

The Price of Conformism*

Amil Dasgupta

Andrea Prat

Michela Verardo

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Abstract

As previous agency models have shown, fund managers with career concerns have an incentive to imitate the recent trading strategy of other managers. We embed this rational conformist tendency in a stylized financial market with limited arbitrage. Equilibrium prices incorporate a reputational premium or discount, which is a monotonic function of past trade between career-driven traders and the rest of the market.

Our prediction is tested with quarterly data on US institutional holdings from 1983 to 2004. We find evidence that stocks that have been persistently bought (sold) by institutions in the past 3 to 5 quarters underperform (overperform) the rest of the market in the next 12 to 30 months. Our results are of similar magnitude to, but distinct from, other known asset pricing anomalies.

Our findings challenge the mainstream view of the roles played by individuals and institutions in generating asset pricing anomalies.

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1 Introduction

The institutional ownership of corporate equity around the world has substantially increased in recent decades.¹ Many commentators believe that institutional investors tend to imitate each other, and that such conformist behavior generates systematic mispricing followed by subsequent corrections. For example, describing the recent incentives and actions of fund managers, Jean-Claude Trichet, President of the European Central Bank, remarked: “Some operators have come to the conclusion that it is better to be wrong along with everybody else, rather than take the risk of being right, or wrong, alone... By its nature, trend following amplifies the imbalance that may at some point affect a market, potentially leading to vicious circles of price adjustments and liquidation of positions.”²

Our goal in the present paper is to study the aggregate effect of conformist behavior by institutions. On the theory front, we study a stylized financial market where, in response to the dynamic implicit incentives they face, institutional investors have an incentive to trade in conformist manner. This pressure to herd translates into systematic mispricing: a stock is overpriced (underpriced) if it has been bought (sold) systematically by institutions in the recent past. We proceed to test this prediction, by studying the net trade between institutional investors and regular investors, and its connection to long-term returns. We show that stocks which have been bought by institutional investors for three or more quarters systematically underperform the market in the next two years. Conversely, stocks that have been sold for three or more quarters systematically outperform the market.

The paper begins with a minimalist model of financial markets with institutional and individual investors. The building blocks of our theory can be traced back to the well-known model of reputational herding by Scharfstein and Stein [54], which has been recently extended to a setting with endogenous prices by Dasgupta and Prat [20]. In our simplified version of Dasgupta and Prat’s model, a number of career-concerned fund managers trade with rational traders over several trading rounds before uncertainty over asset valuation is resolved (our dynamic trading model is a

¹On the New York Stock Exchange the percentage of outstanding corporate equity held by institutional investors has increased from 7.2% in 1950 to 49.8% in 2002 (NYSE Factbook 2003).

²Jean-Claude Trichet, then Governor of the Banque de France. Keynote speech delivered at the Fifth European Financial Markets Convention, Paris, 15 June 2001: “Preserving Financial Stability in an increasing globalised world.”

modification Glosten and Milgrom [35]). To allow for the possibility of mispricing, asset supply is assumed not to be infinitely elastic. Fund managers receive a private signal about the liquidation value of the stock and they differ in the accuracy of their signal. They are evaluated by their investors based on their trades and the eventual liquidation value of their portfolios. The future income of a manager depends on how highly investors think of his signal accuracy.

In equilibrium, when past purchases and sales balance each other, a fund manager's willingness to pay for an asset depends only on its expected liquidation value. However, things change if past trade has a persistent sign. If, for instance, most managers have bought the asset in the recent past, a manager with a negative signal is reluctant to sell, because he realizes that: (1) his negative realization is in contradiction with the positive realizations observed by his colleagues; (2) this is probably due to the fact that his accuracy is low; and (3) by selling, he is likely to appear like a low-accuracy type to investors. The manager faces a tension between his desire to maximize expected profit (which induces him to follow his private information and sell) and his reputational concerns (which make him want to pretend his signal is in accordance with those of the others). Conversely, a manager with a positive signal who trades after a sequence of buys is even more willing to buy the asset, because his profit motive and his reputational incentive go in the same direction.

Hence, the willingness to pay for an asset on the part of career-driven investors can differ systematically from the expected liquidation value. It is higher (lower) if past trade by other managers has been persistently positive (negative). If asset supply is not infinitely elastic, this discrepancy between the willingness to pay and the fair price translates into mispricing. Each stock develops a *reputational premium*. Stocks that have been persistently bought (sold) trade at prices that are higher (lower) than their fair value, leading to a correction when the true value is revealed. Our theory, therefore, predicts a negative correlation between net trade between the institutional and individual sectors of the market and long term returns. Our empirical analysis unearths exactly such a relationship.

Before discussing the empirical results in detail, it is important to understand the link between theory and empirics. The model of reputational concerns that we have just sketched provides two distinct predictions. The first prediction links reputational concerns with institutional conformism:

Specific features of institutional investors may endow them with career concerns and thus determine their willingness to engage in conformistic trading. The second prediction links institutional conformism with an asset pricing anomaly: With limited arbitrage, the conformist tendency of institutions leads to stock return predictability. Ideally, both sets of predictions should be tested simultaneously in a structural framework. In practice, this is hard because the model is stylized and available datasets have limitations. This paper focuses on the second class of predictions: in particular, we examine the link between persistent institutional trade and return predictability. This reduced-form empirical strategy cannot pin down reputational concerns as the cause of institutional conformism, but it does quantify the importance of such conformism as a determinant of return predictability. By estimating the potential order of magnitude of this phenomenon, we can gain a sense of whether this is a promising line of research. In the conclusion, we argue that our findings are difficult to explain with alternative financial market models, whether they are based on rational or irrational trading strategies.

Our sample consists of quarterly observations on stock holdings of U.S. institutional investors with at least \$100 million under management for the period 1983-2004. To test our hypothesis, at the end of each quarter we form portfolios based on the persistence of net trading by institutional investors, and track the performance of these portfolios over a period of ten quarters. We then test whether portfolio returns are significantly different across persistence categories, and whether our results are robust when conditioning on a number of different variables. We also test whether trading persistence has the ability to predict returns for individual stocks, beyond the well known predictability coming from past returns – the momentum and reversal phenomena.

We summarize our main empirical results:

1. The persistence of institutional trading has strong power in predicting the cross-section of stock returns at long horizons. Stocks that have been persistently sold by institutions over several quarters outperform stocks that have been persistently bought by them over a period of at least two years in the future. On average, a strategy that buys stocks that have been sold by institutions for five quarters and shorts stocks that have been bought by them for the same period yields a cumulative market-adjusted return of 8% over one year and 17% after two years.

2. Our results are robust to a number of standard controls. We classify stocks into quintiles on the basis of their market capitalization, book-to-market, and relative performance in the past year. Within each such quintile, we find positive returns to our long-short strategy based on the persistence of institutional trading.
3. Our long-short strategy based on institutional trading persistence remains profitable after adjusting for covariation of its returns with risk factors or characteristics. Using monthly portfolio returns calculated in calendar time, we estimate intercepts from time series regressions of the CAPM model, the Fama-French [30] model, and the four-factor model that includes the Carhart [11] momentum factor. The results confirm the presence of a significant and positive return differential between stocks persistently sold and stocks persistently bought by institutions. For example, considering a trading persistence of five quarters, differences in monthly alphas range from 44 to 90 basis points depending on the chosen pricing model and holding period.
4. By estimating cross-sectional regressions at the individual stock level, we find that buy (sell) persistence negatively (positively) predicts returns at horizons of up to two years. The predictability associated with institutional trading persistence is economically important and statistically significant, even after controlling for the stylized patterns of return momentum and reversals previously documented by Jegadeesh and Titman [41], [42], and DeBondt and Thaler [23]. The estimated coefficient associated with institutional trading persistence is larger than the coefficient associated with the size and the book-to-market effect and it is comparable to the coefficient for past returns. For example, the estimated two-year return differential between high-negative persistence stocks (sold for 4 or more quarters) and high-positive persistence stocks is 9 percentage points; the estimated two-year return differential between past losers (top quintile in the past three quarters) and past winners (top quintile) is 9 percentage points as well.
5. As our goal is to study the market effect of institutional trade, most of our analysis is carried out at an aggregate level. However, to interpret our results, we also analyze individual trading by the 270 institutions that are present in every quarter between 1995 and 2003. For

every institution, we compute the probability that it imitates past trade when faced with a high-persistence stock. We find that about three quarters of institutions display conformist patterns when faced with high-persistence stocks (persistently bought or persistently sold for 5+ quarters) – indicating that our aggregate results are due to a generalized conformist tendency rather than few extreme outliers. Bearing in mind the intrinsic limitations of the data in our sample, we also provide some exploratory results on how relative returns of institutions depend on their conformistic trading patterns. It appears that institutions are more likely to engage in money-losing trades when they are faced with high-persistence stocks.

We believe that the findings of our paper challenge the mainstream view on asset pricing anomalies summarized in the recent survey of Barberis and Thaler [5]. This authoritative survey interprets asset pricing anomalies starting from two premises: (1) There are limits to arbitrage; (2) A significant share of investors are affected by systematic biases of a psychological origin. Typically, these irrational investors are identified with non-professional individual investors.

We argue that asset pricing anomalies are not necessarily caused solely by the irrationality of individual investors. We identify a serious asset pricing anomaly and link it to suboptimal behavior on the part of institutional investors. This behavior is consistent with a model of rational response to career concerns. Other authors, such as Lakonishok, Shleifer and Vishny [47], have discussed the possibility of systematic deviations from optimal trading by institutions due to incentive considerations. The results of this paper should encourage us to dig deeper into the effects of agency problems on asset pricing.³

Our paper differs from previous analyses of asset pricing anomalies at a methodological level. Asset price anomalies have typically been first identified in the data (e.g. DeBondt and Thaler [23], Jegadeesh and Titman [41]), and then explained using theoretical models (e.g. Daniel et al. [19], Hong and Stein [40]). Instead, our empirical exercise is theory-driven. It is a test of falsifiable predictions regarding the dynamics of reputational premia that were formulated at an abstract level (Dasgupta and Prat [20]).

The rest of the paper is organized as follows. After a brief discussion of related literature, in the next section we present a reduced-form model to capture our main hypothesis in the simplest

³Other recent papers that consider the agency theoretic implications of asset pricing include Allen and Gorton [1], Ou-Yang [53], Dow and Gorton [28], and Gorton, He, and Huang [37].

possible framework. Sections 3 and 4 contain our main empirical results, while Section 5 presents some preliminary evidence of institutional trading behavior at a disaggregated level. Finally, Section 6 concludes the paper.

1.1 Related Literature

Our theory part is most closely related to Scharfstein and Stein [54] and Dasgupta and Prat [20] (see also the extensive literature survey therein). Other explanations for herd behavior can be found in the works of Banerjee [3], Bikhchandani, Hirshleifer, and Welch [7], Froot, Scharfstein, and Stein [34], and Hirshleifer, Subrahmanyam, and Titman [39]. These explanations are distant from ours in that they do not build on career concerns. In particular, it is important to stress that the rationale behind our kind of conformism (the desire to appear informed) is entirely distinct from the kind of imitation that occurs in statistical information cascades (Banerjee [3], Bikhchandani, Hirshleifer, and Welch [7]): unlike such explanations, our reputation-based story is clearly centered around institutional investors.

While we do not explicitly test for the first prediction of our model (i.e. the link between reputational concerns and institutional conformism), several papers provide empirical evidence that career concerns are related to herding behavior by institutions (see for example Chevalier and Ellison [15] and, more recently, Dass, Massa, and Patgiri [22] and Massa and Patgiri [48]).

Our paper is related to a number of recent empirical studies on the price impact of institutional trading. There is now ample evidence that institutions herd. However, evidence on the impact of such herd behavior on prices is scant. Wermers [60] finds that stocks heavily bought by mutual funds outperform stocks heavily sold during the following two quarters, and interprets this finding as evidence of a stabilizing effect of institutional trade on prices. Sias [57] [58] concludes that institutional trading pushes prices towards equilibrium values by showing that securities most heavily purchased tend to outperform securities most heavily sold by institutions.⁴

Several empirical papers report results that are somewhat complementary to ours. Dennis and Strickland [26] examine stock returns on days of large market movements and find that, for stocks

⁴Other papers finding evidence of a positive correlation between institutional demand and future returns include Nofsinger and Sias [51], Sias, Starks and Titman [59], Grinblatt, Titman and Wermers [38]. Cohen, Gompers and Vuolteenaho [16] find a positive relationship between institutional ownership and future stock returns. Chen, Hong and Stein [13] find that portfolios of stocks experiencing an increase in the fraction of mutual funds owning them outperform stocks for which mutual funds ownership has decreased.

mostly owned by institutions, cumulative abnormal returns are positive in the 6 months after a market drop. They interpret this finding as evidence that institutional trading drives prices away from fundamental values on the event day, and prices slowly revert to fundamentals over time. Sharma, Easterwood and Kumar [55] examine herding by institutional investors for a sample of internet firms during the bubble and crash period 1998-2001. They find evidence of reversals after buy herding in the quarter following institutional trading, and document one-quarter reversals after buy and sell herding cumulated during two quarters.⁵ Kaniel, Saar, and Titman [43] examine data on individual trading on the NYSE, aggregated to a weekly frequency. They find that individual investors trade in a contrarian manner and make profits in the following month.

Finally, recent work by Frazzini and Lamont [32], Braverman, Kandel and Wohl [8], and Coval and Stafford [18] find a negative relationship between net mutual fund flows and long-horizon returns. We examine the relationship of our results to retail flows in the conclusion.

2 Modelling Reputational Premia

In order to provide a conceptual reference point to guide our empirical analysis, we first present an extremely stylized theoretical framework, which is a much simplified version of the dynamic agency model of Dasgupta and Prat [20]. The model illustrates how the career concerns of institutional traders can be incorporated into asset prices via persistent trade, and can show up as “reputational premia.”

The first ingredient is a model of financial markets with asymmetric information. We use an adapted and abridged version of Glosten and Milgrom [35].⁶ Consider a sequential trade market with T fund managers, where a fund manager is identified with the (unique) time at which he trades. There is a single Arrow asset, with equiprobable liquidation values $v = 0$ or 1 . The realized value of v is revealed at time $T + 1$. Manager t trades with a short-lived monopolistic market maker (MM), who trades at time t only, and posts a bid (p_t^b) and an ask price (p_t^a) to buy or sell one unit of the asset.⁷ The manager has three choices: he can buy one unit of the asset from the MM

⁵They measure herding as in Lakonishok, Shleifer and Vishny [46].

⁶For an in-depth discussion of this class of models, see Brunnermeier [9].

⁷Formally, our model has features of both Glosten and Milgrom [35], which is a multi-period model with a competitive market maker, and Copeland and Galai [17] which is a single-period model with a monopolistic market maker. Needless to say, it is complex to model a monopolistic market maker in a multi-period setting, and our assumption of short-livedness simplifies the problem.

($a_t = 1$), sell one unit of the asset to the MM ($a_t = 0$), or not trade ($a_t = \emptyset$). We also assume that the market maker faces a large penalty K if in period t no trade occurs. This guarantees that the market never breaks down.⁸

The key assumption here is that the market maker is a monopolist. In Glosten and Milgrom [35] the market is made by a number of Bertrand-competing uninformed traders. Hence, Glosten and Milgrom is characterized by unlimited arbitrage: the price never deviates from the expected liquidation value based on public information. Our monopoly setting is a crude (but tractable) way to allow for limited arbitrage. We deviate from Glosten and Milgrom in another, less important aspect: there is no noise trade in our set-up. However, noise traders could be added to our model without modifying the qualitative properties of our price dynamics.⁹

Manager t can be either smart (type $\theta = g$) or dumb (type $\theta = b$), with equal probability. The managers do not know their own types.¹⁰ The smart manager observes a perfectly accurate signal: $s_t = v$ with probability 1. The dumb manager observes a purely noisy signal: $s_t = v$ with probability $\frac{1}{2}$. Manager t maximizes a linear combination of his trading profits (χ_t) and his reputation (γ_t), which are defined below.

Trading profit is standard:

$$\chi_t = \begin{cases} v - p_t^a & \text{if } a_t = 1 \\ p_t^b - v & \text{if } a_t = 0 \\ 0 & \text{if } a_t = \emptyset \end{cases}$$

The reputational benefit is given by the posterior probability (at $T + 1$) that the manager is smart given his actions and the liquidation value:

$$\gamma_t = \Pr[\theta_t = g | a_t, v]$$

For simplicity, we assume that when the manager does not trade his reputational payoff is unaffected, that is

$$\gamma_t = \Pr[\theta_t = g | a_t = \emptyset, v] = \frac{1}{2}$$

This is equivalent to assuming that the manager is able to signal a credible reason not to trade.¹¹

⁸The no-trade penalty assumption is discussed below (see also footnote 12).

⁹Obviously, the main effect of the absence of noise traders is that both sides get zero expected profits. As in Glosten and Milgrom, the introduction of noise trade would generate positive profits.

¹⁰Dasgupta and Prat [20] consider the case where managers receive informative signals about their types, and show that the central results are unaffected as long self-knowledge is not very accurate.

¹¹The model of reputational premia in Dasgupta and Prat [20] does not require this restriction. For a microfounded model of incentives to trade, and the reputational effect of not trading, see Dasgupta and Prat [21].

This assumption complements the assumption that the MM faces a stiff penalty if he does not trade. Together, they greatly simplify analysis. As we shall see: (1) Trade occurs in every period; (2) The MM prices the asset in a way that makes the fund manager indifferent between trading and not trading; (3) The MM makes zero profit in expectation; (4) The stock price process follows a martingale.¹²

The manager's total payoff is

$$\chi_t + \beta\gamma_t$$

where $\beta > 0$ measures the importance of career concerns.

Let us first lay out some notation. Let h_t denote the history of prices and trades up to period t (thus excluding the trade that occurs at t). Let $v_t = E[v|h_t]$, denote the public expectation of v . Finally, let $v_t^0 = E[v|h_t, s_t = 0]$ and $v_t^1 = E[v|h_t, s_t = 1]$ denote the private expectations of v of a manager who has seen signal $s_t = 0$ or $s_t = 1$ respectively. Clearly, $v_t^0 < v_t < v_t^1$. Simple calculations show that

$$\begin{aligned} v_t^1 &= \frac{3v_t}{2v_t + 1} \\ v_t^0 &= \frac{v_t}{3 - 2v_t} \end{aligned}$$

It is obvious that v_t is a weighted average of v_t^0 and v_t^1 , as follows:

$$v_t = \Pr(s_t = 1|h_t)v_t^1 + \Pr(s_t = 0|h_t)v_t^0$$

As a benchmark, we first analyze the case where $\beta = 0$, that is, there are no career concerns. In this case, it is easy to see that the only possibility is that managers trade sincerely in equilibrium, that is, buy if they see $s_t = 1$ and sell if they see $s_t = 0$. The MM, in turn, sets prices to extract the full surplus: bid price $p_t^b = v_t^0$ and ask price $p_t^a = v_t^1$. We summarize:

¹²However, it is not difficult to see what the equilibrium of our game would look like in the absence of these two assumptions. In this case, when there has been one or more buy orders the market maker would still wish to sell to fund managers who received signal 1, at prices that strictly above liquidation value. Such trades are advantageous to the market maker. On the other hand, in the same situation, the market maker would not wish to buy from managers with signal zero at a price at which that manager was willing to sell. Thus, after one or more buy orders, the market maker would price to sell to optimistic fund managers, and exclude pessimistic ones. Thus conformism, as well as mispricing, would arise simultaneously: following a buy order, there would be another buy order or no trade, and the expected transaction price - the ask price - would be strictly higher than expected liquidation value. The case for prices following one or more sell orders is symmetric. Thus, the return predicability identified in the model would persist, a fortiori, in this modification of the model.

Proposition 1 When $\beta = 0$, managers choose $a_t = s_t$, and the market maker sets prices $p_t^b = v_t^0$ and $p_t^a = v_t^1$.

Thus the *average transaction price* when $\beta = 0$ is v_t . We now analyze the more general case when $\beta > 0$.

Define

$$\begin{aligned} w_t^1 &= E_v[\gamma(a_t = 1)|s_t = 1, v] \\ w_t^0 &= E_v[\gamma(a_t = 0)|s_t = 0, v] \end{aligned}$$

The following is an equilibrium of the game with $\beta > 0$:¹³

Proposition 2 When $\beta > 0$, managers choose $a_t = s_t$, and the market maker sets prices

$$\begin{aligned} p_t^a &= v_t^1 + \beta \left(w_t^1 - \frac{1}{2} \right) \\ p_t^b &= v_t^0 + \beta \left(\frac{1}{2} - w_t^0 \right) \end{aligned}$$

Proof. See Appendix. ■

In this equilibrium, both sides – the fund managers and the MM – get a zero expected payoff. This fact, which can be checked algebraically, is the result of the combination of these features: (1) the fund managers’s utility depends linearly on the posterior; (2) the expected posterior on the equilibrium path is equal to the prior (1/2); and (3) the fund manager can secure the prior by choosing not to trade. Hence, the expected equilibrium reputational benefit for the fund manager is 1/2 and there is no monopoly rent to be extracted.¹⁴

2.1 Reputational Premia

The equilibrium characterization given above indicates that there is a systematic difference between prices in the benchmark case without career concerns ($\beta = 0$) and prices in the general case with career concerns ($\beta > 0$). This is due to the reputational incentives of fund managers.¹⁵

¹³In fact, one could prove that this is the only *non-perverse* equilibrium of the game. A perverse equilibrium arises when the fund manager is strictly more likely to buy when he has a negative signal rather than a positive signal. In a perverse equilibrium, the bid price is higher than the ask price.

¹⁴If noise traders were present, the MM would have a strictly positive expected payoff. She would still charge the same prices and extract a zero-rent from informed traders. But she would make a trading profit from noise traders because of the bid-ask spread.

¹⁵As in Glosten and Milgrom [35], the equilibrium price process still forms a martingale in every period from 1 to T . It is easy to check that the expected price at any time $t + s$ given the public information available at the end

To illustrate these incentives, consider the following hypothetical scenario: Suppose the first three managers buy in equilibrium. What should manager number 4 do if he observes $s_4 = 0$? Note that $\Pr(v = 1 | s_1 = s_2 = s_3 = 1, s_4 = 0) = \frac{9}{10}$. Profit maximization incentives would always push the manager towards *selling* (because the manager's private information makes his posterior over the liquidation value more pessimistic than the public belief). However, reputational incentives push the manager towards *buying*. This is because, in equilibrium, selling is bad for reputation: if the manager sold, his expected reputation would be $E(\Pr[\theta_4 = g | s_4 = 0, \text{sell}]) = \frac{2}{30}$ while if he bought, his expected reputation would be $E(\Pr[\theta_4 = g | s_4 = 0, \text{buy}]) = \frac{18}{30}$. Thus, the manager who gets signal $s_4 = 0$ would only be indifferent between selling (as he must in this equilibrium) and not trading if the price at which he sold was *above* fair value, providing him with some benefit to offset the loss in reputation. Thus, in equilibrium, after three buy orders, it must be the case that prices are systematically above fair value.

We define the reputational premium (π_t) to be the difference between average equilibrium transaction prices with and without career concerns. By a slight abuse of notation, define

$$v_t(\beta) = \Pr(s_t = 1)p_t^a(\beta) + \Pr(s_t = 0)p_t^b(\beta)$$

Note that $v_t(0) = v_t$, as defined above. For any given $\beta > 0$, and at any time t :

$$\pi_t(\beta) \equiv v_t(\beta) - v_t(0)$$

Simple calculations demonstrate some natural properties of the reputational premium:

$$v_t(\beta) = v_t + \beta \left(\left(\frac{1}{2}v_t + \frac{1}{4} \right) \left(\frac{2}{3}v_t^1 - \frac{1}{2} \right) + \left(1 - \left(\frac{1}{2}v_t + \frac{1}{4} \right) \right) \left(\frac{1}{2} - \frac{2}{3}(1 - v_t^0) \right) \right)$$

Therefore,

$$\pi_t(\beta) = \frac{1}{4}\beta(2v_t - 1)$$

The reputational premium is thus a function of the expected liquidation value at t , with the following properties: (1) it is increasing in v_t ; (2) it is greater than zero if and only if $v_t > \frac{1}{2}$; and (3) its absolute value is an increasing function of the career-concerns parameter β .

of trading period t is equal to the trading price at t . The process is not, however, a martingale from T to $T + 1$. Because of the reputational premium, the price differs systematically from the expected liquidation value.

By iterated application of Bayes' rule, we can compute v_t – and hence the reputational premium – from observed trading. Suppose the first n managers all bought. The expected liquidation value is

$$\Pr(v = 1 | s_1 = \dots = s_n = 1) = \frac{3^n}{3^n + 1}$$

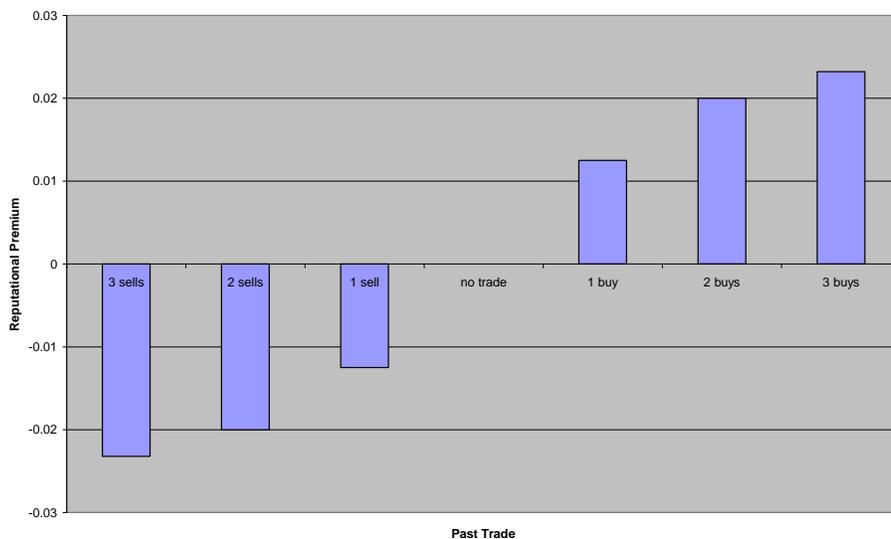
and the reputational premium is

$$\pi_n(n \text{ buys}) = \frac{1}{4}\beta \left(2\frac{3^n}{3^n + 1} - 1 \right)$$

Conversely,

$$\pi_n(n \text{ sells}) = \frac{1}{4}\beta \left(1 - 2\frac{3^n}{3^n + 1} \right)$$

For instance, Figure 1 depicts some values of π_n when $\beta = 1$.



To re-cap:

Proposition 3 *The reputational premium in period t is a function of past trade. If the past n trades were buys (sells), the premium is positive (negative) and strictly increasing (decreasing) in n .*¹⁶

¹⁶The proposition assumes that the n trades of the same sign start at time $t = 1$. The monotonicity part extends to n trades of the same sign starting at any time t . Suppose instead that $t > 1$ (and that the expected liquidation

Our result that the reputational premium is monotonic in past trade leads to a testable implication: the degree of over- or under-pricing of a stock depends on whether it was persistently bought or sold in the recent past.

We have obtained this prediction in an extremely stylized set-up. Rather than focusing on the obvious limitations of the current modelling strategy (many of which are discussed in Dasgupta and Prat [20]), it is more interesting to step away from the details of the model, and ask ourselves: what are the key economic assumptions that drive a result of this kind? We have identified four:

1. A significant share of assets are held by funds who are investing money on someone else's behalf.
2. Fund managers face career concerns.
3. The main dimension on which managers differ is the precision of the information they receive. A manager who observes a signal realization that is different from those of his peers is more likely to be a low-precision type.
4. Asset supply at the fair price is not infinitely elastic (if it were, the fact that a proportion of traders ascribe a reputational benefit to a certain asset would not affect the price of that asset)

The first assumption is uncontroversial in modern financial markets. The second one appears to be reasonable at least for certain classes of institutional investors. See for instance Chevalier and Ellison [14], [15] for mutual funds, and Lakonishok, Shleifer, Thaler and Vishny [45] for pension funds.

Assumption 3 is discussed at length by Scharfstein and Stein [54] and Ottaviani and Sorensen [52]. One could build different information structures, where having a different signal realization is

value is v_t). If time t is followed by n buys or n sells, the reputational premium is given by

$$\begin{aligned}\pi_n(n \text{ buys}) &= \frac{1}{4}\beta \left(2 \frac{3^n v_t}{3^n v_t + 1 - v_t} - 1 \right); \\ \pi_n(n \text{ sells}) &= \frac{1}{4}\beta \left(1 - 2 \frac{3^n v_t}{3^n v_t + 1 - v_t} \right),\end{aligned}$$

which – like in the earlier case – are strictly monotonic in n .

The only part of Proposition 3 which does not go through is that the reputational premium is positive if the n trades are buys and negative if the trades are sells. But this part would be true, on average, if we consider all possible histories before time t .

good news about the manager’s type. Assumption 3 may be violated if fund managers have precise information about their type but it is still valid if their self-knowledge is limited.¹⁷ Unfortunately, we cannot invoke any empirical evidence in favor of or against it, except for anecdotal evidence or the opinion of insiders, such as Trichet.

Finally, in our model Assumption 4 takes an extreme form: the MM is a monopolist. However, much less is needed for our main result to be true. If the first three assumptions are correct, there exists a systematic difference in the willingness to pay on the part of traders with career concerns and traders without career concerns. All that is needed for that difference to affect the equilibrium price is that traders without career concerns have an imperfectly elastic supply function. In other words, Assumption 4 holds if there are limits to arbitrage, a fact which is now generally accepted by the finance literature ([56], [5]).

3 Data and descriptive statistics

The sample consists of quarterly observations for firms listed on NYSE, AMEX and NASDAQ, during the period 1983-2004. Data on institutional ownership are obtained from the CDA/Spectrum database maintained by Thomson Financials. All institutions with more than \$100 million under discretionary management are required to report to the SEC all equity positions greater than either 10,000 shares or \$200,000 in market value.¹⁸

Data on prices, returns, and firm characteristics are from the Center for Research in Security Prices (CRSP) Monthly Stock Files, and data on book values of equity come from Compustat. The sample includes common stocks of firms incorporated in the United States.¹⁹

Each quarter, we compute the total number of managers reporting their holdings in each security, the cross-sectional average of the number of securities in their portfolio, the value of their equity holdings, the aggregate value managed by all institutions, and portfolio turnover. Table I reports time-series averages of these quarterly cross-sectional summary statistics.

Our sample consists of an average of 1,130 managers each quarter (varying from 640 to 2023).

¹⁷For a detailed discussion of this assumption see Dasgupta and Prat [20].

¹⁸The Thomson data on institutional holdings are adjusted for stock splits, stock distributions, mergers and acquisitions and other corporate events that occur between the report date and the filing date.

¹⁹ADRs, SBIs, certificates, units, REITs, closed-end-funds, and companies incorporated outside the U.S. are excluded from the sample.

These managers hold, on average, a portfolio of approximately \$2,108 million in value. Portfolio turnover for manager j is calculated as the sum of the absolute values of buys and sells in stock i in a given quarter, divided by the value of the manager’s stock holdings: $Turnover_t^j = \frac{\sum_i |n_t^{i,j} - n_{t-1}^{i,j}| p_t^i}{\sum_i n_t^{i,j} p_t^i}$.

This measure includes trading that is unrelated to flows.

We define net trade by institutional managers in security i as the ratio of the weight of security i in institutional investors’ aggregate portfolio, from the end of quarter $t - 1$ to the end of quarter t . The institutional portfolio at the end of quarter t is represented by

$$S_{i,t} = \sum_i s_{i,j,t}$$

The change in weight in the institutional portfolio is then obtained as:

$$d_{i,t} = \frac{S_{i,t} - S_{i,t-1}}{S_{i,t-1}}$$

This is equivalent to measuring changes in the value of investors’ portfolios, where portfolio values are calculated at constant prices to avoid changes that are purely attributable to price movements.

To compute the persistence of net trades by institutional investors, we first define net buys as stocks with a value of $d_{i,t}$ above the cross-sectional median in each quarter t , and net sells as those stocks with a value of $d_{i,t}$ below the median. This definition guarantees that, at every quarter, 50% of stocks are buys and 50% are sells. A definition based on the sign of $d_{i,t}$ could create a correlation between the proportion of stocks that are buys and capital inflows into institutions. As the latter is linked to past returns, it may lead to an identification problem.²⁰

Each quarter t , stocks are assigned to different portfolios conditional on the persistence of institutional net trade, i.e. conditional on the number of consecutive quarters for which we observe a net buy or a net sell for stock i . For example, a persistence measure of -3 indicates that a stock has been sold for three consecutive quarters, from $t - 2$ to t . Persistence 0 includes stocks that have been bought or sold in t (and were sold or bought at $t - 1$). The portfolio with persistence -5 (5) includes stocks that have been sold (bought) for *at least* five consecutive quarters.

²⁰However, our results are qualitatively similar if we classify net buys and net sells according to the sign of $d_{i,t}$.

4 Trading persistence and the cross-section of stock returns

In this section, we test the main theoretical predictions of the paper and conduct several robustness checks. In essence, we test whether the persistence of institutional trading has any predictability for returns, after controlling for a number of other variables that are known to forecast the cross-section of stock returns.

We first investigate such predictability by assessing the profitability of portfolio strategies based on trading persistence. We form portfolios based on institutions' net trades, track their returns in the future ten quarters, and test whether quarterly portfolio returns are significantly different across persistence categories in event time. As a robustness test, we repeat this analysis for each quintile of the distribution of market capitalization, Book-to-Market, and past one-year returns. Furthermore, we perform the same analysis in different sub-periods in our sample.

We also compute monthly returns to persistence portfolios in calendar time and estimate intercepts from different asset pricing models, to account for risk and stock characteristics that can potentially affect the variability of stock returns.

Finally, we investigate the predictability of institutional trading persistence at the individual stock level, by estimating panel and Fama-MacBeth [31] regressions of two-year returns on past persistence, past returns, and other controls.

4.1 Portfolio returns

At the end of each quarter t , we form portfolios based on the persistence of net trading by institutional investors. Figure 2 shows the histogram of the market-adjusted returns to each persistence portfolio, cumulated over a period of two years after portfolio formation. The negative relationship between trading persistence and future returns can be easily gleaned from the graph. The difference in cumulative returns between the portfolios with highest persistence reaches 17% after two years.

Table II illustrates the characteristics of stocks across persistence portfolios, calculated as time-series averages of cross-sectional statistics. Market capitalization, turnover, and Book-to-Market are measured at the end of quarter t . Since Nasdaq is a dealer market and thus volume is double-counted, we divide Nasdaq volume by two so that turnover is comparable across different ex-

changes.²¹ The findings show that size tends to increase across persistence portfolios, although the variation is small. Turnover increases with net buy persistence, suggesting that institutions tend to buy stocks that are more liquid. Furthermore, the portfolio characteristics suggest that institutions tend to sell value stocks (high B/M) and tend to buy growth stocks (low B/M). Average institutional ownership is higher among stocks with positive net trading by institutions. Finally, past returns are negative for stocks that have been persistently sold and positive for stocks that have been bought by institutions. This result indicates that institutional managers engage in momentum trading and is consistent with previous findings (Sias [58]). As expected, the frequency of net trades is concentrated around 0, meaning that more stocks have been bought or sold in the current quarter than in n consecutive quarters. The frequency of net consecutive buys (or sells) decreases with the number of quarters considered.

Table III reports market-adjusted portfolio returns in event time, for ten quarters after portfolio formation. The returns are equally weighted and are obtained by subtracting the quarterly buy-and-hold market return from the quarterly buy-and-hold return of each portfolio. We also compute the difference in portfolio returns across positive and negative persistence groups. For example, portfolio (-5,5) buys stocks that have been sold by institutions for 5 quarters and shorts stocks that have been bought for 5 quarters. We form analogous long-short portfolios for trading persistence of 4 and 3 quarters. The returns of these persistence portfolios exhibit a clear monotonic pattern: stocks that have been persistently sold outperform stocks that have been persistently bought. The difference in returns between the portfolios of longer trading persistence (-5,5) is about 1.5% in the first quarter after portfolio formation (not statistically significant), and becomes larger and significant in the subsequent quarters, reaching 3% in the 4th quarter. It then starts to slowly decline afterwards, but is still positive and significant eight quarters after portfolio formation (1.67%).²² The returns of the long-short portfolios based on shorter persistence (-4,4 and -3,3) are smaller in magnitude but follow similar patterns.

²¹The results do not change if we subtract from each stock's volume the average volume of the exchange in which the stock is traded.

²²This is an extremely stringent test. The magnitude and statistical significance of the portfolio returns in Table III separately consider *each* quarter after portfolio formation (between $t+1$ and $t+10$). The requirement that a portfolio return be statistically significant and economically important in each quarter subsequent to portfolio formation during the period considered is more stringent than simply testing the economic significance of the average return over the same post-formation period.

In Figure 3, we plot the cumulative market-adjusted returns for each persistence portfolio over a period of 10 quarters after portfolio formation. The graph gives a clear representation of the monotonic reversal pattern in returns conditional on institutional trading persistence.

Our findings are not inconsistent with studies documenting a positive relationship between institutional herding and future stock returns. Wermers [60] finds that stocks heavily bought by mutual funds outperform stocks heavily sold by them for a period of two quarters in the future, while Sias [57] finds that the fraction of institutions buying a stock is (weakly) positively correlated with returns in the following one to four quarters.²³ In this paper, we focus on *long horizon* predictability, and we condition on the *persistence* of institutional net trading rather than on the measure of contemporaneous herding that is more widely adopted in the literature (Lakonishok, Shleifer and Vishny [46]).²⁴

It is well known that inference on long-run abnormal returns is better drawn from returns measured in calendar time rather than in event time, especially due to cross-sectional correlation problems.²⁵ We compute average monthly returns from overlapping persistence portfolios formed at the end of each quarter t and held for different periods. This approach implies that, for a holding period of k quarters, $1/k$ of the portfolio is rebalanced every quarter. In Table IV we present results for strategies that buy stocks that have been sold 5, 4, and 3 quarters and sell stocks that have been bought respectively 5, 4, and 3 quarters before portfolio formation. To check that the results are not driven by the covariance of portfolio returns with risk factors, we estimate one-factor and multi-factor regressions for the time-series of the strategy monthly raw returns. We consider the

²³Sias [58] reports that institutional trading pushes prices towards equilibrium values using two measures of institutional trading: the change in the fraction of institutions buying a stock and net institutional demand (number of managers buying a stock less number of managers selling): securities most heavily purchased tend to outperform securities most heavily sold by institutions.

²⁴Wermers [60] finds that stocks heavily bought by mutual funds outperform stocks heavily sold by mutual funds for the next two quarters, during the period 1975-1994. To partially compare our results to Wermers', using our data on institutional managers we separate stocks characterized by positive and negative changes in institutions' portfolios during a particular quarter t . We then rank the stocks of each group into quintiles on the basis of the magnitude of the change, and compute future market-adjusted quarterly returns for stocks heavily bought and stocks heavily sold by institutions. When we truncate our time-series to 1994, we find that the difference in returns is 1.15% after one quarter, 0.5% after two quarters, and becomes negative afterwards. While the two samples are not directly comparable, as they refer to different time periods, different institutional traders, and different measures of net trading, our empirical results are not inconsistent with those of Wermers.

²⁵Long-run event study tests can be problematic because of sample selection biases, model misspecifications, and cross-sectional correlation (Kothari and Warner [44], Barber et al. [4]). Simulations generally show a strong tendency to find positive abnormal performance.

CAPM model, the Fama-French [30] model, and the four-factor model that includes Carhart [11] momentum factor. Table IV reports the estimated intercepts for the long-short portfolios of low minus high trading persistence, estimated from the following time-series regression:

$$R_{p,t} - R_{f,t} = \alpha + \beta (R_{M,t} - R_{f,t}) + s \text{SMB}_t + h \text{HML}_t + u \text{UMD}_t + \varepsilon_t,$$

where $R_{p,t}$ is the return of the portfolio based on trading persistence, $R_{f,t}$ is the one-month yield on Treasury bills, and SMB , HML , and UMD are factors based on size, Book-to-Market, and one-year past returns.

The estimation results show that, for all pricing models, the intercepts are economically large and statistically significant. For example, for the strategy that buys and sells high persistence stocks (-5,5), alphas range between 44bp and 90bp, depending on the chosen regression specification and on the portfolio holding period.

To conclude our portfolio analysis, we conduct some robustness tests to check whether the predictability of trading persistence is confined to a specific sub-sample of stocks. To the extent that institutions tend to buy growth and sell value stocks, or tend to buy winners and sell losers, the observed patterns in portfolio returns could be driven by the reversal phenomenon previously documented in the literature (Jegadeesh and Titman [41] and [42], DeBondt and Thaler [23]). We first partition our sample into quintiles based on NYSE market capitalization, book-to-market, and previous year returns. We then compute return differentials between selling and buying persistence portfolios, for each of the characteristic quintiles. We find that the positive differential in returns due to institutional trading persistence is particularly large for small stocks, value stocks, and past losers, but is strongly present in all sub-samples. Figures 4A-4C show the two-year cumulative return to buying stocks persistently sold for 5 quarters and selling stocks persistently bought for 5 quarters.

Figure 4D shows two-year cumulative returns to long-short portfolios based on persistence for different sub-periods in our sample. We consider two different ways of breaking our sample into sub-periods. We first divide the time series into two parts of roughly equal length, 1983-1992 and 1993-2003, and observe that return differentials are larger for the second period. We also break the sample into pre-1998 and post-1998 periods. The evidence shows that the link between institutional

trading and return predictability becomes particularly strong in the later part of the sample, where two-year cumulative returns from buying and selling high persistence stocks could be as high as 35%. The model in this paper offers two interpretations of this result. First, it is possible that the reversal patterns associated with institutional trading have been exacerbated by the increased institutional share ownership over the years (in our sample, the share doubled between 1983 and 2003). The phenomenon could also be due to the presence of stronger career concerns (exemplified by an increase of the parameter β in our model).

4.2 Regression analysis

The portfolio analysis shows that the persistence of institutional trading can predict stock returns, and that this predictability is robust across different levels of stock characteristics typically associated with investment anomalies. In this section, instead of focusing on the profitability of trading strategies based on persistence, we investigate the association between trading persistence and future returns at the level of an individual security. We run predictive regressions of cumulative two-year market-adjusted returns on past trading persistence, controlling for past returns and other stock characteristics:

$$R_{i,t+1:t+8} = \alpha_0 + \sum_{p=1,2,4,5} \beta_p dPers_{i,t,p} + \sum_{q=1,2,4,5} \gamma_q dR_{i,t:t-n+1} + \delta_0 Cap_{i,t} + \delta_1 BM_{i,t} + \varepsilon_{i,t},$$

where the variables are defined as follows:

$R_{i,t+1:t+8}$ is the two-year return for stock i , cumulated over quarters $(t+1)$ to $(t+8) - t$ is the quarter of portfolio formation;

$dP_{i,t,p}$ is an indicator variable that assumes the value 1 if stock i belongs to group p of trading persistence. Persistence is categorized as follows: group 1: pers= $(-5,-4)$; group 2: pers= $(-3,-2)$; group 3: pers= $(-1,1)$; group 4: pers= $(2,3)$; group 5: pers= $(4,5)$;

$dR_{i,t,q}$ is an indicator variable that assumes the value 1 if stock i belongs to quintile q of the cross-sectional distribution of past n -quarter returns, $R_{i,t:t-n+1}$;

$Cap_{i,t}$ is the quintile rank of market capitalization for stock i in quarter t ;

$BM_{i,t}$ is the quintile rank of Book-to-Market for stock i in quarter t .

Table V shows coefficient estimates from the regressions, where past returns are measured over three years ($n = 12$).²⁶ We account for the cross-sectional and time-series correlation in the data by adopting two different procedures. The estimates from the panel regressions are obtained by including time fixed effects and by clustering the standard errors at the firm level.²⁷ The Fama-MacBeth [31] estimates are time-series averages of coefficients obtained from quarterly cross-sectional regressions. The t -statistics are computed from standard errors that are adjusted for autocorrelation according to Newey-West [49].

Both sets of estimates provide strong evidence of return predictability for institutional trading persistence, beyond the well known predictability associated with past returns. After controlling for size and Book-to-Market, positive persistence tends to dampen future returns, while negative persistence significantly contributes to increasing returns over the next two years. Past returns still predict reversal patterns at the long horizon, but do not subsume the predictive power of trading persistence.

The effect of past returns and persistence is similar in magnitude. Compared to stocks that are median past performers, future two-year returns will be on average 11% higher for past losers, and 2% lower for past winners. Consider now the effect of trading persistence on return predictability after controlling for past returns, size, and book-to-market. Compared to stocks that are bought or sold for one quarter, stocks with relatively high and negative trading persistence (4 or more quarters) earn future returns that are 7% higher, whereas stocks with positive trading persistence (4 or more quarters) earn future returns that are on average 6% lower.

Different specifications of the regression model consistently show a strong and negative relationship between trading persistence and future returns. When we measure persistence and past returns in levels or percentile ranks instead of using dummy variables for quintiles, the coefficient on persistence remains statistically negative, even though comparisons across different regressors become less immediate. Adding turnover and the level of institutional ownership among the controls does not alter our results.

²⁶Varying the return horizon does not change the estimate of the coefficients on the persistence variables. We choose to measure past returns over three years to fully capture the reversal effect in returns documented in the literature (DeBondt and Thaler [23]).

²⁷Alternatively, we estimate the panel regression by including both time and firm fixed effects, and by forming firm-quarter clusters. We present results for the specification with time fixed effects and firm clusters because it yields standard errors that are more conservative across all alternatives.

5 A preliminary analysis of institutional trading behavior

While our main empirical analysis is carried out at the aggregate level, in this section we analyze a sub-sample of data that are disaggregated at the manager level. The purpose of this section is twofold. First, we ask whether the persistence in trading behavior uncovered in the aggregate sample is driven by the extreme behavior of a fraction of institutional managers. Second, we attempt to provide some very preliminary evidence on the relationship between institutions' conformist behavior and the returns of securities traded by conformist managers. A more detailed analysis addressing these issues is the object of future work.

We restrict our sample to include all managers with valid share ownership data in each quarter of the period 1995-2003. Limiting the sample to the later period possibly increases the chances of continuity in the structure of the institution, its identity, management style, etc. The filtered sample consists of 270 managers. For each manager j and quarter t , we construct a measure of conformism, $sheep_{j,t}$, defined as follows:

$$sheep_{j,t} = \frac{\Pr(j \text{ buys} \mid \text{pers} = 5) + \Pr(j \text{ sells} \mid \text{pers} = -5)}{2} - \frac{1}{2},$$

where persistence is defined with respect to the trading behavior of all managers in the sub-sample and is measured, as before, as the number of consecutive quarters in which a particular security is bought/sold by institutional managers. From the definition, the variable $sheep_{j,t}$ is positive for conformists, and negative for anti-conformist managers. It varies between $-\frac{1}{2}$ and $\frac{1}{2}$, and equals zero if a manager trades randomly.

Figure 5-A plots the distribution of $sheep_{j,t}$ for the 270 managers in the sample, averaged over time,. The plot clearly indicates that our measure of conformism is pervasive in our sub-sample, with the majority of managers displaying a positive $sheep_j$ value. These managers display a tendency to buy stocks that have been persistently bought in the past and are thus overpriced (given the results from our main empirical analysis), and to sell stocks that have been sold in the past and are underpriced. As can be gleaned from the selected group of managers listed in Table VI, there is no clear relationship between our conformism measure and the type under which an institutional investor is classified.²⁸

²⁸Thomson classifies institutional managers into 5 different types: banks, insurance companies, mutual funds, investment advisors, and a residual category that includes pension funds and university endowments, among others.

The information in our sample does not allow us to estimate profits and losses that derive from the trading decisions of the managers under consideration. We only have data on changes in share ownership at a quarterly frequency, and lack information on inflows and outflows into specific funds. However, we can construct an artificial portfolio choosing the securities that experience relative weight changes in the portfolio of the managers in our sub-sample. Specifically, for every manager j and quarter t , we classify trades in stock i into either buys or sells with respect to the median distribution of manager j 's trades (i.e., we classify manager j 's trades into 50% buys and 50% sells). We then construct a portfolio that buys stock i if it is classified as a buy, and shorts stock i if it is classified as a sell, and compute the cumulative two-year return to such portfolio for each manager in our sub-sample. Table VI shows the results for the 20 managers with the highest portfolio value (measured in the first quarter of 1995). The returns to the portfolios we construct are all negative - a result that, given the limitations described above, does not allow us to draw any inference on the ability of the managers under consideration. However, focusing on the *relative* difference in returns across trading persistence, Figure 5-B shows that the returns to our artificial portfolios (averaged across managers) are lower for stocks that exhibit higher aggregate trading persistence (positive or negative).

In the cross-section of managers under consideration, we also find some evidence of a negative association between the returns to the artificial portfolios and our measure of conformism ($sheep_j$), after accounting for manager-specific variables like portfolio value and manager type.²⁹

Interestingly, Brunnermeier and Nagel [10] show that hedge funds were able to anticipate and profit from the mispricing of technology stocks during the bubble period 1998-2000. Hedge fund managers tilted their portfolios towards technology stocks, and cut back their holdings just before prices collapsed. The managers in our sample, instead, do not seem to sell (buy) in a timely manner stocks that they have persistently bought (sold), even though these can be identified as underperformers (overperformers).

The disaggregated data appears to indicate that conformism is a generalized phenomenon among

²⁹We examine the association between returns to the artificial portfolios and managers' conformism by estimating the following regression (estimates are reported below each coefficient, t -statistics are in parentheses):

$$R_j = \alpha + \beta \textit{Sheep}_j + \gamma_0 \textit{Value}_j + \gamma_1 \textit{Bank}_j + \gamma_2 \textit{Insurance}_j + \gamma_3 \textit{MutualFund}_j + \gamma_4 \textit{Advisor}_j + \varepsilon_j$$

$\begin{matrix} -0.317(-3.78) & -0.002(0.50) & -0.0013(-0.09) & 0.005(0.02) & -0.0061(-0.26) & 0.130(0.68) \end{matrix}$

institutions and that it may lead to losses concentrated on high-persistence stocks. However, the evidence presented in this section is only preliminary, and needs to be interpreted with caution. In a separate study, we are investigating the behavior of institutional managers at a more detailed level.

6 Conclusion

Under a variety of formulations, we find that stocks that have been persistently sold by institutions outperform stocks that have been persistently bought by them. This is true whether we focus on the profitability of trading strategies that are based on trading persistence, or we estimate cross-sectional regressions at the level of individual stocks. The return predictability that is associated with the persistence of institutional trading is not subsumed by the well-known patterns of momentum and reversal in returns.

Our empirical findings are consistent with the simple career-concern model presented in the theory section, which in turn captures ideas discussed by a number of authors, including Scharfstein and Stein [54] and Dasgupta and Prat [20]. However, is our empirical evidence also consistent with other interpretations?

First, the negative return predictability associated with institutional trading could be the result of a behavioral bias, rather than a rational response to incentives. For some psychological reasons, some investors are keen to imitate the past net trade of institutions. However, if we accept this explanation, we must explain why this bias affects primarily professional investors rather than individual investors.

Second, it is possible that the patterns of return predicability arise because institutions trade against insiders with superior knowledge of future cash-flows. For example, informed players in the market for corporate control can slowly acquire large positions in the shares of a company (by buying from institutional shareholders) to gain a toe-hold prior to announcing a hostile takeover, thus raising the share price. Shares sold to or repurchased from institutions by insiders could constitute another example of such trade. However, for our findings to be explained in this manner, it must be the case that professional money managers trade, on average, against better informed insiders, and are systematically unaware of this fact.

Third, institutions may want to unload or acquire large positions in a particular stock. If they do so, it is optimal to dilute trade over time to avoid an excessive price response. This explanation encounters two orders of difficulty. It is reasonable to assume that these type of trading strategies have a time horizon of days or perhaps weeks, while our persistence spans years. Also, rational institutions would want to acquire or unload positions because, on average, it is optimal to do so. This must be the case even at the end of the trading strategy. So, this theory does not explain the presence of systematically wrong trades.

Fourth, the third explanation above could be amended by assuming that institutions *must* unload or acquire large positions in a certain stock. For instance, mutual funds are subject to inflows and outflows, which are outside their control. As Frazzini and Lamont [32] show, these flows may be negative predictors of past returns. In order to examine whether retail flows can fully explain our results, we redo our analysis while excluding mutual funds. We find that our results remain qualitatively unchanged and of a similar order of magnitude.³⁰ The fact that our results persist even after eliminating institutions that are directly affected by retail flows suggests that such flows are not the main driver of our aggregate results.

³⁰The CDA Spectrum database classifies institutions into five categories: mutual funds, independent advisors, banks, insurance companies, and "others". The boundary between the first two categories is not watertight in the dataset. To be conservative in excluding all institutions directly affected by retail flows, we drop both these categories (over 40% of our observations). Nevertheless, we find that the persistence -5 portfolio yields a market-adjusted two-year return of around 8%, while the persistence +5 portfolio yields around -5%.

Appendix: Proof of Proposition 2

To verify that this is a (perfect Bayesian) equilibrium of the game, we first check that managers find it in their interest to act according to their prescribed strategies.

Consider first a fund manager at t who observes $s_t = 1$. On the equilibrium path, his expected payoff is

$$v_t^1 + \beta w_t^1 - p_t^a = \frac{1}{2}\beta.$$

If the same manager sells instead of buying, he obtains expected payoff

$$p_t^b - v_t^1 + \beta w_{t,sell}^1 = v_t^0 - v_t^1 + \beta \left(\frac{1}{2} - w_t^0 + w_{t,sell}^1 \right)$$

where

$$\begin{aligned} w_{t,sell}^1 &= \Pr(v = 1 | s_t = 1) \Pr(\theta = g | a_t = 0, v = 1) \\ &\quad + \Pr(v = 0 | s_t = 1) \Pr(\theta = g | a_t = 0, v = 0) \\ &= v_t^1 \cdot 0 + (1 - v_t^1) \cdot \frac{2}{3} = \frac{2}{3}(1 - v_t^1) \end{aligned}$$

Note that

$$\begin{aligned} w_t^0 &= \Pr(v = 1 | s_t = 0) \Pr(\theta = g | a_t = 0, v = 1) \\ &\quad + \Pr(v = 0 | s_t = 0) \Pr(\theta = g | a_t = 0, v = 0) \\ &= v_t^0 \cdot 0 + (1 - v_t^0) \cdot \frac{2}{3} = \frac{2}{3}(1 - v_t^0) \end{aligned}$$

The expected payoff can then be re-written as

$$\begin{aligned} &v_t^0 - v_t^1 + \beta \left(\frac{1}{2} - \frac{2}{3}(1 - v_t^0) + \frac{2}{3}(1 - v_t^1) \right) \\ &= v_t^0 - v_t^1 + \beta \left(\frac{1}{2} + \frac{2}{3}(v_t^0 - v_t^1) \right), \end{aligned}$$

which is smaller than $\frac{1}{2}\beta$.

If the manager chooses not to trade instead of buying, he obtains the outside option $\frac{1}{2}\beta$. The argument to show that selling is a best response when $s_t = 0$ is symmetric.

Now we check that it is optimal for the MM to stick to his strategies. Suppose that the MM in t posts bid/ask prices different from those dictated by the equilibrium strategy. If these prices

induce the fund manager not to trade, the MM faces the penalty K . As K is assumed to be large, a deviation to such prices is suboptimal.³¹ If instead the MM deviates to another pair of prices $(\tilde{p}_t^a, \tilde{p}_t^b)$ that still induce the manager to buy if $s_t = 1$ and to sell if $s_t = 0$, it is easy to see that $\tilde{p}_t^a \leq p_t^a$ and $\tilde{p}_t^b \geq p_t^b$, where p_t^a and p_t^b are the equilibrium prices (because the manager is already indifferent between trading and not trading). Hence, the MM cannot gain from such a deviation.

Finally suppose the MM chooses a pair of prices that induce a pooling or a semi-separating equilibrium. Suppose, for instance, that the fund manager buys for sure if $s_t = 1$ and buys with probability $a \in (0, 1]$ if $s_t = 0$. The ask price must satisfy

$$p_t^a \leq v_t^0 + \beta \left(w_{t,\text{buy}}^0 - \frac{1}{2} \right), \quad (1)$$

where $w_{t,\text{buy}}^0$ denotes the expected equilibrium posterior for a manager who buys after receiving $s_t = 0$. It is easy to check that in this putative equilibrium $w_{t,\text{buy}}^0 < w_t^1$, where the latter is, as before, the expected equilibrium posterior for a manager who buys after receiving $s_t = 1$. Thus,

$$p_t^a \leq v_t^0 + \beta \left(w_t^1 - \frac{1}{2} \right) \quad (2)$$

The bid price must satisfy

$$p_t^b \geq v_t^0 + \beta \left(\frac{1}{2} - w_t^0 \right) \quad (3)$$

The expected profit of the MM is then

$$\begin{aligned} & \Pr(s_t = 1|h_t) (p_t^a - v_t^1) + \Pr(s_t = 0|h_t) \left(a (p_t^a - v_t^0) + (1-a) (v_t^0 - p_t^b) \right) \\ \leq & \Pr(s_t = 1|h_t) \left(v_t^0 + \beta \left(w_{t,\text{buy}}^0 - \frac{1}{2} \right) - v_t^1 \right) \\ & + \Pr(s_t = 0|h_t) \left(a\beta \left(w_{t,\text{buy}}^0 - \frac{1}{2} \right) + (1-a)\beta \left(w_t^0 - \frac{1}{2} \right) \right) \\ < & \Pr(s_t = 1|h_t) \left(v_t^0 + \beta \left(w_t^1 - \frac{1}{2} \right) - v_t^1 \right) \\ & + \Pr(s_t = 0|h_t) \left(a\beta \left(w_{t,\text{buy}}^0 - \frac{1}{2} \right) + (1-a)\beta \left(w_t^0 - \frac{1}{2} \right) \right) \\ = & \Pr(s_t = 1|h_t) (v_t^0 - v_t^1) < 0 \end{aligned}$$

where: the first inequality follows from (1) and (3); the second inequality is due to $w_{t,\text{buy}}^0 < w_t^1$; and the following equality is due to the observation that in a perfect Bayesian equilibrium the expected

³¹A sufficient condition to guarantee that the market maker will wish to trade is that $K > \frac{1}{2}\beta$.

posterior (over all possible signal realizations and equilibrium actions) must equal the prior:

$$\Pr(s_t = 1|h_t)w_t^1 + \Pr(s_t = 0|h_t) (aw_{t,\text{buy}}^0 + (1 - a)w_t^0) = \frac{1}{2}.$$

The other cases of semi-separating or pooling equilibria are analogous.³²

³²A natural restriction on the model is that $p_t^a \in (0, 1)$ and $p_t^b \in (0, 1)$. This is ensured as long as neither β or T is too large, as the following argument establishes. Prices can be guaranteed to lie between 0 and 1 by ensuring that $v_t^1 \in \left(\frac{\frac{1}{2}\beta}{1+\frac{2}{3}\beta}, \frac{1+\frac{1}{2}\beta}{1+\frac{2}{3}\beta}\right)$ and $v_t^0 \in \left(\frac{\frac{1}{6}\beta}{1+\frac{2}{3}\beta}, \frac{1+\frac{1}{6}\beta}{1+\frac{2}{3}\beta}\right)$. Note that for $\beta > 0$, both upper bounds are decreasing in β and both lower bounds are increasing in β . How far away v_t^1 and v_t^0 can get from a starting prior of $v_1 = \frac{1}{2}$, depends on the number of possible rounds of trade. In other words, the restriction on prices translates into a restriction on (β, T) : either β is not too large, or T is not too large. The more general analysis in Dasgupta and Prat [20] does not require this restriction.

Table I
Descriptive statistics

This table reports time-series averages of equal-weighted quarterly cross-sectional means and medians for the institutional managers included in the sample. The sample consists of quarterly observations for firms listed on NYSE, AMEX and NASDAQ, during the period 1983-2004. Each quarter, we compute the total number of managers reporting their holdings in each security; the mean and median value of managers' equity holdings; the aggregate value managed by all institutions. Portfolio turnover for manager j is calculated as the sum of the absolute values of buys and sells in stock i in a given quarter, divided by the value of the manager's stock holdings:

$$Turnover_t^j = \frac{\sum_i |n_t^{i,j} - n_{t-1}^{i,j}| p_t^i}{\sum_i n_t^{i,j} p_t^i}.$$

Year	Number of managers	Holdings per mgr		Aggregate stock holdings (\$mill)	Mkt share	Portf turnover	
		Mean (\$mill)	Median (\$mill)			Mean	Median
1983	640	762.19	257.55	487802.77	0.28	0.30	0.21
1985	768	854.08	261.46	655929.82	0.31	0.33	0.23
1987	881	851.33	225.29	750023.11	0.32	0.35	0.25
1989	937	1093.68	284.94	1024782.69	0.34	0.36	0.23
1991	1009	1331.40	291.49	1343385.12	0.36	0.31	0.20
1993	1044	1603.42	297.79	1673971.96	0.36	0.44	0.21
1995	1299	2049.37	299.68	2662130.78	0.42	0.35	0.24
1997	1461	3062.10	372.76	4473731.52	0.45	0.34	0.24
1999	1703	4386.91	405.83	7470913.92	0.47	0.39	0.25
2001	1751	3864.52	319.54	6766770.27	0.53	0.36	0.21
2003	2023	3581.46	309.92	7245302.93	0.56	0.37	0.23
Average	1,133	2,108.43	301.88				

Figure 2
 Cumulative two-year market adjusted return, by trading persistence

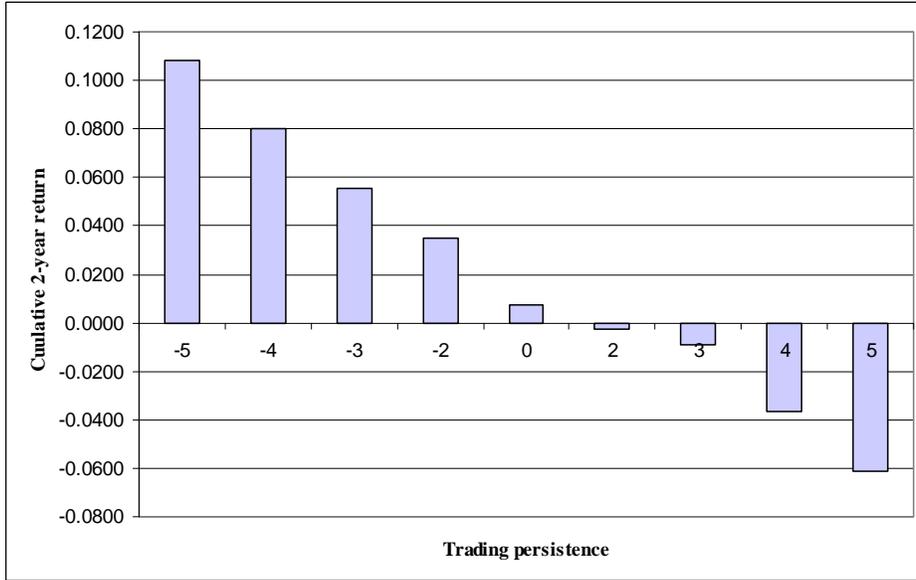


Figure 3
 Quarterly market-adjusted returns to trading persistence portfolios
 One to ten quarters after portfolio formation

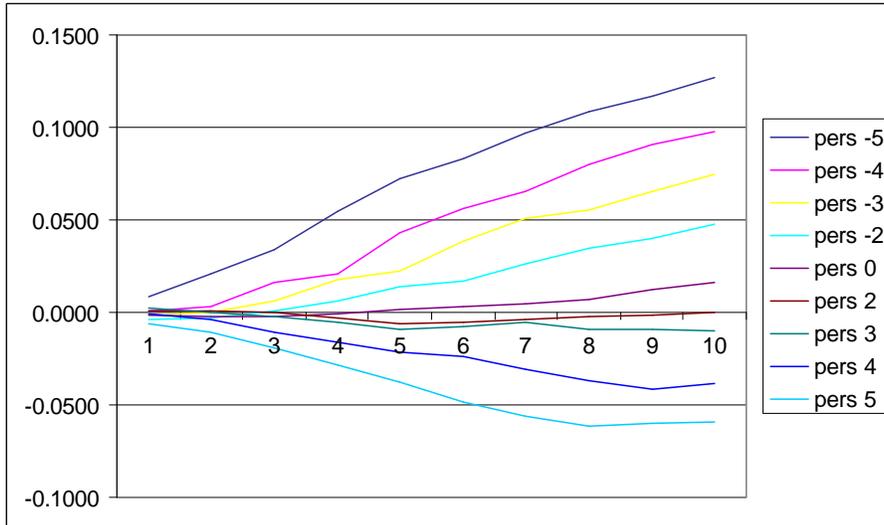


Table II
 Characteristics of portfolios based on trading persistence

This table presents time-series averages of equal-weighted quarterly cross-sectional means and medians for characteristics of persistence portfolios. Persistence is defined as the number of consecutive quarters for which we observe a net buy or a net sell for stock i . Net trade by institutional managers in security i is defined as the change in weight of security i in institutional investors' aggregate portfolio, from the end of quarter $t - 1$ to the end of quarter t : $d_{i,t} = \frac{S_{i,t} - S_{i,t-1}}{S_{i,t-1}}$, where $S_{i,t}$ is the institutional portfolio in quarter t for stock i . Net buys (sells) are stocks with a value of $d_{i,t}$ above (below) the cross-sectional median in each quarter t . Each quarter, stocks are assigned to different portfolios conditional on the persistence of institutional net trade. For example, a persistence measure of -3 indicates that a stock has been sold for three consecutive quarters, from $t-2$ to t . Persistence 0 includes stocks that have been bought or sold in t . The portfolio with persistence -5(5) includes stocks that have been sold (bought) for at least five consecutive quarters. Market cap is the market capitalization (\$ billions) measured at the end of quarter $t-1$. B/M is the book-to-market ratio measured at the end of quarter $t-1$; the book value is measured at the end of the previous fiscal year. Turnover is the monthly trading volume scaled by total shares outstanding, measured in the last month of quarter $t-1$; this measure is divided by two for Nasdaq stocks. Ownership is the number of shares held by institutional investors, divided by total shares outstanding. Past Ret is the quarterly equal-weighted return of the portfolio measured in the quarter prior to portfolio formation.

Persistence	N. stocks		Market Cap		B/M	Turn	Own	Past Ret
	Avg	Freq	Avg	Med	Avg	Avg	Avg	Avg
-5	160	0.037	855,397	37,381	1.06	0.45	0.21	-0.001
-4	136	0.031	1,041,765	60,422	1.08	0.49	0.23	-0.014
-3	256	0.059	1,065,765	72,142	0.97	0.52	0.25	-0.019
-2	514	0.118	1,039,411	85,867	0.88	0.53	0.26	-0.028
0	2220	0.511	1,021,318	90,738	0.74	0.53	0.28	0.037
2	498	0.115	953,024	130,213	0.63	0.58	0.30	0.107
3	250	0.058	882,471	151,822	0.56	0.63	0.31	0.109
4	134	0.031	933,862	177,346	0.53	0.69	0.33	0.111
5	174	0.040	1,037,566	220,110	0.47	0.76	0.36	0.111

Table III
Market-adjusted returns to trading persistence portfolios

This Table presents time-series averages of equal-weighted quarterly returns for portfolios of stocks ranked on institutional trading persistence. Returns are computed in event time, 1 to 10 quarters after portfolio formation. The returns are market-adjusted. Portfolio (-5,5) buys stocks that have been persistently sold and shorts stocks that have been persistently bought in quarters t-4 to t. Portfolio (-4,4) considers quarters t-3 to t, and Portfolio (-3,3) considers quarters t-2 to t. Returns are reported in percent per quarter. t-statistics are in parentheses.

Persistence	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
-5	0.84 (1.33)	1.23 (1.90)	1.31 (2.15)	2.05 (3.27)	1.77 (2.67)	1.11 (1.95)	1.39 (2.67)	1.15 (2.32)	0.85 (1.72)	1.00 (2.48)
-4	0.06 (0.10)	0.28 (0.62)	1.30 (2.91)	0.44 (0.92)	2.26 (3.93)	1.32 (2.58)	0.92 (1.77)	1.42 (2.99)	1.07 (2.03)	0.69 (1.23)
-3	-0.16 (-0.54)	0.18 (0.37)	0.60 (1.77)	1.16 (3.42)	0.47 (1.22)	1.61 (3.79)	1.22 (3.00)	0.48 (1.35)	0.99 (2.70)	0.90 (2.33)
-2	-0.39 (-1.56)	0.07 (0.29)	0.37 (1.04)	0.60 (2.29)	0.76 (3.25)	0.25 (0.86)	0.95 (2.72)	0.87 (2.80)	0.49 (1.85)	0.78 (2.82)
0	-0.17 (-2.02)	-0.08 (-0.81)	-0.01 (-0.13)	0.19 (1.44)	0.22 (1.55)	0.17 (1.07)	0.13 (0.80)	0.28 (1.62)	0.49 (2.71)	0.42 (2.15)
2	0.11 (0.57)	-0.03 (-0.14)	-0.11 (-0.52)	-0.32 (-1.38)	-0.24 (-1.03)	0.08 (0.34)	0.15 (0.68)	0.11 (0.47)	0.10 (0.39)	0.17 (0.84)
3	0.26 (0.75)	-0.23 (-0.75)	-0.30 (-0.87)	-0.30 (-1.04)	-0.32 (-1.16)	0.12 (0.39)	0.21 (0.68)	-0.36 (-1.15)	-0.02 (-0.06)	-0.08 (-0.33)
4	-0.04 (-0.10)	-0.36 (-0.78)	-0.66 (-1.63)	-0.57 (-1.56)	-0.55 (-1.31)	-0.24 (-0.61)	-0.62 (-1.35)	-0.63 (-1.91)	-0.52 (-1.41)	0.37 (0.90)
5	-0.63 (-1.26)	-0.43 (-0.92)	-0.83 (-1.85)	-0.93 (-2.12)	-0.92 (-2.20)	-1.14 (-2.55)	-0.73 (-1.65)	-0.51 (-1.33)	0.10 (0.24)	0.07 (0.18)
-5,5	1.47 (1.40)	1.66 (1.67)	2.15 (2.30)	2.98 (3.24)	2.69 (2.89)	2.25 (2.48)	2.12 (2.67)	1.67 (2.29)	0.75 (1.16)	0.92 (1.55)
-4,4	0.10 (0.11)	0.64 (0.81)	1.96 (2.78)	1.01 (1.42)	2.81 (3.45)	1.55 (2.08)	1.54 (1.86)	2.05 (3.31)	1.59 (2.32)	0.33 (0.47)
-3,3	-0.42 (-0.75)	0.41 (0.57)	0.89 (1.50)	1.46 (2.89)	0.79 (1.44)	1.48 (2.38)	1.00 (1.71)	0.85 (1.58)	1.01 (2.09)	0.98 (2.15)

Table IV

Average monthly returns to portfolio strategies based on persistence of institutional trading

This table presents average monthly returns from portfolios that buy stocks persistently sold for n quarters and short stocks that have been persistently bought for n quarters. Institutional trading persistence is measured over 5, 4, and 3 quarters. At the end of each quarter, $1/n$ of the portfolio is rebalanced for a holding period of n quarters. Holding periods are 3 months to 30 months. Raw returns are means of portfolio returns. CAPM alphas are estimated intercepts from the CAPM model. Fama-French + Momentum alphas are estimated intercepts from the Fama-French (1993) model inclusive of a momentum factor. Returns are reported in percent per month. Heteroskedasticity-consistent t -statistics are in parentheses.

Holding period	3 m	6 m	9 m	12 m	15 m	18 m	24 m	30 m
Raw returns								
Pers (-5,5)	0.56 (1.81)	0.56 (1.99)	0.60 (2.23)	0.65 (2.51)	0.67 (2.67)	0.66 (2.74)	0.63 (2.85)	0.56 (2.82)
Pers (-4,4)	0.18 (0.68)	0.19 (0.82)	0.38 (1.83)	0.36 (1.89)	0.43 (2.40)	0.43 (2.49)	0.42 (2.66)	0.38 (2.70)
Pers (-3,3)	0.02 (0.08)	0.10 (0.53)	0.15 (0.90)	0.23 (1.60)	0.22 (1.67)	0.25 (1.98)	0.26 (2.19)	0.26 (2.44)
CAPM alphas								
Pers (-5,5)	0.80 (2.49)	0.80 (2.81)	0.84 (3.11)	0.88 (3.39)	0.90 (3.72)	0.89 (3.89)	0.85 (4.17)	0.76 (4.26)
Pers (-4,4)	0.33 (1.17)	0.35 (1.33)	0.53 (2.37)	0.52 (2.61)	0.59 (3.01)	0.58 (3.18)	0.57 (3.50)	0.51 (3.75)
Pers (-3,3)	0.09 (0.49)	0.20 (1.12)	0.26 (1.43)	0.34 (2.21)	0.34 (2.54)	0.37 (2.75)	0.37 (3.13)	0.36 (3.49)
Fama-French alphas								
Pers (-5,5)	0.38 (1.30)	0.41 (1.69)	0.47 (2.06)	0.50 (2.40)	0.52 (2.63)	0.53 (2.82)	0.52 (3.07)	0.48 (3.10)
Pers (-4,4)	0.06 (0.23)	0.03 (0.14)	0.25 (1.29)	0.25 (1.46)	0.34 (2.03)	0.34 (2.11)	0.34 (2.41)	0.32 (2.48)
Pers (-3,3)	-0.03 (-0.13)	0.03 (0.15)	0.03 (0.22)	0.13 (0.98)	0.15 (1.26)	0.20 (1.65)	0.21 (2.00)	0.22 (2.32)
Fama-French+momentum alphas								
Pers (-5,5)	0.77 (2.45)	0.63 (2.30)	0.60 (2.28)	0.54 (2.30)	0.52 (2.38)	0.52 (2.46)	0.48 (2.55)	0.44 (2.59)
Pers (-4,4)	0.40 (1.43)	0.29 (1.28)	0.41 (1.97)	0.33 (1.80)	0.36 (2.01)	0.31 (1.88)	0.34 (2.15)	0.31 (2.18)
Pers (-3,3)	0.44 (1.59)	0.36 (1.63)	0.28 (1.58)	0.29 (1.92)	0.26 (1.88)	0.26 (1.89)	0.24 (1.95)	0.25 (2.18)

Figure 4-A
Cumulative two-year returns from strategy based on persistence (long pers=-5, short pers=5)
By NYSE market capitalization quintiles

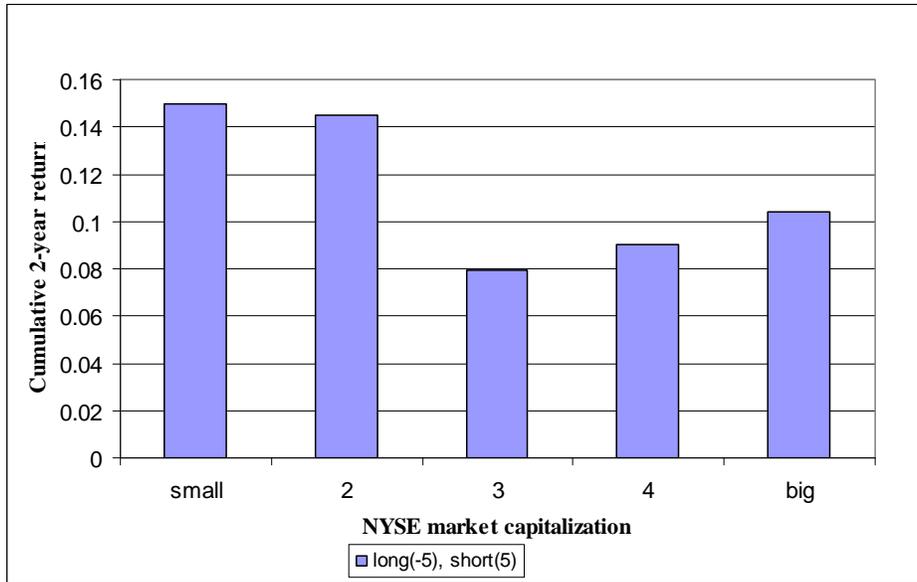


Figure 4-B
Cumulative two-year returns from strategy based on persistence (long pers=-5, short pers=5)
By Book-to-Market quintiles

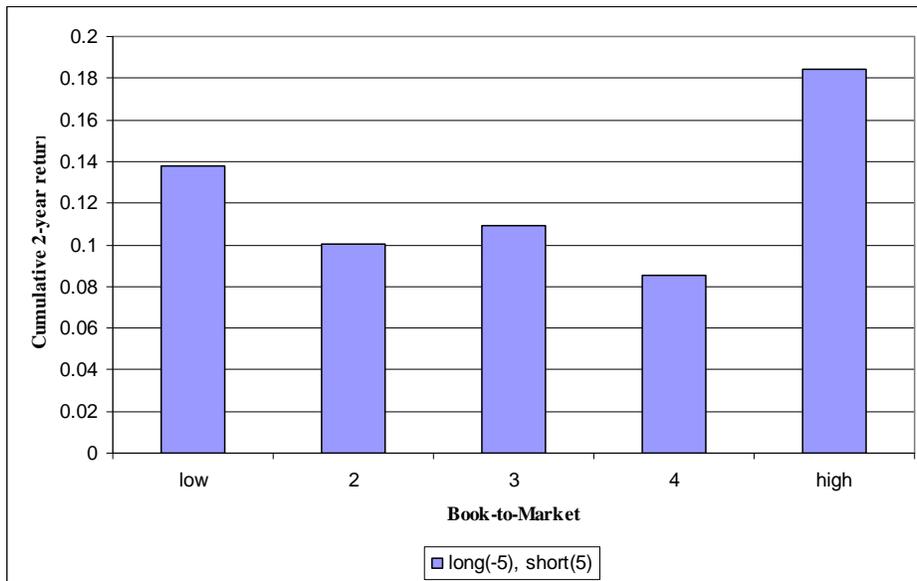


Figure 4-C
 Cumulative two-year returns from strategy based on persistence (long pers=-5, short pers=5)
 By past one-year return quintiles

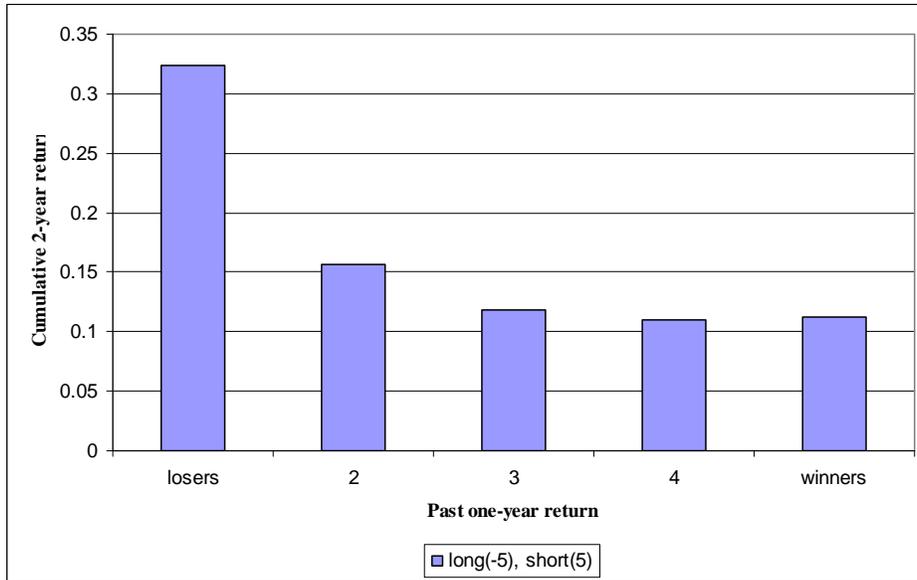


Figure 4-D
 Cumulative two-year returns from strategy based on persistence (long pers=-5, short pers=5)
 By sub-periods

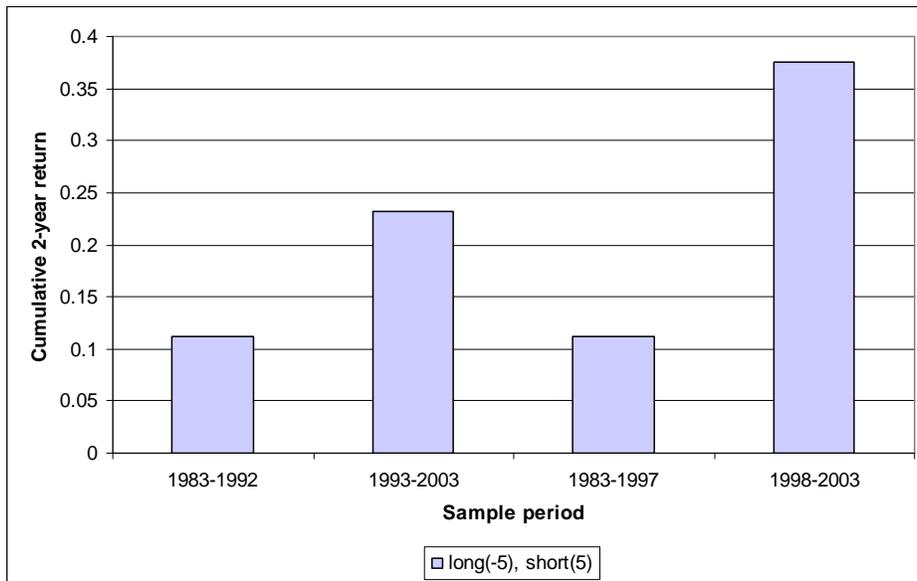


Table V
Cross-sectional predictive regressions

This table presents coefficient estimates from predictive regressions of cumulative two-year returns on past trading persistence, past returns, and control variables. $R_{i,t+1:t+8}$ is the two-year return for stock i , cumulated over quarters $(t + 1)$ to $(t + 8)$, where t is the quarter of portfolio formation. $dP_{i,t,p}$ is an indicator variable that equals 1 if stock i belongs to group p of trading persistence. Persistence is categorized as follows: group 1: pers= $(-5,-4)$; group 2: pers= $(-3,-2)$; group 3: pers= $(-1,1)$; group 4: pers= $(2,3)$; group 5: pers= $(4,5)$. $dR_{i,t,q}$ is an indicator variable that equals 1 if stock i belongs to quintile q of the cross-sectional distribution of past 12-quarter returns, $R_{i,t:t-n+1} \cdot cap_{i,t}$ is the quintile rank of market capitalization for stock i in quarter t . $bm_{i,t}$ is the quintile rank of Book-to-Market for stock i in quarter t . The panel regression is estimated with time fixed effects, and standard errors are clustered by firm. The Fama-MacBeth regression is estimated from quarterly cross-sectional regressions; coefficient estimates are averaged over time, and standard errors are adjusted for autocorrelation as in Newey-West (1987). t -statistics are in parentheses.

Dependent var: $R_{i,t+1:t+8}$	Panel regression	Fama-MacBeth regression
<i>Independent variables:</i>		
$dP_{i,t,1}$	0.0721 (6.03)	0.0552 (4.34)
$dP_{i,t,2}$	0.0257 (5.35)	0.0182 (3.67)
$dP_{i,t,4}$	-0.0100 (-2.20)	-0.0070 (-1.56)
$dP_{i,t,5}$	-0.0588 (-5.98)	-0.0433 (-5.10)
$dR_{i,t,1}$	0.1093 (8.60)	0.0899 (1.47)
$dR_{i,t,2}$	-0.0013 (-0.20)	-0.0074 (-0.43)
$dR_{i,t,4}$	0.0069 (1.11)	0.0066 (0.68)
$dR_{i,t,5}$	-0.0186 (-1.79)	-0.0196 (-0.77)
$cap_{i,t}$	-0.0388 (-10.03)	-0.0277 (-2.04)
$bm_{i,t}$	0.0171 (3.96)	0.0134 (0.87)
Fixed effects	yes	no
R^2	0.0258	0.0612

Figure 5A

Sheep Index
 $(\text{Prob}(\text{Buy if Pers} = 5) + \text{Prob}(\text{Sell if Pers} = -5))/2 - 1/2$

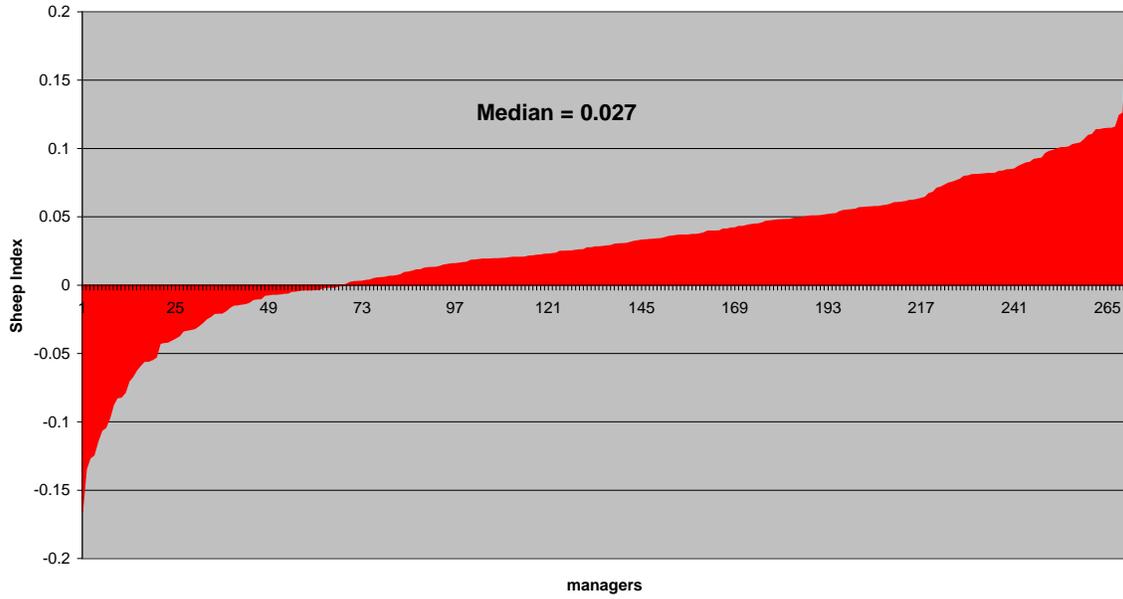


Figure 5B

Average Return from Trading like our Managers, by Persistence

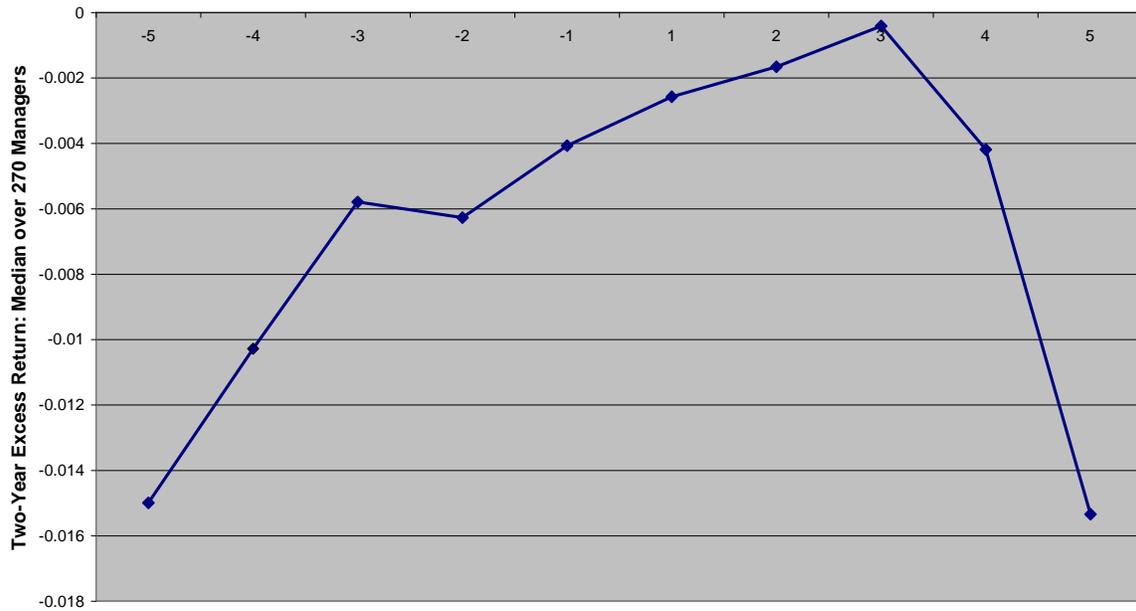


Table VI
Trading behavior of selected managers, and return from mimicking portfolios

Manager Name	Type	1995 Value (billions)	Buy if 5 (0,1)	Sell if -5 (0,1)	Sheep (-1,+1)	Return if 5 (-1,+8)
Wellington Management	4	150	0.53	0.69	0.114	-0.005
Barclays	1	531	0.56	0.64	0.103	-0.147
TIAA-CREF	2	165	0.59	0.61	0.100	-0.118
T. Rowe Price	4	107	0.57	0.63	0.100	-0.092
Northern Trust	1	121	0.56	0.60	0.082	-0.116
Mellon Bank	1	245	0.55	0.61	0.081	-0.094
Massachusetts Finl Svcs	3	136	0.56	0.60	0.080	0.000
Capital Research and Mgmt	3	227	0.39	0.73	0.059	-0.089
US Trust of New York	1	59	0.53	0.58	0.055	-0.092
Axa Financial	2	318	0.52	0.58	0.052	-0.064
AIM	3	124	0.52	0.57	0.048	-0.059
Fidelity	3	653	0.52	0.58	0.047	-0.045
Janus	3	256	0.53	0.56	0.047	-0.175
Putnam Investment Mgmt	4	298	0.52	0.56	0.039	-0.023
JP Morgan Chase	1	191	0.50	0.57	0.037	-0.045
Citigroup	2	218	0.53	0.54	0.036	-0.039
Bank One	1	84	0.52	0.55	0.034	-0.025
American Express Fin Adv	4	119	0.53	0.52	0.026	-0.085
Fayez Sarofim	4	48	0.59	0.46	0.025	-0.047
Zurich Scudder	4	96	0.51	0.51	0.009	-0.016
Median		157	0.53	0.58	0.050	-0.062

1: Banks; 2: Insurance companies; 3: Mutual funds; 4: Investment advisors; 5: Others

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