual sign 2, 4, or 6 more years than the opposite sign. For all hypotheses "n/s" indicates no significant results were found.