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Why do institutional investors chase return trends?

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A R T I C L E I N F O

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A B S T R A C T

We propose and test a simple explanation for institutional investors' tendency to chase return trends. When investors face uncertainty about the precision of their private information, they wait for subsequent confirming news before establishing stock positions. While such news impact the stock price, at the same time they increase investors' estimates of the precision of their information. With low information quality the latter effect dominates and causes investors to purchase the stock after confirming good news. We formalize these ideas in a simple model and test the model's predictions on mutual funds' stock holdings data. Using mutual funds' past return experiences with individual stocks as a proxy for their stock-specific information quality, we find evidence for the prediction that trend chasing is more likely when information quality is low.

1. Introduction

The tendency of institutional investors to chase return trends has received considerable attention in financial economics. Also known as positive-feedback trading or momentum investing, trend-based strategies call for buying (selling) financial assets with high (low) recent returns. Starting with Grinblatt et al. (1995), several papers document that institutional investors engage in trend-based trading strategies. The evidence is especially strong for actively-managed mutual funds, which tend to buy recent winners.[1]

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[1] See below for a detailed review of the literature.

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Despite the large body of work on the subject, very little is known about why institutional investors respond to past returns in formulating their investment strategies. Theoretical studies that focus on the asset-pricing implications of trend chasing typically assume this type of trading behavior rather than provide a rationale for it (De Long et al., 1990; Hong and Stein, 1999). It is tempting to link the evidence on trend chasing to return predictability; perhaps institutional investors implement mechanical strategies designed to exploit the momentum anomaly documented by Jegadeesh and Titman (1993). While some institutional investors indeed specialize on momentum, a closer look at the existing evidence suggests that the momentum anomaly may not be the primary reason for the observed trend chasing behavior. First, the portfolios of institutional investors that engage in trend chasing differ substantially from the Jegadeesh–Titman momentum portfolio, and as a result, these investors fail to earn the momentum profits (Badrinath and Wahal, 2002). Second, institutional investors are trend chasers even in markets that do not exhibit the momentum anomaly (Chae and Lewellen, 2004).

In this paper, we propose and test a simple explanation for trend chasing that does not rely on arguments based on the existence of market anomalies. The main premise of our thesis is that investors face uncertainty regarding the *precision* of their private information and revise their precision estimates in response to subsequent news. When this Bayesian updating effect is sufficiently strong, confirming news raise investors' going-forward return expectations and hence increase their demand for the stock. Since such news also moves the stock price, investors resemble trend chasers in their trading behavior. Investors do not trade stocks based on past returns per se; rather, news that drive stock returns also trigger trades by affecting investors' confidence in the validity of their initial analyses.

The logic underlying our basic argument is illustrated by the following scenario. Suppose that a money manager predicts an increase in the profitability of a firm from next period onwards; however, she thinks that her prediction is based on highly imprecise information. Accordingly, the manager expects a positive but small abnormal return on the firm's stock. In particular, suppose that the manager has other stock picks that offer relatively more attractive returns at the time. Given that the funds under her management are limited, the manager then passes up investing in the firm's stock. Importantly, the manager continues to keep an eye on this stock, since her prediction concerns a sequence of future earnings.

Suppose now that the first subsequent earnings realization of the firm turns out to be relatively high. Consider the implications for the manager's return expectations going forward. On one hand, the high earnings outcome alerts other market participants to the possibility of an increase in long-term profitability and pushes up the stock price. We call this the *convergence effect*, which, all else equal, reduces the manager's return expectation going forward. On the other hand, the high earnings outcome validates the manager's initial prediction and makes her more confident that her original analysis is genuinely informative. We call this the *confirmation effect*, which, all else equal, increases the manager's return expectation going forward. Apparent trend chasing behavior emerges when the confirmation effect is sufficiently strong relative to the convergence effect. In this case, the high earnings outcome drives the stock price up, but it also triggers a purchase decision by raising the manager's going-forward return expectation on the stock.

We develop a simple model of active portfolio management that formalizes the above ideas. The model describes a money manager who trades based on private information. For each firm she analyzes, the manager privately observes a signal on the persistent component of the firm's earnings process. However, the manager faces uncertainty about the signal's precision: the signal is either informative or pure noise. We refer to the manager's prior on the probability of the former case as her *information quality*. The manager updates this prior in subsequent periods as the firm's interim earnings are realized. In this framework, the confirmation effect described above corresponds to the sensitivity of the manager's updated precision estimate to interim earnings news. Applying the standard Bayesian updating rule, we show that the confirmation effect is stronger when information quality is lower. Intuitively, the manager substantially updates her precision estimate in response to earnings news only if she does not have a very strong prior on this precision to start with.

The inverse relationship between the manager's information quality and the confirmation effect delivers our main result on trend chasing. When information quality is relatively low, the manager delays acting on her signal and purchases the stock only after confirming good news. Since such news also increase the stock price, the manager's trading behavior resembles trend chasing. When information quality is high, on the other hand, the manager acts on her signal as soon as she receives it. In this case, the purchase decision does not relate to the recent return on the stock in any particular way.

We analyze mutual funds' stock purchase decisions to test whether trend chasing is indeed more likely when information quality is low. The empirical analysis requires a proxy for fund managers' perceptions about the quality of their private information. We develop a novel proxy of information quality that is based on funds' past return experiences with individual stocks. Specifically, we take whether a mutual fund has made losses or profits by holding a stock in the past as a measure of the fund's stock-specific information quality. Our presumption is that the fund manager feels relatively less (more) confident about her ability to produce useful information about a stock if a past position in the stock has generated losses (profits) for her.

We use the proxy for information quality described above to test several predictions of the model. First, funds should be less likely to initiate new positions in their past loss makers relative to their past profit makers. While this prediction is not the main focus of our analysis, to the best of our knowledge this is the first paper to explore whether stock-specific past performance affects mutual funds' purchase decisions. Second, we test the main prediction of the paper – that trend chasing is more likely when information quality is low. Specifically, we analyze whether funds exhibit a stronger tendency to purchase recent winners in the case of their past loss makers relative to their past profit makers. Third, trend chasing behavior should emerge when the convergence effect is not too strong; that is, when the recent stock price runup is positive but not too large. The results confirm all three predictions. Mutual funds exhibit a significantly lower probability of initiating new positions in their past loss makers. Furthermore, abnormal stock returns prior to position initiations are substantially higher in the case of past loss makers. In other words, funds are reluctant to buy stocks on which they lost money in the past, and if they do buy such stocks, the purchase decision tends to follow high abnormal returns. We find that the relevance of a fund's past experience with the stock fades away slowly; the results are significant up to two years after the closing of a previous position. Finally, the trend chasing tendency is concave is the recent stock return; it is strongest for stocks with modestly positive recent returns and weakens for stocks with very large recent runups.

The second part of the empirical analysis concerns the robustness of our findings to alternative explanations. Anecdotal evidence suggests that mutual funds may trade according to price targets, buying or selling stocks after their prices reach certain thresholds. If so, our information quality proxy, which is based on past holding performance, may be affected by trading based on price targets. Specifically, stocks with high past performance may be those that were sold after having exceeded a price target. Funds may then repurchase these stocks only if their prices go below the target. In this way, high information quality stocks would appear to have low runups prior to being repurchased. Another alternative explanation for our main findings is that funds screen out stocks with small market capitalizations. Under this explanation, some of the past losers of funds may be stocks that became too small in market capitalization to hold. A precondition for these stocks to be bought back would be an increase in the stock price. In this way, low information quality stocks would appear to have high runups prior to being repurchased. We devise a number of tests to evaluate these alternative explanations and show that our main results are robust to them.

Our main tests are designed to evaluate the model's predictions regarding information quality. However, these analyses are also of interest on their own as descriptions of mutual fund trading behavior from a holding cycle perspective. The last part of the empirical analysis adds to and expands the main tests in this regard by considering several additional aspects of holding cycles. Our primary focus in these additional tests is on holding size, adjusted for the stock's market capitalization and the fund's assets under management. We find strong persistence in the size of consecutive holdings; funds tend to initiate larger positions in stocks for which they had larger holdings in the past. Funds are also more likely to repurchase stocks for which they had larger holdings in the past. We find that the information quality effects – lower initiation likelihood and larger pre-initiation runups for past losers –

are stronger for larger holdings of the funds. Finally, we find that our information quality measure predicts not only a higher likelihood of position initiations, but also a higher likelihood of subsequent additions to those positions. Taken together, these findings suggest positive interactions between our past-performance based information quality measure and holding size. In additional analyses, we also examine stock-level public information measures such as analysts' forecast dispersion and earnings surprise, and find that our main results are stronger for stocks with lower-quality public information (i.e., high forecast dispersion and high earnings surprise).

Our paper relates to several strands of literature. On the empirical side, the most relevant studies are those that analyze institutional investors' trading behavior. Grinblatt et al. (1995) provide the first empirical analysis of trend chasing in the context of mutual funds. Their findings indicate that mutual funds tend to buy recent winners on average, and that this tendency is especially common among growth and aggressive-growth oriented funds. Wermers (1999) and Badrinath and Wahal (2002) confirm these findings in larger samples of institutional investors. Our paper contributes to this literature by providing a rationale for the observed trading patterns and testing its implications.

There is a large theoretical literature on informed trading dynamics. Our paper relates to two groups of papers in this area. A first group of relatively more closely related papers are Romer (1993), Avery and Zemsky (1998), and especially Cao et al. (2002). All three papers present multi-period models in which some informed investors trade early and others trade late. Similar to the confirmation effect in our model, price movements resulting from early trades help late investors better interpret their own signals and affect their trading behavior. We provide a more detailed discussion on comparisons to these three models after presenting the specifics of our own below.

A second group of papers generate trading behavior that resembles trend-chasing, but for different reasons than ours. Wang (1993, 1994) develops dynamic asset-pricing models that feature risk-averse and asymmetrically informed investors. In these models, uninformed investors infer informed investors' past signals through stock price realizations and respond by rebalancing their portfolios. A high realized return, for instance, reveals that the uninformed investors have underestimated the expected dividend of the stock and hence underinvested in it, causing them to buy. In this way, uninformed investors resemble trend chasers. Our paper differs from Wang's not only in terms of the rationale it develops for trend chasing, but in focus as well. Wang's analysis concerns efficiency of risk sharing in general equilibrium; accordingly, the stock in his models is the only risky asset in the economy (e.g., the market index). Our model and empirical analysis focus on trend chasing at the individual stock level, which is unlikely to be driven by risk sharing considerations.

Hirshleifer et al. (1994) and Brennan and Cao (1996) also generate return-sensitive trading patterns due to risk aversion, albeit in more stylized setups than Wang (1993, 1994). While the two papers are quite different from each other, they both model dynamic trading by risk-averse informed investors. These investors partially reverse their initial positions to reduce their risk exposures once prices more fully reflect their private information (which happens due to the arrival of additional informed traders in Hirshleifer et al. (1994) and the arrival of public information in Brennan and Cao (1996)). Thus, informed investors act like contrarians (e.g., selling the security after a price runup), whereas uninformed investors resemble trend chasers by taking the other side of these trades.

The idea that privately-informed investors learn gradually about their ability to analyze a stock also appears in Daniel et al. (1998) and Gervais and Odean (2001). Both papers emphasize asset pricing implications of behavioral biases. Specifically, they analyze the impact of biased self-attribution on informed investors' trading dynamics. Daniel et al. (1998) model private information as being long-lived, in which case biased self-attribution causes trend chasing by informed investors (e.g., buying more of the stock after a confirming signal increases the stock price). In contrast, private information is short-lived in Gervais and Odean (2001), which rules out trend chasing by construction.

The remainder of the paper is organized as follows. Section 2 presents the model and its empirical implications. Section 3 describes data and empirical methodology. Section 4 presents the empirical findings. Section 5 concludes.

2. Model and hypothesis development

In this section, we present a simple model of active portfolio management that fleshes out our basic argument. The model describes the stock selection problem of a money manager who trades on private information. After developing the model, we discuss its relation to prior theoretical work and present its empirical predictions.[2]

2.1. The model

2.1.1. The stock

The investment opportunity we consider is the stock of a firm that lives for three dates, $i = 0,1,2$. At dates $i = 1$ and $i = 2$ the firm generates and pays out to its shareholders cash flows C_i, which are drawn i.i.d. from a Bernoulli distribution. The average long-term profitability of the firm, captured by the success probability of the Bernoulli distribution, is uncertain. Specifically, the firm is either in a *high* profitability regime with probability z, or in a *normal* profitability regime with probability $1 - z$. In the high profitability regime the success probability is $\delta^H = 1$. In the normal profitability regime the success probability is $\delta^N = \frac{1-2z}{2(1-z)}$.[3] At the initial date 0, nature picks the profitability regime. Market participants do not observe nature's pick; however, they know the unconditional probabilities z and $1 - z$. We interpret the normal regime as the status quo (e.g., average profitability in the unmodeled recent past), and the high regime as a fundamental, long-term change in profitability.

The firm's stock trades at dates 0 and 1 in a competitive, risk-neutral market. The discount rate is normalized to zero. Given risk-neutrality and the zero discount rate, the stock price at date i is simply the sum of the expected values of the firm's future cash flows, where the expectations are conditional on all publicly available information. At date 0, the public only knows the prior distribution of the profitability regime. Therefore the stock price at date 0 is given by

$$P_0 = E(C_1 + C_2) = 2[(1 - z)\delta^N + z\delta^H] = 1. \tag{1}$$

At date 1, the public updates its prior on the profitability regime based on the observed value of C_1. Let P_1^{up} and P_1^{down} denote the stock price at date 1 after observing $C_1 = 1$ and $C_1 = 0$, respectively. A straightforward application of Bayes' Rule gives

$$\begin{aligned} P_1^{up} &= \frac{1}{2(1-z)} > \frac{1}{2}, \\ P_1^{down} &= \frac{1-2z}{2(1-z)} < \frac{1}{2}. \end{aligned} \tag{2}$$

Notice that a high (low) realization of C_1 increases (decreases) the posterior probability of the high profitability regime and consequently raises (lowers) P_1 relative to the unconditional expectation $E(C_2) = 1/2$. Also, notice that this change is more sensitive to the realization of C_1 (i.e., deviates more from 1/2) for higher values of z. Thus, z parameterizes the degree to which market participants learn about the profitability regime from cash flow realizations.

2.1.2. The manager

The investor we focus on is a money manager who receives private information about the firm's profitability regime. Specifically, after nature picks the profitability regime but before trading takes

[2] A more general version of the model that exhibits multiple stocks can be found in the discussion paper version Altı et al. (2011).

[3] We set δ^N as a function of z and $\delta^H = 1$ to economize on notation and to simplify some of the expressions that we derive below. All of the qualitative results from the model continue to hold in the more general case $1 \geqslant \delta^H > \delta^N \geqslant 0$. Also, notice that for δ^N to be a properly-defined probability the requirement $z < 0.5$ has to be met. We assume that this is the case in what follows.

place at date 0, the manager privately observes a signal that takes one of the two values $\{N,H\}$ (normal or high). The signal is either *informative*, in which case it correctly specifies the firm's profitability regime, or it is *pure noise*, in which case its normal and high values are realized with their respective unconditional probabilities $1-z$ and z. The manager's prior belief is that the signal is informative with probability q. We refer to q as the manager's *information quality*; lower values of q imply that the manager believes her signal to be less informative.[4,5]

At each trading date $i = 0,1$, the manager can invest in either the stock, or an alternative asset with an expected return of $r^* > 0$. We assume that the manager can hold at most one share of the stock, and that she trades without price impact.[6] The *hurdle rate* r^* represents the expected return on the next best alternative to the stock available to the manager. The idea is that the manager has limited investable funds relative to her informed investment opportunities; as a result, the opportunity cost of investing in the stock is strictly positive.[7] We assume that the manager is restricted from borrowing and short selling securities. This assumption is made for simplicity; our results only require that the manager has limited ability to use leverage as an additional source of investable funds.

2.1.3. Manager's trading dynamics

In deciding whether to buy the stock at any given date, the manager compares her expectation of the stock return to the hurdle rate r^*. In what follows, we refer to the former as the *manager's expected return*, defined as the going-forward one-period expected stock return conditional on the manager's private information and all available public information.

There are six different states of the world, which are combinations of the manager's private signal $\{N,H\}$ and three publicly observable states summarized by the stock prices $\{P_0, P_1^{up}, P_1^{down}\}$. Four of these cases, however, are trivial to analyze. First, consider (N, P_0) and (N, P_1^{up}). It is easy to show that the manager's expected return is strictly negative in these cases, as she possesses unfavorable private information (signal N) relative to publicly available information. Next, consider (N, P_1^{down}) and (H, P_1^{down}). In these cases, the low cash flow realization $C_1 = 0$ reveals that the profitability regime is normal, since in the high regime $C_1 = 1$ with probability one. As a result, the manager's private information is irrelevant going forward and her expected return is zero. In all four cases, the manager chooses not to hold the stock as her expected return is below $r^* > 0$.

We are thus left with the two main cases of interest: (H, P_0) (the manager has a high signal and considers buying the stock at date 0), and (H, P_1^{up}) (the manager has a high signal and considers buying the stock at date 1 following a high cash flow realization $C_1 = 1$). Let us denote the manager's expected return in these two cases with r_0 and r_1, respectively. We have

$$\begin{aligned} r_0 &= q\left[\frac{1+P_1^{up}}{P_0} - 1\right] = \frac{q}{2(1-z)}, \\ r_1 &= q\frac{2}{1+q}\left[\frac{1}{P_1^{up}} - 1\right] = q\frac{2}{1+q}[1-2z]. \end{aligned} \tag{3}$$

[4] It is worth emphasizing that q represents the manager's *own perception* of her information quality. This perception may be objective, but it may be subjective as well. The distinction is not relevant for most of our analysis, since we are primarily interested in the manager's trading dynamics, not her return performance.

[5] For simplicity, we take the manager's information quality q as exogenously given. More generally, one can think of q as partly being the outcome of the manager's (unmodeled) past experiences with the stock. For example, previous analyses that proved to be correct (incorrect) may make the manager more (less) confident about her ability to analyze the specific stock. See Section 3.2 for a further discussion of this point.

[6] The assumptions of a binary holding size and no price impact are made for simplicity and do not affect our qualitative results. Our focus is on whether the manager chooses to hold some or none of the stock, which depends on whether the manager's expected return on the stock exceeds the hurdle rate. In an alternative model where arbitrary quantities can be purchased with price impact, the manager would still purchase some positive quantity if and only if her expected return on a marginal share (i.e., an infinitesimally small purchase with no price impact) exceeds the hurdle rate.

[7] For the sake of brevity we treat r^* as exogenous. In the discussion paper version of the article we provide a model with multiple stocks and derive the hurdle rate endogenously as a function of total funds under management.

In Eq. (3), manager's expected return is given by the product of two terms. The term in square brackets is the net return from investing in the stock conditional on the manager's signal being informative. The term that multiplies the brackets is the probability that the manager's signal is informative.[8]

The relative magnitudes of these two terms determine the manager's expected return dynamics. First, consider the net return from investing conditional on the signal being informative:

$$\left[\frac{1+P_1^{up}}{P_0}-1\right] > \left[\frac{1}{P_1^{up}}-1\right] \text{ iff } z > 1-1/\left(\sqrt{5}-1\right) \simeq 0.19. \tag{4}$$

When inequality (4) is satisfied, we say that the stock returns exhibit the *convergence effect*: A high realization of C_1 increases the public's posterior on the high profitability regime, pushes up the date-1 stock price, and thus leaves a smaller potential profit for the manager. Inspecting Eq. (3), one can see that the convergence effect becomes stronger for higher values of z.

Next, consider the probability that the manager's signal is informative. The manager's prior at date 0 is that her signal is informative with probability q. Upon observing a high realization of C_1, the manager updates this prior to $\frac{2q}{1+q} > q$. This is what we call the *confirmation effect*: The manager becomes more confident that her initial private signal is informative if the date-1 cash flow realization agrees with the signal. The strength of the confirmation effect is determined by the ratio $\frac{2q}{1+q}/q = \frac{2}{1+q}$, which is decreasing in q. Intuitively, when the manager is initially highly confident that her signal is informative, she cannot get much more confident as new data arrives. In the case of weak initial confidence, however, the effect of new data on the posterior is large relative to the small value of the prior.

We say that the manager's expected returns exhibit *positive-feedback dynamics* if $r_1 > r_0$. This definition captures the idea that a manager with a high signal finds holding the stock relatively more attractive (in the expected return sense) following a positive stock price surprise at date 1. From Eq. (3), it is easy to show that the manager's expected returns exhibit positive-feedback dynamics if and only if

$$q < 4(1-z)(1-2z)-1. \tag{5}$$

Recall that $z \in (0, 1/2)$. In this interval, the right-hand side of inequality (5) is strictly decreasing in z, and ranges from 3 to -1. Thus, positive-feedback dynamics is more likely to obtain for low values of q (strong confirmation effect), and low values of z (weak convergence effect).[9]

Next, we define the tendency of the manager to trade in ways that resemble trend chasing. Recall that a high realization of C_1 triggers a positive stock return at date 1. We say that the manager is a *trend chaser* if she purchases the stock only in this state of the world and none other. Clearly, a necessary condition for the manager to be a trend chaser is that her expected returns exhibit positive-feedback dynamics. However, whether the manager is a trend chaser depends on the hurdle rate r^* as well. For trend chasing to obtain, the hurdle rate must be low enough so that at least some stocks with positive-feedback return dynamics are attractive enough to be purchased at date 1. The bound on the hurdle rate below which trend chasing is feasible is given by

$$\bar{r} = \begin{cases} \frac{4(1-z)(1-2z)-1}{2(1-z)} & \text{if } z > 1-1/\left(\sqrt{5}-1\right), \\ 1-2z & \text{if } z \leqslant 1-1/\left(\sqrt{5}-1\right). \end{cases} \tag{6}$$

The terms on the right-hand side of Eq. (6) are r_1 computed at the highest possible value of q that is consistent with trend chasing in the two relevant regions of z. When inequality (4) is satisfied, inequality (5) is a binding constraint on q for positive-feedback dynamics to obtain; the first line of

[8] If the manager's signal is pure noise, her net expected return from investing in the stock equals zero.

[9] Since q is a probability, inequality (5) cannot be satisfied when the right-hand side is negative, which is the case for $z > (3-\sqrt{3})/4 \simeq 0.32$. In other words, the convergence effect is too strong to allow for positive-feedback dynamics when $z > 0.32$. Also, notice that inequality (5) is satisfied for all values of $q \in [0, 1]$ when the right-hand side exceeds one, which is the case for $z < 1-1/(\sqrt{5}-1) \simeq 0.19$.

Eq. (6) is r_1 computed at $q = 4(1-z)(1-2z)-1$ in this case. When inequality (4) is not satisfied, positive-feedback dynamics obtains for all q values; the second line of Eq. (6) is r_1 computed at $q = 1$ in this case.

The following proposition describes how trend chasing relates to information quality:

Proposition 1. *Suppose that $r^* < \bar{r}$, and let $\underline{q} \equiv r^*/(2-4z-r^*)$, $\bar{q} \equiv 2(1-z)r^* > \underline{q}$:*

(i) *If $q < \underline{q}$, the manager never purchases the stock.*
(ii) *If $q \in [\underline{q}, \bar{q})$, the manager is a trend chaser.*
(iii) *If $q \geqslant \bar{q}$, the manager purchases the stock at date 0 upon observing a high signal and hence is not a trend chaser.*

The proof of the proposition is straightforward and hence omitted. Proposition 1 shows that trend chasing behavior is more likely when information quality is low. Not surprisingly, the manager does not buy the stock at either date 0 or date 1 if q is very low (part i). Thus, the range of information quality that is relevant for stock purchases is $q \geqslant \underline{q}$. Within this range, the manager acts like a trend chaser for relatively low values of q by delaying a purchase until confirming news arrives at date 1 (part ii). For relatively high values of q, the manager buys the stock immediately after observing a high signal at date 0. Since date 0 is not preceded by any particular return pattern, the manager is not a trend chaser in this case (part iii).

2.2. Discussion and relation to previous work

The stylized model above features the two key ingredients that our main argument hinges on. The first ingredient is positive-feedback dynamics in manager's expected returns. The manager is privately informed about *long-term* profitability, while the public observes only *short-term* profit realizations. As a result, the manager has a relative advantage in interpreting the information content of those profit realizations. It is this relative advantage that decouples the confirmation effect from convergence and thus allows for positive-feedback dynamics in the model.

The second key feature of the model is the hurdle rate r^*. The assumption of a strictly positive r^* captures the idea that the manager faces a binding resource constraint in picking stocks. In other words, she cannot take an arbitrarily large aggregate position in her research picks by borrowing or shorting other securities. This is what generates the delayed use of information in the model. If the manager could lever up without limit, the appropriate benchmark for buying a stock would be an expected abnormal return of zero. In that case the manager would buy the stock as soon as she observes a high signal, instead of waiting for further confirmation by subsequent news.[10]

The simple model we develop is intended to motivate our empirical tests. As discussed in the introduction, variants of the basic ingredients of our model can be found in some earlier theoretical studies on informed trading dynamics. The most relevant paper in this regard is Cao et al. (2002). The authors present a model in which informed investors observe noisy signals of firm fundamentals. These investors face a fixed trading cost, which makes them delay their trades until they expect at least to break even. In equilibrium, low-cost investors trade first, whereas high-cost investors wait until price movements resulting from the early trades confirm their signals. Thus, the late informed traders resemble trend-chasers.

The basic mechanism of trend chasing in our model is quite similar to that in Cao et al. (2002). The trading cost in their model is akin to the hurdle rate in ours, and the late informed trades are triggered by a confirmation effect in both analyses. However, there are substantial differences between the two models in terms of focus and structure. Cao et al. (2002) are primarily interested in how gradual information aggregation generates conditional return volatility and skewness patterns. Our model focuses instead on the cross-section of trading behavior as a function of information quality. Analytically, the

[10] In practice, financing and investment restrictions on mutual funds are quite common. Most mutual funds, for example, are either explicitly or implicitly restricted from borrowing and short selling (Almazan et al., 2004).

two models illustrate two related but distinct ways in which positive-feedback dynamics may obtain. In Cao et al. (2002), the market maker is uncertain as to whether informed traders exist, which limits the price impact of early trades and thus weakens the convergence effect relative to the confirmation effect. As described above, a similar outcome obtains in our model because of the long-lived nature of the manager's information. This alternative channel for generating positive-feedback dynamics not only complements the one in Cao et al. (2002), but also more directly relates to information quality, which is our empirical focus.

We briefly mention two other papers, Avery and Zemsky (1998) and Romer (1993), whose models exhibit parallels with Cao et al. (2002).[11] Avery and Zemsky (1998) present a model in which informed traders with noisy signals arrive sequentially. Similar to Cao et al. (2002), the market maker faces uncertainty about the existence of informed traders, which weakens the convergence effect. In this setup, Avery and Zemsky (1998) illustrate the interesting result that late informed traders may sometimes exhibit *herd behavior* by trading against their own signals. Romer (1993) also presents a model in which informed traders arrive sequentially. In contrast to the other two models, the information structure in Romer (1993) is more standard; the market maker does not face uncertainty about the existence of informed traders. As a result, the convergence effect always dominates the confirmation effect in Romer's (1993) analysis. The broad feature that our model shares with these three models is that informed traders condition on past price movements (due to earnings realizations in our case, versus price impact of trades in the other three models) in formulating their trading strategies.

2.3. Model predictions

We now present the empirical predictions of the model that relate the manager's stock purchase decisions to her information quality. These predictions constitute the basis for the empirical tests in subsequent sections.

We start with the likelihood of a purchase as a function of information quality. Formally, this is the probability of reaching at least one state of the world in which the manager's expected return exceeds r^* and hence she decides to hold the stock.

Prediction 1. The likelihood of a purchase is increasing in information quality.

Prediction 1 directly follows from Proposition 1. Upon observing a high signal, the manager never buys the stock if q is relatively low (part (i)), buys the stock only after confirming news at date 1 if q is in the middle range (part (ii)), and buys the stock immediately after observing the signal at date 0 if q is relatively high (part (iii)). Therefore, the probability of a purchase is an increasing step function in q. Intuitively, higher information quality makes the manager's expected return more sensitive to her private information, making it easier to beat the hurdle rate in case of a high signal.

Next we turn to model predictions regarding trend chasing. Following the empirical literature, we first focus on stock returns preceding purchases. In the model, the manager buys the stock in one of two circumstances: (1) at date 0, upon observing a high signal; (2) at date 1, upon observing confirming news (and having observed a high signal at date 0). Date-0 purchases are not preceded by any particular return pattern; one can assume the average stock return in the unmodeled past prior to date 0 to be zero. Date-1 purchases are preceded by positive returns triggered by the confirming news (i.e., the high cash flow realization $C_1 = 1$). Accordingly, stock returns preceding date-1 purchases are higher than those preceding date-0 purchases This provides us with the main prediction of the model:

Prediction 2. The stock return preceding a purchase is decreasing in information quality.

Prediction 2 constitutes the main prediction of the paper. This prediction follows from parts (ii) and (iii) or Proposition 1, which indicate the information quality regions for date-1 and date-0 purchases, respectively. When information quality is relatively high (i.e., $q \geqslant \overline{q}$), the manager buys the stock at

[11] For a more detailed comparison of the models in these three papers, see Cao et al. (2002).

date 0. When information quality is lower (i.e., $q \in [\underline{q}, \overline{q})$), the manager buys the stock at date 1 only upon observing confirming news. Thus, purchases of stocks for which information quality is relatively low are preceded by positive returns and resemble trend chasing.

The final model prediction concerns a refinement of apparent trend-chasing behavior with respect to the *magnitude* of the stock return. Recall that trend-chasing purchases require not only a strong confirmation effect (which obtains with low information quality q), but also a weak convergence effect (parameterized by z in the model). When the convergence effect is strong (i.e., z is high), a positive cash flow realization at date 1 reveals "too much" information to the public, triggering a relatively large positive return and leaving too little expected profit for the manager going forward. So, even with low information quality, the manager may not buy the stock following confirming news at date 1 if such news trigger relatively large returns. In other words, the model predicts a non-monotonic relationship between the stock return and the purchase decision for stocks for which the manager's information quality is low:

Prediction 3. When information quality is low, the relationship between the stock return and the likelihood of a purchase is inverse-U shaped. That is, the manager is more likely to purchase the stock following moderately high return realizations than low or very high return realizations.

3. Data and empirical methodology

3.1. Sample construction and variable definitions

We test the model's implications by analyzing stock position initiations of growth and aggressive-growth oriented mutual funds. Our sample choice is motivated by two reasons. First, trend chasing behavior is mainly observed in position initiation decisions; institutional investors do not act as trend chasers when changing or terminating their ongoing positions (Badrinath and Wahal, 2002). Second, among various types of institutions, growth and aggressive-growth oriented mutual funds exhibit the strongest tendency for trend chasing (Grinblatt et al., 1995; Badrinath and Wahal, 2002). The main ingredients of our model are also more relevant for these types of funds. Growth and aggressive-growth oriented mutual funds are similar to the manager in the model, in that they emphasize active portfolio management and stock-picking ability (as opposed to, say, balanced funds, for which diversification is a relatively more important objective).

Our primary data source is the Thomson Financial Mutual Fund Holdings Database, which reports common stock holdings of US mutual funds between 1980 and 2009. The database consists of quarterly snapshots of funds' portfolios, not individual trades. As in previous studies that use holdings data, we approximate fund's trades by taking the difference between the quarterly snapshots. For example, if a stock position appears in a date-t snapshot but is missing at dates $t-1$ and $t+1$, we assume that the stock position is initiated at date t and terminated at date $t+1$.[12] The stocks included in the analysis are those that trade on NYSE, AMEX, or NASDAQ. Stock price and return data are from CRSP.

Throughout the analysis, we calculate stocks' abnormal returns as returns in excess of size and book-to-market benchmark portfolios. At the beginning of each quarter, all stocks are sorted into size quintiles using the market capitalization as of the last day of the previous quarter and NYSE breakpoints. Stocks within each size quintile are then sorted into book-to-market quintiles using the accounting information from the last available quarterly report. The benchmark returns are calculated as equal-weighted returns of the 25 portfolios over the quarter. Each stock's abnormal return is the difference between its raw return and the return of the portfolio it is assigned to at the beginning of the quarter.

[12] One concern with this approach to identify funds' trades is the possibility of data errors and omissions. Specifically, funds' stock holdings may be missing in some quarters, due to either errors in Thomson database or fund managers who file quarterly at times and semi-annually at others (we thank one of the referees for pointing out this potential issue). In unreported analyses, we gauged the extent of this problem by measuring the frequency of observations where the number of shares in initiation is close to (specifically, within 5% of) the number of shares in termination. We found that these initiations constitute a small fraction of our sample. Furthermore, our main results on trend chasing remain quantitatively very similar after excluding these observations. The results of these unreported analyses are available upon request.

The unit of observation in most of the analysis below is a *holding cycle*, which is a sequence of consecutive quarters that starts with the initiation of a position in a stock and ends with its termination. Variable definitions are as follows. The length of a holding cycle is denoted by *qheld* and is measured in number of quarters. *Stock size* is the logarithm of the market value of the stock in 2009 dollars. *Stock volatility* is the annualized standard deviation of daily stock returns measured over one quarter. *Fund size* is the logarithm of the total net assets of the fund. *Fund return* is the return of the fund over the past four quarters. *Fund flow* is quarterly flows into the fund divided by total net assets. We calculate quarterly flows as the difference between end-of-quarter total net assets and the quarter-end market value of beginning-of-quarter stock holdings. Observations in the first and the 99th percentiles of stock size, stock volatility, and fund size (fund return and fund flow) are winsorized (dropped as outliers). Using the raw data does not affect our results in any significant way.

Table 1 reports summary statistics. After dropping the outliers, we have 355,068 distinct holding cycles in 15,587 stocks by 2272 mutual funds. As the breakdown of these holding cycles shows, funds tend to keep their stock positions open for relatively short periods of time. The most frequent holding cycle lasts only one quarter (39% of all holding cycles). Only 18% of holding cycles last for more than four consecutive quarters.

3.2. Measuring information quality

The main predictions of the model relate a money manager's trading behavior to her perceived information quality. Since the information in question is private, its quality is not directly observable. To develop an empirical proxy for information quality, we look at mutual funds' past return experiences with individual stocks. The basic idea is to exploit the potential persistence in perceived information quality. Consider a fund/stock pair at some date t. Suppose that the fund has previously held the stock; say, most recently at date $t-k$. We take the abnormal return earned on that previous

Table 1
Summary statistics.

Number of funds		2272	
Number of stocks		10,698	
Average number of stocks per fund/quarter		127	
Median number of stocks across fund/quarters		67	
Number of holding cycles			
Total		355,068	(100%)
qheld = 1		137,720	(39%)
qheld = 2		77,367	(22%)
qheld = 3		45,602	(13%)
qheld = 4		29,571	(8%)
qheld > 4		65,258	(18%)

	Mean	Median	Standard deviation
Stock size	13.32	13.25	1.79
Stock volatility	0.47	0.40	0.28
Fund size	19.48	19.48	1.61
Fund return	0.089	0.101	0.25
Fund flow	0.028	−0.01	0.23

The table reports the summary statistics of the data. The variable *qheld* denotes the length of a holding cycle in number of quarters.*Stock size* is the logarithm of the market value of the stock in 2009 dollars. *Stock volatility* is the annualized standard deviation of daily stock returns measured over one quarter. *Fund size* is the logarithm of the market value of all shares classes of the fund. *Fund return* is the return on the fund in the past four quarters. *Fund flow* is quarterly flows into the fund divided by the larger of beginning-of-quarter and end-of-quarter total net assets. Reported means, medians, and standard deviations are calculated across all stock-quarters or all fund-quarters in the hold-cycles dataset.

position as a measure of the fund's stock-specific information quality at date t. The idea here is that the fund manager becomes relatively more (less) confident about her ability to analyze the stock after earning positive (negative) abnormal returns. Profits made on the previous position reinforce the fund manager's belief that she is using the right methods in evaluating the stock. Losses, on the other hand, make her question the validity of those methods. We hypothesize that what the manager learns from that previous experience at date $t-k$ about her ability to analyze the stock carries over at least in part to date t. Accordingly, our main interest is in the fund's trading behavior in the stock at date t (in particular, its tendency toward trend chasing) as a function of the return performance of the previous position terminated at $t-k$.[13]

The specific construction of the information quality measure is as follows. First, we identify all holding cycles for all mutual funds in our data set. As described above, a holding cycle is a sequence of consecutive quarters that starts with the initiation of a position in a stock and ends with its termination. For each holding cycle, we calculate the cumulative quarterly abnormal return on the stock during the quarters in which the stock is held. Our fund/stock/time specific information quality measure is the dummy variable *IQ*, which equals one if a holding cycle's cumulative abnormal return is positive, and zero otherwise.[14] We utilize *IQ* to characterize the fund's trading patterns in the stock subsequent to the termination of the holding cycle.

Measuring perceived information quality through *IQ* has several advantages. The main advantage is that *IQ* captures the quality of a mutual fund's *private information* on a stock. Other variables, such as analyst coverage, may be good indicators of how much *public information* about a stock is produced, but our hypotheses relate to the quality of private, not public, information. In this regard, notice that *IQ* may take different values for two funds that both held the same stock in the past but earned different abnormal returns (e.g., one positive and the other negative).

Another important advantage of our approach is that *IQ* is unlikely to be correlated with various other factors that affect mutual funds' holdings. Funds may tend to buy stocks with certain characteristics more often than others; for example, they may prefer liquid stocks, stocks of established companies, etc. Using an information quality measure that is correlated with such characteristics could generate spurious findings. This is much less of a concern in our case, since abnormal stock returns (which constitute the input of *IQ*) are by definition surprises that cannot be predicted using publicly observable firm characteristics.

A potential disadvantage of our approach is that *IQ* provides a noisy representation of perceived information quality. Since abnormal returns are unpredictable to a large extent, a fund manager is likely to attribute much of the abnormal return earned on a past position to good luck rather than high quality information. More importantly, a manager may feel that she had high quality information in the past but not currently, or vice versa. In short, *IQ* may reflect only a small part of the manager's current assessment of her information quality. If this is the case, the explanatory power of *IQ* in characterizing funds' trading behavior is likely to be quite small. We would like to emphasize, however, that the predictive ability of *IQ* itself is not our main interest. Rather, we intend to use *IQ*simply as a proxy variable that is correlated with the unobserved information quality.

A limitation of the *IQ* measure is that it is available only for those stocks that a fund has a record of holding. There may be other stocks that the fund has analyzed in the past but not purchased (possibly because of unfavorable information at the time), or stocks that the fund is currently analyzing for the first time. These stocks are not included in our analysis due to lack of a trading history. However, this limitation does not appear to generate any particular bias.

[13] To clarify; information quality q in the model is exogenously given, whereas information quality in our empirical analysis is a function of past investment performance. The distinction is a minor one that results from our modeling strategy. We view information quality as a dynamic variable that evolves through Bayesian updating; our empirical approach reflects this view. One can then think of q in the model as the outcome of unmodeled past updates. A repeated version of the model would exhibit such updates formally; we present the one-shot version for expositional simplicity.

[14] In unreported analysis, we defined *IQ* alternatively based on the holding cycle's cumulative raw return or cumulative market-adjusted abnormal return. The results with these alternative definitions are qualitatively similar.

Table 2
Information quality and the probability of position initiations: Univariate analysis.

T	1	2	3	4	5	6	7	8	9	10
A. All stocks	6.39	5.10	4.61	4.08	3.54	3.27	2.98	2.88	2.71	2.65
B. Information quality sub-samples										
$IQ = 1$	7.46	5.97	5.19	4.52	3.82	3.50	3.27	2.84	2.67	2.77
$IQ = 0$	5.74	4.59	4.28	3.84	3.39	3.13	2.81	2.91	2.74	2.58
Difference	**1.71**	**1.38**	**0.91**	**0.68**	**0.43**	**0.36**	**0.46**	−**0.07**	−**0.07**	**0.19**
z-Score	(**10.15**)	(**9.36**)	(**4.99**)	(**4.93**)	(**2.82**)	(**2.31**)	(**2.62**)	(**0.45**)	(**0.37**)	(**0.88**)

The table reports position initiation probabilities for previously-held stocks. Columns correspond to different values of T, which denotes the number of quarters in which the stock was not held following the termination of the most recent holding cycle in the stock. The probabilities are reported in percentage terms. Panel A reports initiation probabilities for all stocks. Panel B reports initiation probabilities for sub-samples of stocks for which the information quality variable IQ equals one or zero. Robust z-scores of sub-sample differences, calculated by clustering observations at the fund level, are reported in parentheses.

4. Results

4.1. Tests of model predictions

In this subsection, we present the main empirical findings of the paper. The analysis is structured to provide tests of the model predictions developed in Section 2.3, and the presentation follows the same order as in that section.

Prediction 1. The likelihood of a purchase is increasing in information quality.

To test this prediction, we estimate probabilities of position initiations and relate them to the information quality measure IQ. Recall that for each fund, we focus on those stocks for which the fund has a past record of holding. Accordingly, our sample is defined as the set of completed holding cycles across all funds throughout their available histories. Consider those holding cycles for which the termination date is followed by a period of T quarters during which the fund does not report a holding in the same stock. At the end of this period, a subset of these stocks are available for trading, and others are delisted for various reasons. We define those that are available for trading as the pool of stocks that are candidates for a quarter-$T+1$ position initiation. Using this pool, we estimate the probability of initiation $T+1$ quarters after termination.

Panel A of Table 2 reports the initiation probabilities for the whole sample up to ten quarters after termination. An initiation is most likely in the first quarter that follows the termination of a holding cycle. As would be expected, the probability of an initiation declines with the time elapsed since termination. Overall, the probability of an initiation within the first ten quarters after termination, conditional on the survival of the fund and the stock, is 32.32% (not reported directly; calculated using the per-quarter initiation probabilities reported in Table 2).

Of greater interest is the relationship between the initiation probability and the information quality measure IQ. Based on Prediction 1, we expect the initiation probability to be lower for stocks with low information quality. Panel B of Table 2 shows that this is indeed the case. The probability of an initiation is significantly lower for $IQ = 0$ stocks than for $IQ = 1$ stocks for the first seven quarters after a termination. As one would expect, the relevance of past experiences is stronger at shorter lags. Nevertheless, IQ captures substantial differences in initiation probabilities relative to the unconditional probabilities in Panel A. It thus appears that funds pay attention to their past return experiences when formulating their investment strategies.

The analysis in Table 2 is univariate. To control for other potential determinants of funds' stock purchase decisions, we estimate Probit regressions of the form

$$\Pr(\text{Initiation at}\,t|T) = F\big(c_0 + c_1 IQ + c_2' X_t\big). \tag{7}$$

Regression (5) estimates the probability that a fund initiates a position in a stock T quarters after the termination of a holding cycle in the same stock. The potential initiation date is denoted by t. The

Table 3
Information quality and the probability of position initiations: Multivariate analysis.

T	1	2	3	4	5	6	7	8	9	10
IQ	**1.23**	**0.91**	**0.52**	**0.31**	**0.10**	**0.04**	**0.20**	**−0.27**	**−0.24**	**−0.02**
	(**7.73**)	(**6.60**)	(**2.84**)	(**2.37**)	(**0.69**)	(**0.26**)	(**1.27**)	(**1.71**)	(**1.39**)	(**0.12**)
qheld	−0.16	−0.10	−0.08	−0.02	−0.03	0.01	0.00	0.02	−0.05	0.03
	(3.47)	(3.88)	(1.87)	(0.54)	(0.99)	(0.26)	(0.04)	(0.39)	(1.53)	(0.76)
Stock size	1.21	1.07	0.89	0.92	0.75	0.78	0.66	0.64	0.59	0.72
	(11.00)	(13.62)	(7.72)	(9.27)	(11.10)	(11.16)	(7.39)	(6.84)	(8.61)	(8.90)
Stock volatility	0.63	0.50	0.25	1.38	0.23	0.80	0.82	0.97	0.56	1.01
	(1.73)	(1.64)	(0.63)	(3.76)	(0.63)	(2.13)	(1.98)	(2.21)	(1.42)	(1.78)
Fund size	0.21	0.12	−0.01	0.02	0.07	0.01	0.09	0.08	0.25	0.05
	(1.99)	(1.33)	(0.07)	(0.29)	(1.04)	(0.11)	(1.23)	(0.85)	(2.71)	(0.62)
Fund return	−2.00	−1.73	−1.68	−1.15	−0.90	0.03	−1.24	−1.12	−0.84	−0.62
	(4.95)	(4.56)	(2.69)	(2.37)	(1.97)	(0.07)	(2.34)	(2.26)	(1.34)	(1.05)
Fund flow	0.63	0.71	0.45	0.97	0.97	1.18	1.03	1.09	0.88	0.67
	(2.01)	(2.06)	(1.51)	(2.45)	(1.92)	(2.40)	(1.88)	(1.97)	(2.54)	(1.65)
R^2	2.17%	2.39%	1.89%	2.23%	1.98%	2.16%	2.22%	2.07%	2.22%	2.94%

The table reports marginal effects in probit regressions of the form

$$\Pr(\textit{Initiation at } t|T) = F(c_0 + c_1 IQ + c_2' X_t),$$

which estimate position initiation probabilities for previously-held stocks. The potential initiation quarter is denoted by t. Columns correspond to different values of T, which denotes the number of quarters in which the stock was not held since the termination of the most recent holding cycle in the stock. *IQ* is the information quality dummy variable. The term X_t represents the vector of control variables measured in quarter t, which includes *qheld*, *stock size*, *stock volatility*, *fund size*, *fund return*, and *fund flow*. The variable *qheld* denotes the length of a holding cycle in number of quarters.*Stock size* is the logarithm of the market value of the stock in thousands of 2009 dollars. *Stock volatility* is the annualized standard deviation of daily stock returns measured over one quarter. *Fund size* is the logarithm of the market value of the reported holdings of the fund in 2009 dollars. *Fund return* is the holding-weighted abnormal return on the fund's reported holdings in the past four quarters. *Fund flow* is quarterly flows into the fund divided by beginning-of-quarter total net assets. The variables *stock size*, *stock volatility*, and *fund size* are lagged one quarter relative to t. Marginal effects are computed at the means of the explanatory variables (except for the dummy variable *IQ*) and are reported in percentage terms. Robust z-scores, calculated by clustering observations at the fund level, are reported in parentheses.

term X_t represents a vector of control variables measured at date t, which includes the length of the most recent holding cycle *qheld*, *stock size, stock volatility, fund size, fund return, and fund flow* (see Section 3.1 for variable definitions). Stock size, stock volatility, and fund size are lagged one quarter relative to t; fund return and fund flow are measured at date t. The standard errors are calculated by clustering observations at the fund level.

Table 3 reports the marginal effects and their z-scores from the Probit regressions.[15] As the table illustrates, the probability of a stock position initiation is significantly affected by a variety of factors. Most important for our analysis, the information quality dummy *IQ* retains its significance for up to four quarters after termination even after introducing the control variables. The length of the most recent holding cycle *qheld* typically has a negative effect, but it is small and not always significant. Stock characteristics size and volatility are significantly positive; funds tend to purchase larger and more volatile stocks more often. At the fund level, fund return has a negative effect on position initiations, whereas fund flow has a positive effect. The latter finding is consistent with the idea that funds attempt to diversify their portfolios further as assets under management grow.

Overall, the results in Tables 2 and 3 provide support for our empirical strategy of using past return experiences as a proxy for information quality. It appears that funds feel more confident to purchase their past profit makers relative to their past loss makers.

[15] Marginal effects are calculated at the mean values of explanatory variables except in the case of dummy variables.

Table 4
Information quality and trend chasing: Univariate analysis.

T	1	2	3	4	5	6	7	8	9	10
A. All position initiations										
$\overline{R}_t - 1$	2.15	2.70	3.04	3.45	3.86	3.53	3.07	2.55	4.75	4.24
$\overline{R}_t - 2$	–	0.96	2.03	1.49	1.94	2.42	1.33	2.20	1.23	3.02
B. Information quality sub-samples										
$\overline{R}_{t-1}\|IQ = 1$	0.67	1.16	1.03	1.54	1.18	2.10	2.92	2.60	3.53	3.60
$\overline{R}_{t-1}\|IQ = 0$	3.33	3.88	4.46	4.75	5.60	4.45	3.17	2.53	5.45	4.64
Difference	−2.66	−2.72	−3.43	−3.21	−4.42	−2.35	−0.25	0.07	−1.92	−1.04
t-Value	(6.74)	(5.99)	(6.01)	(5.34)	(6.58)	(3.07)	(0.24)	(0.06)	(1.71)	(0.88)
$\overline{R}_{t-2}\|IQ = 1$	–	0.24	1.28	0.40	1.39	1.13	0.48	1.85	0.77	2.83
$\overline{R}_{t-2}\|IQ = 0$	–	1.50	2.55	2.23	2.29	3.26	1.91	2.41	1.49	3.14
Difference	–	−1.26	−1.27	−1.82	−0.90	−2.13	−1.43	−0.55	−0.71	−0.32
t-Value	–	(2.74)	(2.47)	(3.28)	(1.24)	(2.41)	(1.51)	(0.58)	(0.64)	(0.27)

The table reports average abnormal stock returns prior to position initiations of previously-held stocks. Quarter *t* denotes the first quarter in which a stock is known to be held. Columns correspond to different values of *T*, which denotes the number of quarters in which the stock was not held since the termination of the most recent holding cycle in the stock. The term $\overline{R}_t - 1$ denotes the average abnormal stock return in the most recent quarter prior to the initiation quarter. The term $\overline{R}_t - 2$ denotes the average abnormal stock return in the second most recent quarter prior to the initiation. The abnormal returns are reported in percentage terms. Panel A reports $\overline{R}_t - 1$ and $\overline{R}_t - 2$ for the whole sample of position initiations. Panel B reports $\overline{R}_t - 1$ and $\overline{R}_t - 2$ for sub-samples of stocks for which the information quality variable IQ equals one or zero. The values reported are in percentage terms. Robust *t*-values of sub-sample differences, calculated by clustering observations at the fund level, are reported in parentheses.

Next we test the main prediction of the model that links trend chasing behavior to information quality:

Prediction 2. The stock return preceding a purchase is decreasing in information quality.

In order to document mutual funds' tendency toward trend chasing, previous studies analyze average abnormal stock returns prior to funds' purchase decisions (see, for example, Grinblatt et al., 1995). Higher average abnormal returns prior to purchases indicate a stronger trend-chasing tendency. To test Prediction 2, we start by calculating similar averages for our sample, which consists of position initiations of stocks that were previously held by mutual funds (i.e., those for which we can define *IQ*). Specifically, for each position initiation in the sample we calculate R_{t-1}, which denotes the abnormal return on the stock in the most recent full quarter prior to the initiation date *t*.[16] We then report $\overline{R}_{t-1}$, which is the equal-weighted average of R_{t-1} across all the initiations in the sample. For robustness, we also report $\overline{R}_{t-2}$, which is the average abnormal return on the stock in the second most recent full quarter prior to the initiation at date *t*.

Panel A of Table 4 presents the results. As in Tables 2 and 3, we report $\overline{R}_{t-1}$ and $\overline{R}_{t-2}$ for different values of *T*, which denotes the number of quarters elapsed since the termination of the most recent holding cycle in the stock. The results confirm the finding from previous studies that mutual funds strongly tend to buy winners. Average abnormal returns prior to position initiations are positive in all cases, ranging around 0.96–4.75% per quarter. The average cumulative abnormal return for the two pre-initiation quarters combined (i.e., the sum of the two numbers for each *T* reported in Panel A) ranges between 3.66% and 7.26%.

Panel B of Table 4 presents our main empirical findings that relate the tendency to buy winners to information quality. As in Panel A, we report average abnormal returns prior to position initiations, but now we calculate these averages for *IQ* = 1 and *IQ* = 0 sub-samples separately and test whether they are significantly different. The results strongly confirm Prediction 2, namely, that the tendency to buy winners is negatively correlated with *IQ*. The abnormal return differences across the two groups are statis-

[16] As noted above, abnormal returns are calculated relative to size and book-to-market characteristic benchmark portfolios. The results are qualitatively the same when abnormal returns are calculated relative to the value-weighted CRSP index.

Table 5
Information quality and trend chasing: Multivariate analysis.

T	1	2	3	4	5	6	7	8	9	10
IQ	**−2.77**	**−2.59**	**−3.22**	**−3.01**	**−4.17**	**−1.88**	**0.07**	**0.07**	**−1.76**	**−1.04**
	(**7.30**)	(**5.64**)	(**5.66**)	(**4.96**)	(**6.11**)	(**2.38**)	(**0.07**)	(**0.06**)	(**1.55**)	(**0.87**)
qheld	−0.28	−0.22	−0.15	−0.34	−0.16	−0.08	−0.31	−0.17	0.05	−0.38
	(4.55)	(2.84)	(2.09)	(3.41)	(1.37)	(0.63)	(1.81)	(1.29)	(0.31)	(1.52)
Stock size	−0.57	−0.93	−0.68	−0.80	−0.37	−1.42	−0.99	−0.66	−1.10	−0.87
	(4.00)	(5.32)	(3.76)	(3.45)	(1.41)	(5.20)	(3.24)	(1.76)	(2.56)	(2.27)
Stock volatility	−5.36	−4.82	−2.08	−2.53	2.47	−2.96	−5.27	−4.51	2.25	−1.89
	(4.69)	(3.37)	(1.23)	(1.19)	(0.97)	(1.15)	(1.79)	(1.12)	(0.61)	(0.38)
Fund size	0.06	0.18	0.21	0.23	−0.11	0.39	−0.33	0.45	−0.39	0.09
	(0.44)	(0.98)	(1.17)	(0.87)	(0.34)	(1.32)	(0.94)	(1.22)	(0.95)	(0.19)
Fund resturn	−1.75	−3.72	−5.54	−4.46	−3.98	−1.37	−0.63	−1.45	1.90	0.17
	(1.54)	(2.64)	(3.69)	(2.68)	(1.92)	(0.65)	(0.29)	(0.43)	(0.74)	(0.05)
Fund flow	−0.49	1.26	0.94	1.15	1.82	−2.48	0.19	3.31	0.13	−1.73
	(0.72)	(0.93)	(0.91)	(0.66)	(0.95)	(1.60)	(0.16)	(1.07)	(0.06)	(0.83)
R^2	1.30%	1.45%	1.58%	1.64%	2.20%	2.30%	1.36%	0.77%	1.88%	1.26%

The table reports coefficient estimates in OLS regressions of the form

$$R_{t-1} = c_0 + c_1 IQ + c_2' X_t$$

The sample consists of position initiations of previously-held stocks. Columns correspond to different values of *T*, which denotes the number of quarters in which the stock was not held since the termination of the most recent holding cycle in the stock. The term denotes the abnormal stock return in the most recent quarter prior to the initiation quarter. *IQ* is the information quality dummy variable. The term X_t represents the vector of control variables measured in quarter *t*, which includes *qheld*, *stock size*, *stock volatility*, *fund size*, *fund return*, and *fund flow*. The variable *qheld* denotes the length of a holding cycle in number of quarters.*Stock size* is the logarithm of the market value of the stock in thousands of 2009 dollars. *Stock volatility* is the annualized standard deviation of daily stock returns measured over one quarter. *Fund size* is the logarithm of the market value of the reported holdings of the fund in 2009 dollars. *Fund return* is the holding-weighted abnormal return on the fund's reported holdings in the past four quarters. *Fund flow* is quarterly flows into the fund divided by beginning-of-quarter total net assets. The variables *stock size*, *stock volatility*, and *fund size* are lagged one quarter relative to *t*. Coefficient estimates are reported in percentage terms. Robust *t*-statistics, calculated by clustering observations at the fund level, are reported in parentheses.

tically highly significant and economically large. For many values of *T*, a move from *IQ* = 1 to *IQ* = 0 more than doubles the average abnormal return in the two quarters prior to initiations. The impact of *IQ* on the tendency to buy winners is quite persistent; it does not start to fade away until *T* = 7. [17, 18]

Next we investigate whether the findings in Table 4 generalize to a multivariate specification. Funds' tendency to buy recent winners may potentially depend on fund- or stock-specific factors. To account for such heterogeneity, we estimate OLS regressions of abnormal returns prior to initiations on *IQ* and several control variables. For brevity, we report the coefficient estimates for regressions of R_{t-1} only; the findings for R_{t-2} are similar. The results, presented in Table 5, show that the effect of *IQ* continues to be significant up to *T* = 6 in this multivariate specification as well. Among stock characteristics, only size has a consistently significant effect; the tendency to buy recent winners is more pronounced for small stocks. Fund characteristics such as fund size, past returns, and flows do not appear to have any consistent effects.

[17] Notice that the tendency to buy winners is present even for *IQ* = 1 stocks. This is to be expected, as our information quality measure is defined in *relative*, not *absolute*, terms. In other words, information quality may be low even for *IQ* = 1 stocks. More important for our analysis is the result that the tendency to buy winners is stronger for *IQ* = 0 stocks relative to *IQ* = 1 stocks.

[18] The *t*-statistics reported in Table 4 may potentially overstate the significance of *IQ* sub-sample differences due to a selection issue. Specifically, since funds tend to initiate *IQ* = 1 stocks (as shown in Panel B of Table 2) and stocks with positive recent abnormal returns (as shown in Panel A of Table 4), initiations of *IQ* = 0 stocks may select on having unusually high abnormal returns. In unreported analysis, we evaluate this potential bias by generating simulated distributions of $\overline{R}_{t-1}$ and $\overline{R}_{t-2}$ for the two *IQ* groups under the null hypothesis that funds do not treat the recent abnormal returns of *IQ* = 0 and *IQ* = 1 stocks differently. The statistical significance levels obtained via these simulations, available upon request, closely mirror the significance levels of the*t*-statistics reported in Table 4, suggesting that the empirical impact of the potential selection bias is negligible.

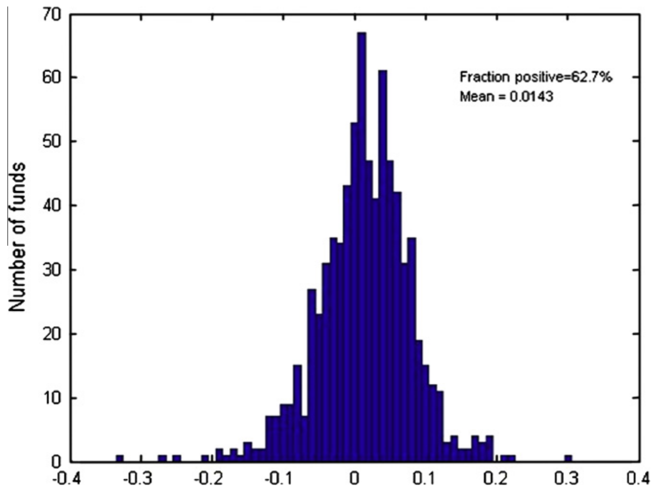

Fig. 1. Histogram of fund-specific average of abnormal stock returns prior to initiations.

The analyses in Tables 4 and 5 assign equal weights to all stock position initiations in the sample. One can also organize the data at the fund level and analyze the tendency to buy winners across funds. We present these fund-level results through a sequence of histograms. For brevity, we again report the results only for R_{t-1}; the results for R_{t-2} are similar. We start with funds' overall tendency to buy winners. For each fund j we calculate $\overline{R}^j_{t-1}$, which is the equal-weighted average of R_{t-1} across all the initiations by fund j. Fig. 1 shows the histogram of $\overline{R}^j_{t-1}$ across all funds. Consistent with previous studies, a majority of funds exhibit a tendency to buy winners. The statistic $\overline{R}^j_{t-1}$ is positive for 67.6% of the funds in the sample, and the average of $\overline{R}^j_{t-1}$ across all funds is 2.72%.

Next, we replicate this exercise for $IQ = 1$ and $IQ = 0$ stocks separately. Specifically, for each fund j we calculate $(\overline{R}^j_{t-1}|IQ = 1)$ and $(\overline{R}^j_{t-1}|IQ = 0)$. These statistics are similar to $\overline{R}^j_{t-1}$ but calculated for sub-samples of initiations by fund j for which $IQ = 1$ and $IQ = 0$, respectively. Fig. 2 shows the corresponding histograms. A comparison of the two histograms reveals that the tendency to buy winners is stronger in the case of $IQ = 0$ stocks. For example, while 69.5% of all funds exhibit positive average abnormal returns prior to initiations of $IQ = 0$ stocks, the same fraction for $IQ = 1$ stocks is only 57.6%. For the average fund, an initiation of an $IQ = 0$ stock is preceded by an average abnormal return of 4.03%; the corresponding figure for an $IQ = 1$ stock is only 1.34%. To facilitate a formal comparison of $IQ = 0$ and $IQ = 1$ initiations, we calculate the difference between $(\overline{R}^j_{t-1}|IQ = 0)$ and $(\overline{R}^j_{t-1}|IQ = 1)$ for each fund j. Fig. 3 plots the histogram of this difference. As the figure shows, initiations of $IQ = 0$ stocks follow higher abnormal returns than initiations of $IQ = 1$ stocks for 59.8% of funds. For the average fund, the average return difference between initiations of $IQ = 0$ stocks and $IQ = 1$ stocks is 2.06%.

To summarize, the results in Tables 4 and 5 and Figs. 1–3 suggest that mutual funds' tendency to buy recent winners varies according to their past return experiences with the purchased stocks. Initiations of stocks on which funds lost money in the past ($IQ = 0$) follow significantly and substantially higher abnormal returns than initiations of stocks on which funds made money in the past ($IQ = 1$).

Our analysis of trend chasing so far follows the standard approach in previous studies by focusing on average abnormal returns prior to initiations (e.g., Grinblatt et al., 1995; Badrinath and Wahal, 2002). This approach allows us to document the stronger tendency to buy winners among low information quality stocks, which is the main prediction of our model. However, the model also predicts that stocks with *very low* information quality are not likely to be purchased at all. For such stocks, the purchase decision should exhibit a low sensitivity to recent abnormal stock return. Thus, we should observe a hump-shaped pattern for the sensitivity of the initiation decision to recent abnormal

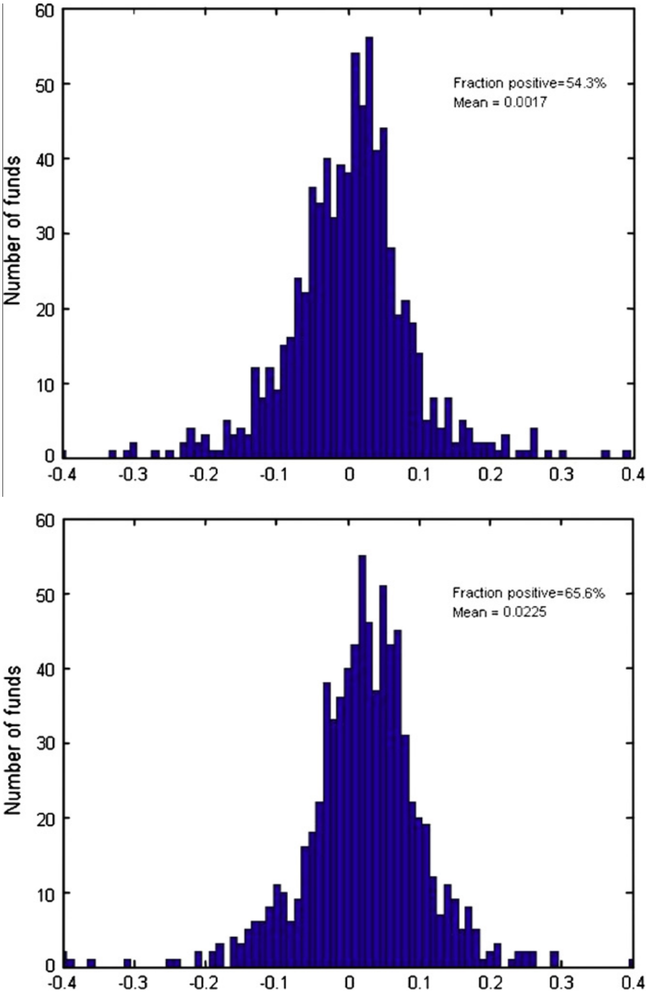

Fig. 2. Histograms of fund-specific average of abnormal stock returns prior to initiations of $IQ = 1$ and $IQ = 0$ stocks.

stock return: low for stocks with high information quality, higher for stocks with relatively low information quality, and low again for stocks with very low information quality.

To evaluate this prediction, we define a new *IQ* variable that splits the sample of previously held stocks into three, instead of two, groups. Specifically, we assign each previously held stock into one of three groups, IQ^L, IQ^M, and IQ^H, based on the previous holding period average return being in the bottom, the middle, and the top third of its distribution, respectively. We then estimate Probit regressions of the initiations decision on the recent abnormal stock return R_{t-1} for each of the three *IQ* groups. The results, presented in the first three columns of Table 6, are consistent with a hump-shaped pattern. The middle group IQ^M exhibits the highest initiation sensitivity to recent abnormal stock return. Pairwise return sensitivity differences are statistically significant at 1% level in all cases (significance level of the differences are not reported in the table).

Finally, we turn to the model prediction that relates stock purchase decisions to the size of prior abnormal returns:

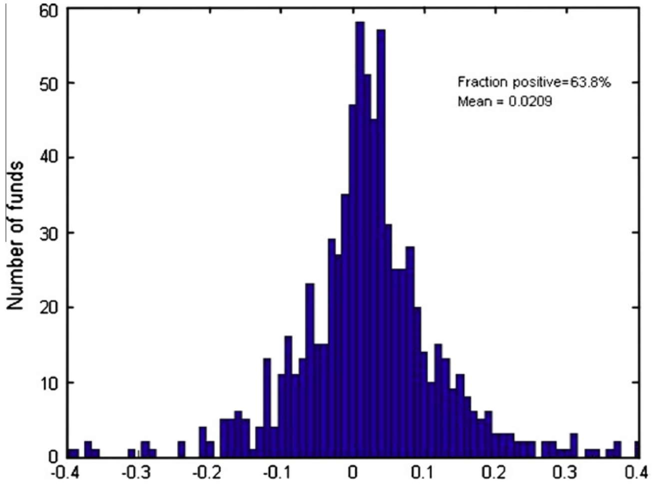

Fig. 3. Histogram of fund-specific difference between average abnormal stock returns prior to initiations of $IQ = 1$ and $IQ = 0$ stocks.

Prediction 3. When information quality is low, the relationship between the stock return and the likelihood of a purchase is inverse-U shaped. That is, the manager is more likely to purchase the stock following moderately high return realizations than low or very high return realizations.

To test this prediction, we again resort to Probit regressions. Specifically, we estimate Probit regressions of the stock initiation decision on the recent abnormal stock return R_{t-1} and its squared value R_{t-1}^2 for each of the $IQ = 0$ and $IQ = 1$ sub-samples. According to Prediction 3, the positive impact of R_{t-1} on the initiation decision of $IQ = 0$ stocks should be reduced or eliminated at relatively high values of R_{t-1}. Accordingly, we expect a positive coefficient on R_{t-1} but a negative coefficient on R_{t-1}^2 in the Probit regression for $IQ = 0$ stocks. We do not expect to see a similar pattern for $IQ = 1$ stocks, for which information quality is relatively high. The estimates, reported in the last two columns of Table 6, confirm these predictions. While the recent abnormal return R_{t-1} has a positive effect on the initiation decision for both sub-samples, the effect is substantially stronger for $IQ = 0$ stocks. More importantly, the squared term R_{t-1}^2 has a significantly negative coefficient for $IQ = 0$ stocks, suggesting that funds avoid initiating $IQ = 0$ stocks that experience very high abnormal returns. Note that this is not the case for $IQ = 1$ stocks; the coefficient of the squared term R_{t-1}^2 for $IQ = 1$ stocks is close to zero and insignificant.

In summary, this section documents three results. First, information quality has a positive effect on the likelihood of a position initiation. Second, the most important implication of the model is confirmed in the data: information quality has a negative effect on the tendency to initiate positions in recent winners. Third, among low information quality stocks, the tendency to initiate recent winners is attenuated when the recent abnormal stock return is very high.

4.2. Alternative explanations

The findings in Table 4 constitute our main result: mutual funds' tendency to buy recent winners is stronger for their past loss makers ($IQ = 0$ stocks) than for their past profit makers ($IQ = 1$ stocks). Insofar as IQ variable captures differences in information quality, this result is consistent with the model prediction that relates the tendency to buy winners to information quality. In this subsection, we evaluate potential alternative explanations for our main result. Specifically, we consider two mechanisms, trading based on price targets and screening out of small stocks, that may generate trading patterns similar to those we document. As we discuss below, trading based on price targets may cause $IQ = 1$ stocks to have low returns prior to initiations, and screening out of small stocks may cause $IQ = 0$ stocks to have high returns prior to initiations.

Table 6
Information quality and trend chasing: Non-linear relationships.

	IQ^L	IQ^M	IQ^H	$IQ = 0$	$IQ = 1$
R_{t-1}	4.20	5.88	2.34	5.45	2.56
	(15.79)	(15.22)	(5.61)	(19.41)	(6.05)
R^2_{t-1}				−4.25	0.78
				(6.06)	(0.90)
qheld	−0.01	−0.08	−0.09	−0.04	−0.09
	(0.20)	(2.85)	(3.96)	(1.07)	(4.33)
Stock size	0.86	1.03	1.04	0.95	1.04
	(8.59)	(14.40)	(12.90)	(11.77)	(13.29)
Stock volatility	1.56	1.88	1.41	1.94	1.34
	(4.53)	(5.93)	(5.33)	(5.68)	(4.80)
Fund size	0.02	0.12	0.14	0.06	0.14
	(0.20)	(1.44)	(1.77)	(0.84)	(1.77)
Fund return	−0.45	−1.32	−1.77	−0.76	−1.77
	(1.15)	(4.17)	(4.85)	(2.24)	(4.98)
Fund flow	0.56	0.79	1.00	0.69	0.97
	(2.06)	(2.94)	(3.16)	(3.15)	(3.05)
R^2	3.22%	2.62%	1.87%	3.09%	1.91%

The table reports marginal effects in probit regressions of the form

$$Pr(Initiation\ at\ T|IQ) = F(c_0 + c_1R_{t-1} + \left[c_2R^2_{t-1}\right] + c_3'X_t)$$

which estimate position initiation probabilities for previously-held stocks. The potential initiation quarter is denoted by t. *IQ* is the information quality dummy variable. IQ^L, IQ^M, and IQ^H indicate that the previous holding period average return is in the low, middle, and high third of its distribution, respectively. The term R_{t-1} denotes the abnormal stock return in the most recent quarter prior to the initiation quarter, and R^2_{t-1} is the square of these returns. The term X_t represents the vector of control variables measured in quarter t, which includes *qheld*, *stock size*, *stock volatility*, *fund size*, *fund return*, and *fund flow*. The variable *qheld* denotes the length of a holding cycle in number of quarters. *Stock size* is the logarithm of the market value of the stock in thousands of 2009 dollars. *Stock volatility* is the annualized standard deviation of daily stock returns measured over one quarter. *Fund size* is the logarithm of the market value of the reported holdings of the fund in 2009 dollars. *Fund return* is the holding-weighted abnormal return on the fund's reported holdings in the past four quarters. *Fund flow* is quarterly flows into the fund divided by beginning-of-quarter total net assets. The variables *stock size*, *stock volatility*, and *fund size* are lagged one quarter relative to t. Marginal effects are computed at the means of the explanatory variables and are reported in percentage terms. Robust z-scores, calculated by clustering observations at the fund level, are reported in parentheses.

An important alternative hypothesis that may explain our main results is that mutual funds invest at certain price targets. This type of strategy calls for buying the stock when its price goes below a buy target price (i.e., the stock becomes " cheap") and selling it when the price goes above a sell target price (i.e., the stock becomes " expensive"). To the extent that funds follow such strategies, the concern is that our *IQ* variable may be correlated with these stock price/target price comparisons. Specifically, consider $IQ = 1$ stocks. Since these are stocks that are sold at a profit in the previous holding period, they are likely to have experienced runups prior to the termination decision. If these termination decisions were triggered by the stock price having exceeded the sell target, a subsequent position initiation would require a decline in the stock price. Hence, the relatively low returns prior to initiations of $IQ = 1$ stocks may simply reflect funds' strategies to wait to buy back the stock until its price goes down below the buy target price again.

To evaluate this alternative hypothesis, we examine the data in a number of ways. First, we analyze cumulative raw returns from termination of the previous holding period to the current initiation period. If fund managers tend to trade according to price targets, one would expect raw returns from previous termination to current initiation to be negative on average. Panel A of Table 7 reports termination-to-initiation raw returns for all position initiations as well as for *IQ* sub-samples for different values of T, which denotes the number of quarters between previous termination and current initiation. As this panel shows, the cumulative raw returns from previous termination to current

Table 7
Price target tests.

T	1	2	3	4	5	6	7	8	9	10
A. Cumulative raw return since most recent termination										
All re-initiations	5.09	8.13	12.76	15.61	17.02	20.57	25.82	28.86	31.95	36.31
IQ = 1	2.88	4.53	8.67	11.56	14.83	16.63	22.42	22.28	26.26	33.00
IQ = 0	6.81	10.82	15.57	18.28	18.41	23.04	28.04	32.41	35.08	38.37
Difference	−3.93	−6.29	−6.90	−6.72	−3.59	−6.41	−5.62	−10.12	−8.82	−5.36
t-Value	(7.14)	(5.85)	(4.48)	(3.10)	(1.65)	(2.52)	(1.34)	(2.12)	(1.83)	(0.96)
B. Cumulative raw return since most recent termination, excluding two quarters prior to initiation										
All re-initiations	–	–	1.31	5.84	7.25	10.32	19.32	21.71	25.85	29.17
IQ = 1	–	–	0.98	5.83	8.43	10.46	18.54	13.72	22.29	26.92
IQ = 0	–	–	1.54	5.85	6.49	10.24	19.85	26.22	27.88	30.60
Difference	–	–	−0.56	−0.02	1.94	0.22	−1.31	−12.51	−5.59	−3.68
t-Value	–	–	(0.82)	(0.02)	(1.15)	(0.09)	(0.37)	(2.84)	(0.99)	(0.63)
C. Price targets sub-sample I										
$\overline{R}_{t-1}\|IQ = 1$	15.69	10.16	8.07	7.29	5.67	4.81	7.07	6.66	6.64	6.78
$\overline{R}_{t-1}\|IQ = 0$	17.90	11.93	10.87	9.22	8.45	8.54	5.00	5.61	7.35	6.98
Difference	−2.21	−1.78	−2.80	−1.92	−2.78	−3.73	2.06	1.06	−0.71	−0.21
t-Value	(2.71)	(2.11)	(3.08)	(1.85)	(2.02)	(2.62)	(1.17)	(0.66)	(0.38)	(0.12)
D. Price targets sub-sample II										
$\overline{R}_{t-1}\|IQ = 1$	4.52	4.64	5.02	5.13	4.98	5.25	6.61	5.70	6.57	6.90
$\overline{R}_{t-1}\|IQ = 0$	6.95	7.41	7.8	7.65	8.02	7.01	5.31	5.52	8.04	6.33
Difference	−2.43	−2.77	−2.78	−2.52	−3.04	−1.77	1.30	0.18	−1.47	0.56
t-Value	(4.94)	(5.03)	(4.17)	(3.34)	(3.83)	(2.04)	(1.07)	(0.15)	(1.24)	(0.43)

The table reports results of the tests that analyze trading based on price targets. Panels A and B report average cumulative raw returns since most recent termination of previously held stocks. Columns correspond to different values of *T*, which denotes the number of quarters in which the stock was not held since the termination of the most recent holding cycle in the stock. Panel A reports cumulative raw returns from previous termination to current initiation. Panel B replicates the analysis in Panel A by excluding the returns of the two quarters prior to initiation, and hence has data only for $T \geqslant 3$. Panels C and D report average abnormal stock returns prior to positions initiations of previously held stocks for sub-samples that do not conform to the price targets theory. Specifically, Panel C includes position initiations for which the lowest price in the current initiation quarter is higher than the highest price in the previous termination quarter. Panel D includes position initiations in Panel C and position initiations for which the lowest price during the current initiation quarter is higher than the lowest price in the previous quarter. Quarter *t* denotes the first quarter in which a stock is known to be held. The term $\overline{R}_{t-1}$ denotes the average abnormal stock return in the most recent quarter prior to the initiation quarter. In all panels, the values reported are in percentage terms. Robust *t*-values of sub-sample differences, calculated by clustering observations at the fund level, are reported in parentheses.

initiation are on average positive in all cases; i.e., for both *IQ* sub-samples and for all values of *T*. Notice that the raw returns are lower for *IQ* = 1 sub-samples. This is to be expected, since the return period in question includes the runup prior to current initiation, and, from Table 4, we already know that these runups are smaller for *IQ* = 1 stocks. In Panel B of Table 7, we replicate the cumulative raw return analysis in Panel A, but by excluding the two-quarter runup period prior to current initiation. Once the runup period is excluded, the differences between *IQ* = 1 and *IQ* = 0 groups become very small and statistically insignificant. Overall, it does not appear that fund managers wait for price declines to reinitiate positions in stocks that they have terminated. The raw returns are positive on average from termination to current initiation, and largely similar for *IQ* = 1 and *IQ* = 0 stocks from termination to two quarters prior to initiation.

Next, we replicate our main test on sub-samples of position initiations that do not conform to the price targets story. Specifically, consider stocks for which the lowest price during the current initiation quarter is higher than the highest price during the previous termination quarter. These stocks are purchased at a higher current price than the previous termination price, therefore, their terminations and initiations are unlikely to be driven by price targets. Panel C of Table 7 (price targets sub-sample I) shows that the *IQ* measure captures significant differences in price runups prior to initiations of these stocks as well up to six quarters following the termination. The criterion for this test (lowest price in the initiation quarter exceeds highest price in the termination quarter) is quite stringent and results in a relatively small sub-sample (21.2% of our full sample). In Panel D (price targets sub-sample II), we consider a less stringent exclusion rule that allows for a larger sub-sample (65.1% of our full sample). Specifically, in addition to stocks in Panel C, we also include stocks for which the lowest price during the initiation quarter is higher than the lowest price in the quarter preceding the initiation. The idea is that, if these initiations were driven by price targets, the initiation would have occurred in the preceding quarter, since the stock price was even lower then. This extended sample in Panel D also mirrors our main results, with significant *IQ* differences up to six quarters after termination. We conclude that the effect of *IQ* on the tendency to buy winners is unlikely to be an artifact of trading based on price targets.

Another concern in interpreting our main result is whether having held the stock in the past indeed matters. Perhaps a mutual fund's tendency to buy recent winners is stronger for stocks that had low returns in the past, regardless of whether the fund held these stocks or not. This may be the case, for example, if mutual funds screen out small stocks. Anecdotal evidence suggests that funds usually do not pay attention to stocks that are below certain market capitalization thresholds. Thus, stocks with low past returns may be those that moved out of funds' "radar screens." A precondition for these stocks to get back into the radar screen is that they gain in market value, which requires positive subsequent returns. This could potentially explain why abnormal returns prior to initiations are high for $IQ = 0$ stocks.

To evaluate this possibility, we analyze funds' initiations of stocks for which they have no holding record within the past three years. For convenience, we call these " previously-unheld stocks." Notice that the information quality variable *IQ* is not defined for initiations of previously-unheld stocks; therefore, these initiations and our main sample constitute mutually exclusive sets. If the findings in Table 4 result only from $IQ = 0$ stocks having low past returns (and not the fact that funds held these stocks), then we would expect to find similar patterns for initiations of previously-unheld stocks as well. To see if this is the case, we sort initiations of previously-unheld stocks into two groups based on these stocks' past returns. Specifically, we consider whether the stock's abnormal one-quarter return T quarters prior to the initiation is positive or negative, where $T \in \{1, \ldots, 10\}$. The results are reported in Table 8. As the table shows, past returns do not have a consistent effect on the tendency to buy winners in the case of previously-unheld stocks. Consider R_{t-1}: for $T \leqslant 4$, stocks with negative past returns have in fact lower, not higher, values of R_{t-1}. For $T = 5$ and $T = 6$, stocks with negative past returns do have higher values of R_{t-1}, but the differences between the negative and positive return sub-samples are smaller in magnitude than the differences between *IQ* sub-samples in Table 4. The results and the comparisons to Table 4 are similar for R_{t-2}. We conclude that the findings in Table 4 point to a genuine relationship between *IQ* and the tendency to buy recent winners. [19] Importantly, the effect of *IQ* is directly related to the fact that funds experienced the past return outcomes. Past returns do not have a similar effect on the tendency to buy winners in the case of previously-unheld stocks.

4.3. Additional analyses

The empirical analysis so far has focused on testing main model predictions. In this subsection, we provide some additional results on the relationship between information quality and mutual funds' trading behavior.

First, we examine the size of mutual fund holdings in relation to information quality. While our main tests concern the relationship between information quality and the decision to initiate a position, the size of mutual fund holdings are likely to be affected by, and informative about, information quality as well. We explore the relevance of holding in size in various ways; the results are collectively reported in Table 9. In all the reported tests, holding size is defined as a normalized variable with respect to fund assets and the market capitalization of the stock. Specifically, we define holding size as (dollar amount held in the stock / total fund assets) − (market capitalization of stock / total market

[19] In unreported analysis, we also performed a test designed to address the specific concern that screening of small stocks may explain our results. Specifically, we replicated the analysis in Table 4 on stocks that are in the highest two size deciles with respect to NYSE size breakpoints. These are the largest stocks in the market, so it is difficult to argue that they ever leave mutual funds' radar screens. The results are similar to those in Table 4, indicating that funds' aversion toward small stocks does not explain our findings.

Table 8
The sample of previously-unheld stocks.

T	1	2	3	4	5	6	7	8	9	10
$\overline{R}_{t-1}\|R_{t-1-T} > 0$	4.79	5.13	4.91	4.63	4.17	4.33	4.56	4.85	4.54	4.59
$\overline{R}_{t-1}\|R_{t-1-T} < 0$	4.16	3.73	3.99	4.36	4.97	4.75	4.44	4.02	4.47	4.40
Difference	**0.64**	**1.40**	**0.92**	**0.27**	**−0.80**	**−0.42**	**0.12**	**0.83**	**0.07**	**0.19**
t-Value	(**3.34**)	(**9.46**)	(**6.14**)	(**1.64**)	(**5.29**)	(**2.64**)	(**0.77**)	(**5.77**)	(**0.54**)	(**1.27**)
$\overline{R}_{t-2}\|R_{t-1-T} > 0$	–	4.89	5.23	5.12	4.54	4.37	4.65	4.54	5.13	4.66
$\overline{R}_{t-2}\|R_{t-1-T} < 0$	–	4.27	3.82	3.97	4.70	4.93	4.55	4.70	3.87	4.53
Difference	–	**0.62**	**1.41**	**1.15**	**−0.16**	**−0.56**	**0.11**	**−0.16**	**1.26**	**0.13**
t-Value	–	(**3.90**)	(**9.70**)	(**7.01**)	(**0.98**)	(**3.60**)	(**0.72**)	(**0.91**)	(**8.36**)	(**0.92**)

The table reports average abnormal stock returns prior to position initiations of previously-unheld stocks. Quarter t denotes the first quarter in which a stock is known to be held. The term $\overline{R}_{t-1}$ denotes the average abnormal stock return in the most recent quarter prior to the initiation. The term $\overline{R}_{t-2}$ denotes the average abnormal stock return in the second most recent quarter prior to the initiation. The term $\overline{R}_{t-1-T}$ denotes the abnormal one-quarter stock return T quarters prior to the initiation quarter, where T ranges from 1 to 10. The table reports $\overline{R}_{t-1}$ and $\overline{R}_{t-2}$ for sub-samples of stocks for which $\overline{R}_{t-1-T} > 0$ and $\overline{R}_{t-1-T} < 0$. The abnormal returns are reported in percentage terms. Robust t-values of sub-sample differences, calculated by clustering observations at the fund level, are reported in parentheses.

capitalization of all stocks held by the fund). This normalized variable captures the extent to which the fund is over- or under-weighted in the stock, controlling for fund and stock size.

The first column in Table 9 is a Probit regression characterizing the probability of initiation in the current period, similar to Table 3. The variable of interest is the size of the previous holding in the stock, which is measured by the normalized size variable described above averaged across all quarters in the previous holding cycle. This variable has a significantly positive effect, suggesting that funds are more likely to reinitiate positions in stocks in which they had relatively larger holdings in the past. We also include an interaction term of previous holding size with *IQ*; this interaction term is significantly positive as well. Thus, the positive impact of *IQ* on the probability of initiation is stronger for stocks with larger historical holdings. One interpretation of these findings is that the size of the previous holding is another indicator of information quality that complements the performance-based measure *IQ*. Fund managers' perceived information quality appears to be especially high for those stocks with larger previous holding sizes and better previous holding performance.

In the second column of Table 9 we analyze the abnormal return prior to the current initiation, again as a function of previous holding size and its interaction with *IQ*. The runup prior to the current initiation is larger for stocks with larger historical holdings. Furthermore, the negative impact of *IQ* on the runup return is also more pronounced for stocks with larger historical holdings. Together, the results in the first two columns indicate that our main results – that funds are more likely to initiate $IQ = 1$ stocks and require smaller runups for doing so – are stronger among stocks with a history of relatively larger holdings. Perhaps fund managers open small stock positions with relatively less concern about the quality of their information (i.e., since the future return realizations will have negligible impact on overall fund return), and apply increased scrutiny only in those cases where the stock position is relatively large.

The third and fourth columns in Table 9 analyze the size of the current initiation. As column 3 shows, *IQ* by itself does not have a significant effect on current initiation size. Controlling for previous holding size in column 4 render the effect of *IQ* significantly negative, but this effect appears to be small economically. The main takeaway from column 4 is that the size of the current initiation is highly correlated with the size of the previous holding: funds tend to initiate large positions in stocks in which they have a history of having large positions in. This illustrates another persistent aspect of the dynamics of stock trading at the fund level.

In the last three columns of Table 9 we examine the evolution of the current holding after the initiation. In particular, we focus on the quarter immediately following the initiation quarter and ask whether the fund is likely to terminate, add to, or reduce its position in the stock as a function of information quality. Termination decisions do not appear to relate to *IQ* in a significant way. The

Table 9
Holding size tests.

	Probability of initiation	Pre-initiation return R_{t-1}	Current holding size	Current holding size	Probability of terminating in second quarter	Probability of increasing position in second quarter	Probability of decreasing position in second quarter
IQ	0.55	−2.68	−0.03	−0.14	0.23	2.61	−1.18
	(7.04)	(12.00)	(0.76)	(7.43)	(0.37)	(2.94)	(1.89)
Previous holding size	8.26	17.51	–	65.89	–	–	–
	(4.02)	(3.58)	–	(24.27)	–	–	–
IQ × Previous holding size	6.38	−15.86	–	5.54	–	–	–
	(2.84)	(2.78)	–	(1.39)	–	–	–
qheld	−0.07	−0.22	−0.03	−0.04	−0.94	−0.32	−0.38
	(2.55)	(5.33)	(2.76)	(8.75)	(6.06)	(1.01)	(2.67)
Stock size	1.03	−0.71	−0.49	−0.13	0.36	1.07	1.12
	(12.45)	(5.03)	(13.89)	(10.96)	(0.92)	(1.45)	(2.64)
Stock volatility	1.14	−3.81	−0.25	0.03	4.02	0.35	2.78
	(4.69)	(4.78)	(2.50)	(0.63)	(1.96)	(0.10)	(1.40)
Fund size	0.08	0.11	0.05	0.02	0.10	2.87	−0.57
	(1.13)	(0.91)	(1.92)	(1.75)	(0.18)	(5.70)	(1.29)
Fund return	−1.19	−2.80	−0.66	−0.22	3.64	0.80	−7.04
	(3.94)	(3.78)	(6.58)	(3.88)	(1.42)	(0.21)	(2.90)
Fund flow	0.86	0.36	−0.11	0.08	−1.73	9.18	−7.97
	(3.75)	(0.88)	(1.32)	(1.54)	(0.73)	(3.16)	(2.55)

The table reports marginal effects in probit regressions and coefficient estimates in OLS regressions of the forms

$$Pr(initiation\ at\ t) = F\left(c_0 + c_1 IQ + c_2 PrevHoldingSize + c_3 IQ \times PrevHoldingSize + c_4' X_t\right)$$
$$R_{t-1} = c_0 + c_1 IQ + c_2 PrevHoldingSize + c_3 IQ \times PrevHoldingSize + c_4' X_t$$
$$CurrentHoldingSize = c_0 + c_1 IQ + c_2 PrevHoldingSize + c_3 IQ \times PrevHoldingSize + c_4' X_t$$
$$Pr(termination, increase, decrease\ at\ t+1) = F\left(c_0 + c_1 IQ + c_4' X_t\right)$$

Pr(*initiation at t*) is the estimated probability for a position initiation for previously-held stocks. The potential initiation quarter is denoted by *t*. *IQ* is the information quality dummy variable. *PrevHoldingSize* is the average of the *NormalizedSize* across all quarters of the previous holding period. *NormalizedSize* is calculated as the dollar amount held in the stock divided by the total assets of the fund minus the market capitalization of the stock divided by the total market capitalization of all stocks held by the fund. *CurrentHoldingSize* is the *NormalizedSize* in the quarter the stock is initiated. The term R_{t-1} denotes the abnormal stock return in the most recent quarter prior to the initiation quarter. The term X_t represents the vector of control variables measured in quarter *t*, which includes *qheld*, *stock size*, *stock volatility*, *fund size*, *fund return*, and *fund flow*. See legend of Table 3 for a definition of these variables. Marginal effects are computed at the means of the explanatory variables and are reported in percentage terms. Coefficient estimates of the OLS regressions are also reported in percentage terms. Robust *z*-scores, calculated by clustering observations at the fund level, are reported in parentheses.

probability of decreasing the position size is lower for *IQ* = 1 stocks, but this effect in only marginally significant. The probability of increasing the position size, however, is significantly related to *IQ*; funds are more likely to add to their positions subsequent to initiations of *IQ* = 1 stocks. Recall, from columns three and four, that *IQ* does not have a significant or economically meaningful effect on the size of position initiations. The fact that *IQ* does predict the likelihood of subsequent size increases suggests that funds build up their positions gradually over time. That is, instead of initiating larger positions for *IQ* = 1 stocks upfront, funds initiate the same position size as *IQ* = 0 stocks on average, but then add to *IQ* = 1 stock positions subsequently. This type of trading strategy may reflect attempts to avoid the price impact large position initiations would cause.

Table 10
Earnings forecast dispersion and earnings surprise sub-samples.

	All	Earnings forecast dispersion sub-samples						Earnings surprise sub-samples					
		Bottom half	Top half	Difference test	Bottom third	Top third	Difference test	Bottom half	Top half	Difference test	Bottom third	Top third	Difference test
$IQ \times I_{Top}$				**−2.82**			**−4.15**			**−2.60**			**−3.59**
				(**6.44**)			(**6.97**)			(**5.59**)			(**5.58**)
IQ	**−2.99**	**−2.49**	**−3.80**	**−1.70**	**−2.36**	**−4.03**	**−1.03**	**−2.29**	**−3.70**	**−1.71**	**−2.13**	**−3.85**	**−1.20**
	(**10.42**)	(**7.35**)	(**8.51**)	(**5.84**)	(**5.56**)	(**6.81**)	(**2.87**)	(**6.79**)	(**7.86**)	(**5.95**)	(**4.99**)	(**6.17**)	(**3.29**)
qheld	−0.20	−0.17	−0.26	−0.21	−0.16	−0.31	−0.24	−0.16	−0.35	−0.24	−0.18	−0.43	−0.29
	(4.96)	(3.56)	(3.99)	(5.21)	(2.71)	(3.35)	(4.32)	(3.88)	(3.45)	(4.37)	(3.59)	(3.17)	(4.00)
Stock size	−1.42	−1.34	−1.80	−1.50	−1.51	−2.00	−1.60	−1.09	−1.72	−1.35	−1.21	−1.90	−1.43
	(11.47)	(9.84)	(10.32)	(12.34)	(9.07)	(9.04)	(10.71)	(8.16)	(7.06)	(8.96)	(7.43)	(5.73)	(7.69)
Stock volatility	5.00	5.19	5.97	5.10	8.10	7.57	6.63	5.11	6.71	5.66	6.41	8.88	6.85
	(3.78)	(3.12)	(3.20)	(3.86)	(3.95)	(3.43)	(4.22)	(3.65)	(3.53)	(4.25)	(3.59)	(3.84)	(4.21)
Fund size	0.13	0.02	0.23	0.13	−0.15	0.19	0.04	0.05	0.21	0.13	0.06	0.26	0.18
	(0.91)	(0.11)	(1.14)	(0.91)	(0.84)	(0.72)	(0.23)	(0.37)	(0.96)	(0.90)	(0.42)	(0.95)	(1.06)
Fund return	1.15	−1.23	3.71	1.11	0.08	7.65	3.61	−1.46	4.08	1.17	−1.91	6.88	2.16
	(1.26)	(1.09)	(2.54)	(1.23)	(0.06)	(4.10)	(3.50)	(1.31)	(2.73)	(1.31)	(1.51)	(3.61)	(2.06)
Fund flow	0.51	0.13	0.98	0.51	−0.26	1.63	0.59	0.82	0.54	0.63	0.01	0.76	0.23
	(0.98)	(0.24)	(1.04)	(0.97)	(0.37)	(1.33)	(0.92)	(1.34)	(0.57)	(1.14)	(0.02)	(0.59)	(0.34)
R^2	2.44%	2.37%	3.05%	2.60%	3.03%	3.55%	2.97%	2.01%	3.01%	2.48%	2.34%	3.33%	2.70%

The table reports coefficient estimates in OLS regressions of the form

$$R_{t-1} = c_0 + c_1 IQ + c_2' X_t.$$

The sample consists of position initiations of previously-held stocks. The term R_{t-1} denotes the abnormal stock return in the most recent quarter prior to the initiation quarter. *IQ* is the information quality dummy variable. The term X_t represents the vector of control variables measured in quarter *t*, which includes *qheld*, *stock size*, *stock volatility*, *fund size*, *fund return*, and *fund flow*. The sample is divided into sub-samples based on earnings forecast dispersion (left panel) and earnings surprise (right panel). The variable I_{Top} (which is interacted with *IQ*) is an indicator that equals one if the observation is in the top sub-sample and zero if it is in the bottom sub-sample. Coefficient estimates are reported in percentage terms. Robust *t*-statistics, calculated by clustering observations at the fund level, are reported in parentheses.

Table 11
Information quality and return performance.

T	1	2	3	4	5	6	7	8	9	10
A. All position initiations										
R_{t+1}	0.08	0.43	0.51	0.39	0.03	−0.38	−0.54	0.59	−0.22	−0.14
R_{t+4}	1.78	0.62	1.27	1.93	0.54	0.97	−0.41	3.15	−0.30	−1.86
B. Information quality sub-samples										
$R_{t+1}\|IQ=1$	−0.43	−0.06	−0.20	0.17	0.80	−0.01	0.05	0.35	1.29	2.31
$R_{t+1}\|IQ=0$	0.48	0.80	1.02	0.54	−0.47	−0.63	−0.93	0.73	−1.09	−1.70
Difference	**−0.91**	**−0.85**	**−1.22**	**−0.37**	**1.27**	**0.62**	**0.99**	**−0.38**	**2.38**	**4.01**
t-Value	(**2.41**)	(**1.88**)	(**2.10**)	(**0.58**)	(**1.72**)	(**0.68**)	(**1.06**)	(**0.38**)	(**1.93**)	(**3.23**)
$R_{t+4}\|IQ=1$	0.17	0.23	1.46	1.13	1.08	−0.67	−2.77	4.48	3.55	−1.55
$R_{t+4}\|IQ=0$	3.08	0.93	1.13	2.48	0.18	2.05	1.17	2.38	−2.53	−2.05
Difference	**−2.91**	**−0.70**	**0.33**	**−1.35**	**0.90**	**−2.72**	**−3.94**	**2.10**	**6.08**	**0.51**
t-Value	(**3.64**)	(**0.68**)	(**0.28**)	(**0.94**)	(**0.61**)	(**1.69**)	(**2.12**)	(**0.84**)	(**2.40**)	(**0.18**)

The table reports average abnormal stock returns of previously-held stocks after re-initiation. The initiation quarter is denoted by t. Columns correspond to different values of T, which denotes the number of quarters elapsed since the termination of the most recent holding cycle in the stock. The term R_{t+1} denotes the average abnormal stock return in the first quarter after the re-initiation in quarter t. The term R_{t+4} denotes the average abnormal stock return in up to four quarters after the re-initiation in quarter t. The abnormal returns are reported in percentage terms. Panel A reports for the whole sample of position initiations, and panel B reports for sub-samples of stocks for which the information quality variable IQ equals one or zero. Robust t-values of sub-sample differences, calculated by clustering observations at the fund level, are reported in parentheses.

The second set of tests in this subsection concern the quality of public information and its interaction with IQ. The information quality measure IQ is based on a fund manager's past return experience with a stock. Yet, some stocks may be inherently harder to analyze than others. To account for such heterogeneity, we consider the difficulty of predicting a stock's earnings. We entertain two measures. The first one is dispersion of analyst earnings forecasts, computed as the eight-quarter rolling average of the standard deviation of analyst forecasts divided by the stock price. The second measure is earnings surprise, defined as the eight-quarter rolling standard deviation of the difference between the realized earnings and the consensus forecast divided by the stock price. Our prediction is that the negative relationship between the tendency to buy winners and IQ should be more pronounced for those stocks with hard-to-predict earnings. The results in Table 10 show that this is indeed the case. The negative effect of IQ is significantly more pronounced for firms in the top half (third) of the earnings-predictability measures relative to firms in the bottom half (third). This can be seen by comparing the coefficient of IQ across the top/bottom sub-samples, as well as considering the interaction term $IQ \times I_{Top}$ in the difference tests columns (I_{Top} is an indicator variable that equals one when the observation is in the top sub-sample and zero if it is in the bottom sub-sample).

Finally, we examine the going-forward return performance of stock position initiations as a function of the information quality measure IQ. The prediction of our model in this regard is towards finding no return differences for initiations of stocks with low versus high information quality. Recall that in the model, the manager buys a stock only if, and as soon as, the expected going-forward return reaches the hurdle rate r^*. Thus, initiations of $IQ = 0$ versus $IQ = 1$ stocks should exhibit similar return performance on average. Of course this is not a sharp prediction of the model; nor is it central to the paper, as we utilize IQ primarily as a measure of *perceived* information quality. Nevertheless, we provide a brief and descriptive analysis of this issue.

We consider two performance metrics for position initiations: (i) the first-quarter abnormal return on the stock following the initiation, R_{t+1}; (ii) the cumulative quarterly abnormal return on the stock (up to four quarters) following the initiation, R_{t+4}.[20] As in most of the previous analyses, we group initiations with respect to T, which denotes the number of quarters elapsed since the termination of the

[20] More specifically, if the stock is terminated within four quarters after initiation, R_{t+4} is calculated as the cumulative abnormal return over the quarters during which the stock is held. If the position is not terminated within four quarters after initiation, then R_{t+4} is calculated as the four-quarter cumulative abnormal return. We impose the four-quarter cutoff in order to prevent positions with very long holding periods (and hence potentially very large positive or negative abnormal returns) from dominating the analysis.

most recent holding cycle. The results are reported in Table 11. For low values of T, there seems to be some return predictability, with $IQ = 0$ stocks performing better than $IQ = 1$ stocks. This is consistent with momentum strategies earning higher returns. At lags longer than $T = 3$ the differences are largely insignificant. Except for the short-term momentum returns, it appears that IQ measure does not have a direct role in predicting future holding returns.

5. Conclusion

The tendency of institutional investors to chase return trends is a well-documented phenomenon. Past research has typically taken such behavior as given and analyzed its asset pricing implications. Yet, very little is known about why investors trade in this way. Without a better understanding of the causes of trend chasing, it is difficult to properly assess its consequences.

In this paper, we propose a simple explanation for investors' tendency to chase return trends. We argue that Bayesian updating of priors on information quality can generate trading behavior that resembles trend chasing. Investors with weak initial confidence in their private information choose to wait for confirmation by subsequent good news before establishing stock positions. While such news impact stock prices, at the same time they increase investors' estimates of the precision of their information. With low information quality the latter effect dominates and causes investors to purchase stocks after confirming good news. In this way, investors appear to be chasing return trends.

We formalize this idea with a simple model and test the model's predictions on mutual funds' stock holdings data. As a proxy for funds' stock-specific information quality, we propose a new measure based on funds' past return experiences with individual stocks. Consistent with the model, we find that initiations of stocks with relatively low information quality tend to follow high abnormal returns. Overall, our results point to a strong link between information quality and the tendency to chase return trends.

Our empirical analysis utilizes the novel methodology of conditioning on stock-specific past investment performance. This approach reveals that mutual funds base their investment decisions in part on their past return experiences with individual stocks. In future work, the same methodology can be extended to analyze the trading behavior of other groups of investors as well. As we indicate above, the trading patterns we document are consistent with both rational and behavioral interpretations. Fund managers appear to believe that they possess superior skills in analyzing their past profit makers. Such beliefs may represent rational expectations or wishful thinking. While the distinction is an important one, an in-depth analysis in this regard is beyond the scope of the current paper and is left to future research.

At a more general level, our paper relates to the discussion on the asset-pricing implications of trend chasing. Previous studies typically view trend chasing as a destabilizing force on asset prices. This view mainly rests on the assumption that trend chasers engage in mechanical return-based strategies. Our theoretical and empirical results show that what at a first look appears to be mechanical trend chasing behavior may in fact represent trading activity by privately informed investors. The impact of such trading activity on asset prices is likely to be stabilizing.

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