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ABSTRACT

Institutional Trade Persistence and Long-Term Equity Returns*

How does the trading behaviour of institutional money managers affect stock prices? In this paper we document a robust relationship between the net trade patterns of institutional money managers and long term equity returns. Examining 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 a similar magnitude to, but distinct from, other known asset pricing anomalies. Furthermore, we find that institutional investors show an aggregate tendency to trade in the direction of past institutional trades, buying stocks that have been persistently bought and selling stocks that have been persistently sold. We present a simple model of career-concerned trading by delegated portfolio managers that generates results consistent with our empirical findings.

JEL Classification: G1, G14 and G23
Keywords: career concerns, institutional investors, return predictability and trading behaviour

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1 Introduction

There is extensive anecdotal evidence that fund managers imitate the investment strategies of their peers. For example, when Nils Taube, widely considered to be the doyen of London fund managers, was recently asked about the secret to his exceptional track record (dating from 1969) he replied: "Plagiarism, of course" (Financial Times, 2006).

The unprecedented expansion of delegated portfolio management in recent decades has made money managers majority owners of corporate equity around the world.[1] Many commentators believe that the conformist behavior of institutional investors can generate 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]

In this paper we examine how the trading patterns of institutional money managers affect stock prices. We find a robust connection between the net trade of delegated portfolio managers and long-term equity returns. Our sample consists of quarterly observations on stock holdings of U.S. institutional portfolio managers with at least $100 million under management for the period 1983-2004. At the end of each quarter we measure the persistence of net trading by money managers for each stock, and test whether trading persistence has the ability to predict returns for individual stocks beyond the well known predictability coming from past returns and other stock characteristics. We also form portfolios based on institutional trading persistence, and track their performance over a period of ten quarters. We then test whether portfolio returns are significantly different across categories of trade persistence. Our findings are as follows:

1. The persistence of institutional trading has strong power in predicting the cross-section of stock returns at long horizons. The results from cross-sectional regressions show that buy

[1] On 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).

[2] Jean-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."

(sell) persistence negatively (positively) predicts individual stock 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 (1993, 2001), and DeBondt and Thaler (1985). The estimated coefficient associated with institutional trading persistence 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 consecutive quarters) and high-positive persistence stocks (bought for 4 or more consecutive quarters) is about 9 percentage points; the estimated two-year return differential between past losers (bottom quintile of past three-year return) and past winners (top return quintile) is about 12 percentage points.

2. Our portfolio analysis confirms that stocks that have been persistently sold by institutions for several quarters outperform stocks that have been persistently bought by them over a period of at least two years in the future. 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 quintile, we find a positive return differential between stocks with negative trade persistence and stocks with positive trade persistence. Using monthly portfolio returns calculated in calendar time, we estimate intercepts from time series regressions of the CAPM model, the Fama-French (1993) model, a four-factor model that includes the Carhart (1997) momentum factor, and a five-factor model augmented by Pastor and Stambaugh (2003) liquidity factor. The return differential between negative and positive institutional trading persistence remains important after adjusting for covariation with risk factors or characteristics. For example, considering a holding period of two years after portfolio formation, differences in monthly alphas between negative and positive persistence stocks can be as high as 96 basis points for an equally-weighted portfolio, and 54 basis points for a value-weighted portfolio.

3. We estimate the likelihood that institutions buy a stock conditional on the history of past institutional trading. We control for a number of stock characteristics that are likely to affect institutional trading decisions. Probit estimates show that the probability that a stock is

bought by institutions increases if the stock has been persistently bought by them in the past, and decreases if a stock has been persistently sold.

There are a number of potential explanations for the patterns we observe. The negative return predictability associated with institutional trading could be the result of a behavioral bias. For example, assume a scenario in which fund managers receive correlated informative signals about the value of an asset at different points in time. If the managers receiving "late" signals ignore the fact that they possess stale information and trade based on their signals, we would obtain the same trading patterns and price effects that we observe empirically.

Another possible explanation for our empirical results is that the trading patterns of money managers are driven by retail inflows and outflows. As shown in Braverman, Kandel and Wohl (2005), Frazzini and Lamont (2006), and Coval and Stafford (2006), these flows may be negative predictors of past returns. This represents an attractive resolution to the puzzle our results pose regarding institutional behavior. In order to examine whether retail flows can fully explain our results, we redo our analysis while excluding institutions that are likely more subject to inflows and outflows, like mutual funds. We find that our results remain qualitatively unchanged and of a similar order of magnitude,[3] suggesting that such flows cannot be the main driver of our aggregate results.

Furthermore, it is possible that the patterns of return predictability 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 (value-improving) takeover, thus raising the share price. Shares sold to or repurchased from institutions by insiders could constitute another example of such trade. While it is difficult to rule out this possibility given the available data, the acceptance of this theory amounts to a profoundly negative indictment of the fund management industry: for our findings to be explained in this manner, it must be the case that professional money managers trade, on average, against better informed

[3] The 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 portfolio with persistence -5 yields a market-adjusted two-year return of around 8%, while the portfolio with persistence $+5$ yields around -5%.

insiders, and are systematically unaware of this fact.

We explore theoretically the possibility that the behavior of fund managers is a consequence of their explicit or implicit compensation structures, which may generate perverse incentives. To formalize this explanation we build a simple model that captures the link between institutional incentives and asset prices in a way that is consistent with our findings. We summarize the model at an intuitive level here and develop the details in the appendix. The building blocks of our model can be traced back to the well-known model of reputational herding by Scharfstein and Stein (1990), which has been recently extended to a setting with endogenous prices by Dasgupta and Prat (2005). In our simplified version of Dasgupta and Prat's model, a number of career-concerned fund managers trade with rational traders over several periods before uncertainty over asset valuation is resolved. Fund managers receive a private signal about the liquidation value of the stock, and 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: (i) his negative realization is in contradiction with the positive realizations observed by his colleagues; (ii) this is probably due to the fact that his accuracy is low; and (iii) 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. Our theory, therefore, predicts a negative correlation between net trade between the institutional and individual sectors of the market and long term returns. This is consistent with our empirical conclusions.

Our empirical results are consistent with a nuanced view of the role of individuals and institutions in generating asset pricing anomalies. It is often argued that asset pricing anomalies originate from the behavioral biases of individual investors and cannot be completely eliminated due to the existence of limits to arbitrage (see, for example, Hirshleifer (2001) and Barberis and Thaler (2003)). Our results, however, leave open the possibility that the biases of individual investors and the actions of those to whom they delegate decisions can actually be *complementary* in generating anomalies. In line with this argument, Hirshleifer (2001) suggests that "...intermediaries have incentives to serve or exploit the irrationalities of potential clients. It is not obvious that layering agency over folly improves decisions."

The rest of the paper is organized as follows. In the next section we provide a brief discussion of related literature. Section 2 describes the data, and Section 3 contains our main empirical results. Section 4 presents some evidence of institutional trading behavior. Section 5 concludes. Details of the model are presented in the appendix.

1.1 Related Literature

Our paper is related to a number of recent empirical studies on the price impact of institutional trading. Wermers (1999) finds that stocks heavily bought by mutual funds outperform stocks heavily sold by them over a period of two quarters, and interprets this finding as evidence that institutional trading has a stabilizing effect on prices. Similarly, Sias (2003, 2004) shows that securities most heavily purchased by institutions tend to outperform securities most heavily sold by them and concludes that institutional trading pushes prices towards equilibrium values.[4] While these papers measure herding as the tendency by institutional managers to buy or sell the same

[4] Other papers finding evidence of a positive correlation between institutional demand and future returns include Nofsinger and Sias (1999), Sias, Starks and Titman (2001), Grinblatt, Titman and Wermers (1995). Cohen, Gompers and Vuolteenaho (2002) find a positive relationship between institutional ownership and future stock returns. Chen, Hong and Stein (2002) 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.

stocks at the same time, we focus on the conformist trading behavior of institutions over a longer period of time. In the section on portfolio analysis, we highlight the differences between our results and previous findings on the price impact of institutional herding.

Consistent with our results, several empirical papers find evidence of return reversals following trading by institutions. Braverman, Kandel and Wohl (2005), Frazzini and Lamont (2006), and Coval and Stafford (2006) find a negative relationship between net mutual fund flows and long-horizon returns. Dennis and Strickland (2002) find that stocks mostly owned by institutions experience return reversals during the six months following a large 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 (2006) examine herding by institutional investors for a sample of internet firms during the period 1998-2001. They document one-quarter reversals after institutional buy herding and one-quarter reversals after buy and sell herding cumulated over two quarters.[5]

Recent work investigates the trading behavior of individual investors and reports results that are somewhat complementary to ours. Kaniel, Saar, and Titman (2006) examine NYSE trading data by individual investors and find that individuals tend to trade as contrarians, buying after prices drop and selling after prices increase. Furthermore, they find that stocks heavily bought by individuals for a week experience positive excess returns over the following month, while stocks heavily sold by individuals experience negative excess returns. Hirshleifer et al. (2006) study individual trading around earnings announcements and show that individual investors do not cause the post-earnings announcement drift, suggesting the possibility that a subset of institutional investors generate the drift phenomenon because of behavioral biases or agency problems.[6]

Finally, while we do not explicitly examine 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 (1999) and more recently Dass, Massa, and Patgiri (2005) and Massa and Patgiri (2005)).

[5] Interestingly, Brunnermeier and Nagel (2004) show that the trading behavior of hedge funds allowed them 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.

[6] Barber and Odean (2006), on the other hand, show that individual investors tend to buy attention-grabbing stocks. They also find that stocks bought by individual investors on high-attention days tend to subsequently underperform stocks sold by those investors.

2 Data and descriptive statistics

The data 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.[7]

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.[8]

Each quarter, we compute the total number of managers reporting their holdings in each security, the value of their equity holdings, the aggregate value managed by all institutions, the share of the market that such value represents (as a share of the value of CRSP), and portfolio turnover. Table I reports cross-sectional summary statistics for these variables, measured in the last quarter of each sample year. Our sample consists of an average of 1,130 managers per quarter (varying from 640 to 2023). 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: $Turnover_t^j = \frac{\sum_i |n_t^{i,j} - n_{t-1}^{i,j}| p_t^i}{\sum_i n_t^{i,j} p_t^i}$.

We are interested in a measure of the aggregate net trade by institutional managers in a specific security. The number of shares of stock i that belong to the aggregate institutional portfolio at the end of quarter t is represented by

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

where $s_{i,j,t}$ is the number of shares of stock i held by manager j at the end of quarter t. We define institutional net trade in security i as the percentage change in $S_{i,t}$ taking place between quarter $t-1$ and quarter t:

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

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

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

Each quarter, we rank stocks on the basis of $d_{i,t}$ and define net buys as those stocks with a value of $d_{i,t}$ above the cross-sectional median, and net sells as those stocks with a value of $d_{i,t}$ below the median.[9]

The persistence of net trade is the number of consecutive quarters in which we observe a net buy or a net sell for stock i. This indicator of persistence is positive for net buys and negative for net sells. For example, a stock that has been bought in quarter t and quarter $t-1$ but has been sold in quarter $t-2$ has persistence 2, while a stock that has been sold in quarter t and quarter $t-1$ but has been bought in quarter $t-2$ has a trade persistence of -2. The maximum trade persistence assigned to a stock is 5 (-5), for stocks that have been bought (sold) for *at least* five consecutive quarters. Persistence values of 1 and -1 (for stocks bought or sold in quarter t only) are consolidated as persistence 0.

We measure trade persistence at the end of each quarter t. Table II illustrates the characteristics of stocks grouped into different persistence portfolios, calculated as time-series averages of cross-sectional statistics. Market capitalization, turnover, and book-to-market (B/M) are measured in the last month of quarter t. Past returns and institutional ownership are measured in 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 exchanges.[10] 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 descriptive statistics 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 suggests that institutional managers engage in momentum trading and is consistent with previous findings (Sias (2003)). 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

[9] This definition guarantees that, in every quarter, 50% of stocks are buys and 50% are sells. We obtain similar results if we classify net buys and net sells according to the sign of $d_{i,t}$. Furthermore, we experiment with alternative definitions of net trade, like the percentage change in the portfolio weight of stock i. The results do not change, and we therefore use the simpler measure $d_{i,t}$.

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

frequency of net consecutive buys (or sells) decreases with the number of quarters considered.

3 Trade persistence and the cross-section of stock returns

In this section we test the link between the persistence of institutional trading and stock returns. We first investigate the cross-sectional predictability of trading persistence at the individual stock level, by estimating Fama-MacBeth (1973) cross-sectional regressions of stock returns on past persistence, past returns, and other control variables.

We then investigate the predictability of institutional trading persistence at the portfolio level. After assigning stocks to portfolios based on institutional trading persistence, we track their returns in the following ten quarters and check whether these portfolio returns are significantly different across persistence categories. 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, and for different sub-periods in our sample. We then 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.

3.1 Regression analysis

In this section we investigate the association between trading persistence and future returns for an individual security. Table III presents estimates from predictive regressions of cumulative n–quarters market-adjusted returns on past trading persistence, controlling for past returns and other stock characteristics:

$$R_{i,t+1:t+n} = \alpha_0 + \sum_{p=1,2,4,5} \beta_p dP_{i,t,p} + \sum_{q=1,2,4,5} \gamma_q dR_{i,t,q} + \delta_0 Cap_{i,t} + \delta_1 BM_{i,t} + \delta_2 Own_{i,t} + \delta_3 Turn_{i,t} + \varepsilon_{i,t},$$

where the variables are defined as follows:

$R_{i,t+1:t+n}$ is the n-quarter market-adjusted return for stock i, cumulated over quarters $(t+1)$ to $(t+n)$;

$dP_{i,t,p}$ is an indicator variable that assumes the value 1 if stock i belongs to group p of trading persistence at the end of quarter t. 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, at the end of quarter t, stock i belongs to quintile q of the cross-sectional distribution of past m-quarter market-adjusted returns, $R_{i,t:t-m+1}$;
$Cap_{i,t}$ is the quintile rank of market capitalization for stock i at the end of quarter t;
$BM_{i,t}$ is the quintile rank of Book–to–Market for stock i at the end of quarter t;
$Own_{i,t}$ is the quintile rank of institutional ownership for stock i at the end of quarter t;
$Turn_{i,t}$ is the quintile rank of turnover for stock i at the end of quarter t.

Panel A of Table III shows coefficient estimates where future returns (dependent variable) are cumulated over periods of 4 or 8 quarters. Past returns (independent variable) are measured over three years.[11] The estimates are time-series averages of coefficients obtained from quarterly cross-sectional regressions, as in Fama-MacBeth (1973). The t-statistics are computed from standard errors that are adjusted for autocorrelation according to Newey-West (1987).[12]

The regression estimates provide strong evidence of return predictability associated with institutional trading persistence, beyond the well known predictability associated with past returns. After controlling for several stock characteristics like size, book-to-market, institutional ownership and turnover, we find that positive trading persistence tends to dampen future returns, while negative persistence significantly contributes to increasing returns over the next n quarters. 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. The coefficient estimates suggest that, compared to stocks that are median past performers, future two-year returns will be on average 7.9% higher for past losers, and 3.8% lower for past winners. Consider now the effect of trading persistence on return predictability after controlling for past returns and other stock characteristics. 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 4.4% higher, whereas stocks with positive trading persistence (4 or more quarters) earn future returns that are

[11] Varying the measurement period for past returns 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 (1985)).

[12] We also estimate panel regressions that include time fixed effects and allow for clustering of the standar errors by firm. Alternatively, we estimate the panel regression by including time and firm fixed effects, or by allowing for firm-quarter clusters. We present results for the Fama-MacBeth (1973) specification because it yields standard errors that are more conservative across all alternatives.

about 4.2% lower.

Different specifications of the regression model consistently show a strong and negative relationship between trading persistence and future returns. In Panel B of Table III the regressors are standardized with respect to their quarterly cross-sectional distribution. Future returns are measured over a two-year period, while past returns are measured over three years ($R_{i,t:t-11}$) or one year ($R_{i,t:t-3}$). The regression estimates confirm the negative link between trade persistence and the cross-section of future stock returns.

Panel C of table III shows regression estimates where the dependent variable is the non-overlapping one-quarter return measured n quarters after the measurement of the independent variables. The table shows two different specifications, where past returns are measured over one-year or three-year intervals. All regressors are standardized with respect to their quarterly cross-sectional distribution. The coefficient estimates suggest that trading persistence has a negative and significant impact on the returns of almost all future quarters during the two-year period considered. It is interesting to note that, as expected, past one-year returns have a positive impact on future returns for the first two quarters, and a negative impact on returns that are measured further out in the future.

3.2 Portfolio analysis

In this section we first provide a set of figures that informally illustrate the return patterns of portfolios based on institutional trading persistence. We then provide a formal test of the difference in portfolio returns across persistence categories by estimating average monthly returns in relation to various asset pricing models.

Figure 2 provides a first illustration of the link between trade persistence and future returns. The histogram shows equally-weighted market-adjusted returns to different trading persistence portfolios, 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.

Figure 3 shows market-adjusted returns in event time, cumulated 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. The graph

illustrates that stocks that have been persistently sold by institutions outperform stocks that have been persistently bought by them. The difference in returns between the portfolios of longer trading persistence (-5,5) is about 1.5% in the first quarter after portfolio formation, and reaches 3% in the 4th quarter. It then starts to slowly decline afterwards, but is still positive eight quarters after portfolio formation (1.67%). The returns of the long-short portfolios based on shorter persistence (-4,4 and -3,3) are smaller in magnitude but follow similar patterns.

To the extent that institutions tend to buy growth stocks 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 (1993, 2001), DeBondt and Thaler (1985)). We provide a first set of robustness tests by plotting two-year, market-adjusted returns to buying stocks persistently sold for 5 quarters and selling stocks persistently bought for 5 quarters. We partition our sample into quintiles based on NYSE market capitalization, book-to-market, and past one-year returns. Within each quintile, we compute return differentials between portfolios of stocks with sell persistence and portfolios of stocks with buy persistence. These return differentials are positive in all sub-samples, and particularly large for small stocks, value stocks, and past losers, as illustrated in Figures 4A, 4B and 4C.

Figure 4D shows two-year cumulative return differentials between portfolios of stocks with 5-quarter negative and positive 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 1993-2004, 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 can be as high as 35%.[13]

We turn now to formally testing the economic and statistical importance of the return differential between portfolios characterized by different trading persistence. We estimate one-factor and multi-factor regressions for the monthly return differentials between negative and positive persistence

[13] The model presented in the appendix of the 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 2004). The phenomenon could also be due to the presence of stronger career concerns, exemplified by an increase of the parameter β in our model.

stocks. We consider the CAPM model, the Fama-French (1993) model, and the four-factor model that includes Carhart (1997) momentum factor. Furthermore, we augment the four-factor model by including Pastor and Stambaugh (2003) liquidity factor.

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, a fraction $1/k$ of the portfolio is rebalanced every quarter. We then present results for differences in average monthly returns between stocks that have been sold for 5, 4, or 3 quarters before portfolio formation and stocks that have been bought for 5, 4, and 3 quarters. Table IV, Panel A reports the estimated intercepts from time-series multifactor regressions of equally-weighted portfolios. The results show that the intercepts are economically large and statistically significant for all pricing models. For example, for a holding period of two years, alphas range from 29 basis points to 96 basis points per month depending on the number of quarters over which trade persistence is measured. Panel B of Table IV shows intercept estimates for value-weighted portfolios. The intercepts are now smaller, indicating the presence of a size effect. However, they are still large and significant for portfolios with institutional trade persistence of three consecutive quarters.

Our findings are not inconsistent with studies that document a positive relationship between institutional herding and future stock returns. Wermers (1999) 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 (2004) finds that the fraction of institutions buying a stock is (weakly) positively correlated with returns in the following one to four quarters.[14] In this paper we focus on *long horizon* predictability, and we condition on the *persistence* of institutional net trading over a number of periods rather than on the measure of one-period herding that is widely adopted in the literature (Lakonishok, Shleifer and Vishny (1992)).

We partially compare our results to Wermers (1999) using our data on institutional managers. We first 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

[14] Sias (2003) reports that trading by money managers 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.

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 (the sample period studied in Wermers (1999) is 1975-1994), 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.

4 An analysis of institutional trading behavior

In this section we examine the trading behavior of institutional investors and investigate the aggregate tendency of institutions to exhibit conformist trading patterns. In particular, we estimate the extent to which past trades affect institutions' decision to buy a stock in the future. Using probit analysis, we estimate the likelihood that institutions buy stock i in quarter $t+1$, conditional on the persistence of institutional net trades and on various stock characteristics measured at the end of quarter t. The model specification is as follows:

$$Prob(b_{i,t+1} = 1 \mid \Omega_t) = \Phi(\alpha_0 + \beta Pers_{i,t} + \gamma Ret_{i,t} + \delta_0 Cap_{i,t} + \delta_1 BM_{i,t} + \delta_2 Own_{i,t} + \delta_3 Turn_{i,t}),$$

where $b_{i,t+1}$ is an indicator variable that equals one if stock i is an institutional net buy in quarter $t+1$ and zero otherwise, Φ is the cumulative normal distribution function, and Ω_t is the information set at time t.[15]

Table V shows the coefficient estimates from the probit model, as well as the estimated marginal effects averaged over all observations in the sample.[16] In Panel A both institutional trading persistence and past returns are defined as dummy variables that equal one if stock i belongs to a specific quintile of its cross-sectional distribution. $dP_{i,t,3}$ is the omitted category of persistence. $dP_{i,t,1}$ and $dP_{i,t,2}$ represent negative past persistence (persistent selling behavior by institutions)

[15] Recall that institutional net trade in security i is defined as the percentage change in the number of shares owned by institutions as an aggregate ($S_{i,t}$) taking place between quarter $t-1$ and quarter t: $d_{i,t} = \frac{S_{i,t}-S_{i,t-1}}{S_{i,t-1}}$. Each quarter, we rank stocks on the basis of $d_{i,t}$ and define net buys as those stocks with a value of $d_{i,t}$ above the cross-sectional median, and net sells as those stocks with a value of $d_{i,t}$ below the median.

[16] The coefficients from the probit model cannot be directly interpreted as marginal effects on the dependent variable. The marginal effect of independent variable X_k on the conditional probability that institutions buy stock i is given by: $\partial\Phi(X_i'\beta)/\partial X_{ik} = \phi(X_i'\beta)\beta_k$, where β_k is the coefficient estimate corresponding to X_k.

while $dP_{i,t,4}$ and $dP_{i,t,5}$ represent persistent buying behavior.[17] The regression estimates show that the probability of a positive institutional net trade increases if a stock was persistently bought by institutions and decreases if a stock was persistently sold by them. The effect of past returns reflects momentum trading by institutions: the probability that institutional investors increase their ownership of a stock is positively related to a stock's past returns.

Panel B of Table V shows results from a model where the regressors are standardized with respect to their cross-sectional mean and variance. Consistent with the previous specification, the persistence of past trades is positively associated with the probability of a net institutional buy in the future.

We interpret these findings as evidence that institutions, as an aggregate, tend to engage in conformist behavior. Adding to the existing evidence that institutions tend to herd, in the sense that they tend to buy or sell the same stocks at the same time, we show that institutions' trading decisions are affected by the past history of trades.[18]

Unfortunately, the information in our sample does not allow us to estimate profits and losses that derive from the trading decisions of institutional investors. We only observe changes in disclosed share ownership at a quarterly frequency, and are unable to observe interim trades. Therefore, the exact holding period for any particular security in the institutional portfolio is unknown. Since the timing of trading is an endogenous decision by institutional managers, we cannot rely on end-of-quarter disclosures of holdings to accurately compute their portfolio returns. Moreover, we do

[17] The five dummy variables are defined 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);

[18] As our goal is to study the market effect of institutional trade, our analysis is carried out at an aggregate level. However, we also analyze the trades of a small group of institutions to assess whether the persistence in trading behavior uncovered in the aggregate sample is driven by a fraction of institutional managers. We compute the frequency with which institutions imitate past trade when faced with a high-persistence stock. We restrict our sample to include the 270 managers with valid share ownership data in each quarter of the period 1995-2004. For each manager j and quarter t, we construct the following measure of trading behavior:

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

where persistence is defined with respect to the trading behavior of all managers in the sub-sample. The variable $sheep_{j,t}$ varies between $-\frac{1}{2}$ and $\frac{1}{2}$, and equals zero if a manager trades independently of the past history of trades. We then compute $sheep_j$, the time-series average of $sheep_{j,t}$ for each manager j. We find that about three quarters of institutions display a tendency to buy (sell) stocks persistently bought (sold) in the last 5 quarters. This finding suggests that our measure of trading behavior is pervasive in our sub-sample, with the majority of managers displaying a positive *sheep* value. This result is, however, not an accurate measure of conformist behavior since this analysis does not take into account institutions' preferences for specific stock characteristics.

not observe inflows and outflows into specific funds. For these reasons, attempting to estimate the performance of the institutional portfolio based on disclosed holdings would not allows us to draw reliable inference on the performance of the institutional portfolio conditional on trading persistence.

5 Conclusion

In this paper we have examined the link between the conformist trading behavior of institutional investors and asset prices. Under a variety of formulations, we have found that stocks that are persistently sold by institutions outperform stocks that are persistently bought by them. This is true whether we focus on the returns of portfolios formed on the basis of 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.

Furthermore, we have documented that the trading decisions of institutional investors in the aggregate depend on the history of past trades. Institutions tend to buy stocks that have been persistently bought by them in the past and sell stocks that have been persistently sold, after controlling for stock characteristics.

Our empirical findings are consistent with a simple model of career-concerned trading by institutions (detailed in the Appendix), which in turn captures ideas discussed by a number of authors, including Scharfstein and Stein (1990) and Dasgupta and Prat (2005). However, as we have discussed in the introduction, our empirical evidence could potentially be consistent with a number of other explanations.

There is now a small but growing theoretical literature on the perverse effect of agency conflicts on the properties of financial equilibrium.[19] Our results leave the possibility open that institutional incentives may contribute towards the creation and persistence of asset pricing anomalies. We hope that our findings will encourage further work on the link between institutional incentives and asset prices.

[19] Other recent papers that consider the agency theoretic implications of asset pricing include Allen and Gorton (1993), Ou-Yang (2005), Dow and Gorton (1997), He and Krishnamurthy (2006), and Gorton, He, and Huang (2005).

6 Appendix: A Model of Reputational Premia

In this section, we provide a simple model of career-concerned trading by managers to formalize the ideas sketched in the introduction. Our model is a much simplified version of the dynamic agency model of Dasgupta and Prat (2005). It 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 (1985).[20] 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.[21] The manager has three choices: he can buy one unit of the asset from the MM ($a_t = 1$), sell one unit of the asset to the MM ($a_t = 0$), or not trade ($a_t = \varnothing$). 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.[22]

The key assumption here is that the market maker is a monopolist. In Glosten and Milgrom (1985) 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.[23]

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.[24] 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:

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

The reputational benefit is given by the posterior probability (at $T + 1$) that the manager is smart

[20] For an in-depth discussion of this class of models, see Brunnermeier (2001).

[21] Formally, our model has features of both Glosten and Milgrom (1985), which is a multi-period model with a competitive market maker, and Copeland and Galai (1983) 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.

[22] The no-trade penalty assumption is discussed below (see also footnote 26).

[23] Obviously, 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.

[24] Dasgupta and Prat (2005) 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.

given his actions and the liquidation value:

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

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

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

This is equivalent to assuming that the manager is able to signal a credible reason not to trade.[25] 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.[26]

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 $v_t = E\left[v|h_t\right]$, denote the public expectation of v. Finally, let $v_t^0 = E\left[v|h_t, s_t = 0\right]$ and $v_t^1 = E\left[v|h_t, s_t = 1\right]$ 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

$$v_t^1 = \frac{3v_t}{2v_t + 1} \text{ and } v_t^0 = \frac{v_t}{3 - 2v_t}$$

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:

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

$$w_t^1 = E_v[\gamma(a_t = 1)|s_t = 1, v] \text{ and } w_t^0 = E_v[\gamma(a_t = 0)|s_t = 0, v]$$

[25] The model of reputational premia in Dasgupta and Prat (2005) does not require this restriction. For a micro-founded model of incentives to trade, and the reputational effect of not trading, see Dasgupta and Prat (2006).

[26] However, 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.

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

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: 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 $s_t = 1$. His expected equilibrium 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

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

Note that

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

The expected payoff can then be re-written as

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

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.[27] 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

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

probability $a \in (0,1]$ if $s_t = 0$. The ask price must satisfy

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

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,

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

The bid price must satisfy

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

The expected profit of the MM is then

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

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

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

The other cases of semi-separating or pooling equilibria are analogous.[28]

6.1 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.[29]

[28] A natural restriction on the model is that $p_t^a \in (0,1)$ and $p_t^b \in (0,1)$. This holds as long as neither β or T is too large The analysis in Dasgupta and Prat [13] does not require this restriction.

[29] As in Glosten and Milgrom (1985), 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 establish that

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

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.

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

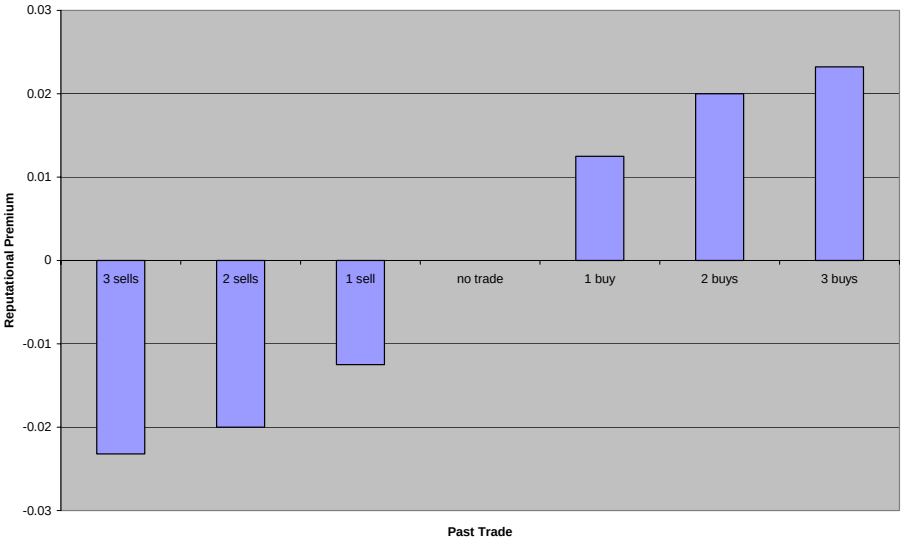
$$\Pr(v = 1|s_1 = ... = s_n = 1) = \frac{3^n}{3^n + 1}$$

and the reputational premium is

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

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

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.



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.*

Our result that the reputational premium is monotonic in past trade is consistent with the empirical results presented earlier: 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. As we have noted at various points, many of our assumptions are made for tractability, and are not necessary to generate the results. For a more general analysis of sequential trade with career concerns, including a discussion of the core set of assumptions, we refer interested readers to Dasgupta and Prat (2005).

Table I
Descriptive statistics

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, and the share of market value (CRSP) represented by the aggregate institutional portfolio. 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: $Turnover_t^j = \frac{\sum_i \left| n_t^{i,j} - n_{t-1}^{i,j} \right| p_t^i}{\sum_i n_t^{i,j} p_t^i}$. This table reports summary statistics for the last quarter of each year in the sample.

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
1984	692	704.73	217.93	487677.15	0.29	0.29	0.19
1985	768	854.08	261.46	655929.82	0.31	0.33	0.23
1986	809	918.17	266.37	742798.99	0.32	0.34	0.24
1987	881	851.33	225.29	750023.11	0.32	0.35	0.25
1988	882	947.19	248.48	835419.52	0.33	0.26	0.18
1989	927	1093.68	284.94	1024782.69	0.34	0.36	0.23
1990	976	998.08	234.83	974126.25	0.34	0.27	0.17
1991	1009	1331.40	291.49	1343385.12	0.36	0.31	0.20
1992	1098	1425.03	285.46	1564683.92	0.38	0.28	0.19
1993	1044	1603.42	297.79	1673971.96	0.36	0.44	0.21
1994	1135	1619.14	281.58	1837720.73	0.40	0.29	0.20
1995	1299	2049.37	299.68	2662130.78	0.42	0.35	0.24
1996	1307	2508.74	327.86	3278919.42	0.43	0.50	0.24
1997	1461	3062.10	372.76	4473731.52	0.45	0.34	0.24
1998	1629	3540.10	345.03	5766823.79	0.47	0.40	0.25
1999	1703	4386.91	405.83	7470913.92	0.47	0.39	0.25
2000	1899	3989.36	324.21	7575795.05	0.53	0.39	0.25
2001	1751	3864.52	319.54	6766770.27	0.53	0.36	0.21
2002	1912	2988.33	231.20	5713681.95	0.58	0.42	0.21
2003	2023	3581.46	309.92	7245302.93	0.56	0.37	0.23
2004	2056	4078.51	335.25	8385418.26	0.64	0.30	0.20
Average	1,133	2,108.43	301.88				

Table II
Characteristics of portfolios based on institutional trade persistence

This table reports time-series averages of quarterly cross-sectional means and medians for characteristics of portfolios based on institutional trade persistence . Trade persistence is defined as the number of consecutive quarters for which we observe a net institutional buy or a net institutional sell for stock i. Net buys have positive persistence and net sells have negative persistence. Net trade by institutional managers in security i is defined as the change in the number of shares of security i in the 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 number of shares of stock i in the institutional portfolio in quarter t. Net buys (sells) are stocks with a value of $d_{i,t}$ above (below) the cross-sectional median in quarter t. At the end of each quarter t, stocks are assigned to different portfolios conditional on the persistence of institutional net trade. Persistence 0 includes stocks that have been bought or sold in quarter t. The portfolio with persistence -5 (5) includes stocks that have been sold (bought) for at least five consecutive quarters. Market cap is the stock's market capitalization ($ thousands) measured at the end of quarter t. NYSE is the average NYSE decile of market capitalization to which a stock belongs; B/M is the book-to-market ratio measured at the end of quarter t; 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; this measure is divided by two for Nasdaq stocks. Ownership is the number of shares held by institutional investors divided by total shares outstanding, measured in quarter t. Past Ret is the quarterly equal-weighted return of the portfolio measured in quarter t.

Persistence	**N. stocks**		**Market Cap**		**NYSE**	**B/M**	**Turn**	**Own**	**Past Ret**
	Avg	Freq	Avg	Med	Avg	Avg	Avg	Avg	Avg
-5	160	0.037	855,397	37,381	2.72	1.06	0.45	0.21	-0.022
-4	136	0.031	1,041,765	60,422	3.07	1.08	0.49	0.23	-0.027
-3	256	0.059	1,065,765	72,142	3.26	0.97	0.52	0.25	-0.032
-2	514	0.118	1,039,411	85,867	3.43	0.88	0.53	0.26	-0.034
0	2220	0.511	1,021,318	90,738	3.58	0.74	0.53	0.28	-0.005
2	498	0.115	953,024	130,213	3.79	0.63	0.58	0.30	0.035
3	250	0.058	882,471	151,822	3.92	0.56	0.63	0.31	0.039
4	134	0.031	933,862	177,346	4.02	0.53	0.69	0.33	0.041
5	174	0.040	1,037,566	220,110	4.32	0.47	0.76	0.36	0.038

Table III: Panels A and B
Cross-sectional predictive regressions of stock returns

This table reports coefficient estimates from predictive regressions of cumulative n-quarter market-adjusted returns ($R_{i,t+1:t+n}$, where n = 8 or 4), on past trading persistence, past returns, and control variables. PANEL A: $dP_{i,t,p}$ 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, $R_{i,t:t-12+1}$. $cap_{i,t}$ 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. PANEL B: All independent variables in Panel B are standardized with respect to their quarterly cross-sectional distribution. $P_{i,t}$ is the standardized persistence measure, $R_{i,t:t-m}$ is the past (m+1)-quarter return, $cap_{i,t}$ is market capitalization, $bm_{i,t}$ is book-to-market, $own_{i,t}$ is institutional ownership, and $turn_{i,t}$ is stock i's turnover. The estimates are obtained from quarterly cross-sectional regressions and then averaged over time, as in Fama-MacBeth (1973). Standard errors are adjusted for autocorrelation as in Newey-West (1987). t-statistics are in parentheses.

Panel A

Dependent Variable	$R_{i,t+1:t+8}$	$R_{i,t+1:t+4}$
Indep. Variables		
$dP_{i,t,1}$	0.0444	0.0218
	(3.78)	(2.96)
$dP_{i,t,2}$	0.0118	0.0039
	(2.37)	(0.78)
$dP_{i,t,4}$	-0.0056	0.0036
	-(1.36)	(0.98)
$dP_{i,t,5}$	-0.0421	-0.0148
	-(5.11)	-(2.40)
$dR_{i,t,1}$	0.0793	0.0249
	(1.42)	(0.77)
$dR_{i,t,2}$	-0.0102	-0.0087
	-(0.64)	-(0.86)
$dR_{i,t,4}$	0.0039	-0.0004
	(0.40)	-(0.07)
$dR_{i,t,5}$	-0.0378	-0.0236
	-(1.38)	-(1.29)
$cap_{i,t}$	-0.0275	-0.0089
	-(2.00)	-(1.10)
$bm_{i,t}$	0.0149	0.0087
	(1.08)	(0.99)
$own_{i,t}$	-0.0155	-0.0068
	-(1.50)	-(1.12)
$turn_{i,t}$	0.0197	0.0055
	(1.27)	(0.59)

Panel B

Dependent Variable	$R_{i,t+1:t+8}$	$R_{i,t+1:t+8}$
Indep. Variables		
$P_{i,t}$	-0.0195	-0.0155
	-(7.52)	-(4.57)
$R_{i,t:t-3}$	-0.0338	
	-(1.75)	
$R_{i,t:t-11}$		-0.0477
		-(1.95)
$cap_{i,t}$	-0.0569	-0.0378
	-(2.47)	-(1.80)
$bm_{i,t}$	0.0562	0.0411
	(2.02)	(1.76)
$own_{i,t}$	-0.0081	-0.0159
	-(0.75)	-(1.53)
$turn_{i,t}$	0.0158	0.0304
	(0.78)	(1.25)

Table III: Panel C

This table reports coefficient estimates from predictive regressions of non-overlapping quarterly market-adjusted returns measured in quarters 1 to 8 (R_{Q1} to R_{Q8}) after the measurement of the independent variables. The independent variables are standardized with respect to their quarterly cross-sectional distribution. $P_{i,t}$ is the standardized measure of trading persistence; $R_{i,t:t-m}$ is the past (m+1)-quarter return, $cap_{i,t}$ is market capitalization, $bm_{i,t}$ is book-to-market, $own_{i,t}$ is institutional ownership, and $turn_{i,t}$ is stock i's turnover. The estimates are obtained from quarterly cross-sectional regressions and then averaged over time, as in Fama-MacBeth (1973). Standard errors are adjusted for autocorrelation as in Newey-West (1987). t-statistics are in parentheses.

	R_{Q1}	R_{Q2}	R_{Q3}	R_{Q4}	R_{Q5}	R_{Q6}	R_{Q7}	R_{Q8}
$P_{i,t}$	-0.0023	-0.0019	-0.0033	-0.0026	-0.0032	-0.0016	-0.0016	-0.0013
	-(2.31)	-(2.17)	-(3.38)	-(3.45)	-(4.02)	-(1.99)	-(1.80)	-(1.62)
$R_{i,t:t-3}$	0.0108	0.0064	0.0000	-0.0047	-0.0053	-0.0077	-0.0089	-0.0092
	(3.13)	(1.88)	-(0.01)	-(1.52)	-(1.65)	-(2.36)	-(2.75)	-(3.10)
$cap_{i,t}$	-0.0053	-0.0055	-0.0068	-0.0070	-0.0048	-0.0051	-0.0047	-0.0050
	-(1.48)	-(1.63)	-(1.88)	-(1.95)	-(1.38)	-(1.47)	-(1.36)	-(1.50)
$bm_{i,t}$	0.0089	0.0046	0.0031	0.0034	0.0082	0.0050	0.0046	0.0005
	(2.92)	(1.80)	(1.08)	(1.11)	(2.38)	(1.27)	(1.15)	(0.13)
$own_{i,t}$	0.0046	0.0033	0.0025	0.0020	0.0007	0.0005	0.0005	-0.0002
	(2.14)	(1.59)	(1.31)	(1.08)	(0.39)	(0.25)	(0.24)	-(0.13)
$turn_{i,t}$	-0.0051	-0.0051	-0.0038	-0.0002	0.0018	0.0026	0.0020	0.0062
	-(1.52)	-(1.34)	-(1.07)	-(0.04)	(0.51)	(0.78)	(0.65)	(1.31)

	R_{Q1}	R_{Q2}	R_{Q3}	R_{Q4}	R_{Q5}	R_{Q6}	R_{Q7}	R_{Q8}
$P_{i,t}$	-0.0003	-0.0010	-0.0021	-0.0019	-0.0027	-0.0022	-0.0025	-0.0021
	-(0.25)	-(1.08)	-(2.21)	-(2.54)	-(3.20)	-(2.78)	-(2.90)	-(2.34)
$R_{i,t:t-11}$	-0.0024	-0.0047	-0.0066	-0.0069	-0.0061	-0.0037	-0.0032	-0.0019
	-(0.69)	-(1.30)	-(1.89)	-(2.03)	-(1.85)	-(1.17)	-(1.16)	-(0.72)
$cap_{i,t}$	-0.0034	-0.0034	-0.0044	-0.0051	-0.0033	-0.0041	-0.0036	-0.0046
	-(0.99)	-(1.07)	-(1.29)	-(1.52)	-(1.02)	-(1.28)	-(1.13)	-(1.42)
$bm_{i,t}$	0.0024	-0.0013	-0.0008	0.0016	0.0060	0.0046	0.0056	0.0016
	(0.87)	-(0.49)	-(0.30)	(0.56)	(2.13)	(1.56)	(1.48)	(0.58)
$own_{i,t}$	0.0005	0.0002	-0.0002	0.0005	-0.0005	0.0006	0.0002	0.0000
	(0.23)	(0.08)	-(0.10)	(0.26)	-(0.24)	(0.29)	(0.12)	-(0.02)
$turn_{i,t}$	0.0002	-0.0016	-0.0001	0.0020	0.0040	0.0023	0.0025	0.0044
	(0.08)	-(0.44)	-(0.04)	(0.56)	(1.09)	(0.68)	(0.76)	(0.92)

Table IV: Panel A
Equally-weighted return differentials between portfolios of negative and positive institutional trade persistence

This table reports average monthly return differentials between portfolios of stocks persistently sold by institutions for n quarters and portfolios of stocks persistently bought by institutions for n quarters $(-n, n)$. Portfolios are equally-weighted. Institutional trade persistence is measured over 3, 4, and 5 or more quarters. Holding periods are 3 months to 30 months. Return differentials are estimated as intercepts (alphas) from the following multifactor models: the CAPM model; the three-factor Fama-French (1993) model; the four-factor model represented by the Fama-French model augmented by Carhart (1997) momentum factor; the five-factor model represented by the four-factor model augmented by Pastor and Stambaugh (2003) liquidity factor. Estimates are reported in percent per month. t-statistics are in parentheses.

Holding period	**3 m**	**6 m**	**9 m**	**12 m**	**15 m**	**18 m**	**24 m**	**30 m**
CAPM alphas								
Pers (-5,5)	0.97	0.98	1.00	1.02	1.02	1.01	0.96	0.87
	(3.52)	(3.90)	(4.29)	(4.63)	(4.88)	(5.06)	(5.30)	(5.33)
Pers (-4,4)	0.41	0.48	0.63	0.60	0.67	0.66	0.64	0.60
	(1.74)	(2.29)	(3.45)	(3.66)	(4.29)	(4.40)	(4.83)	(5.08)
Pers (-3,3)	0.20	0.29	0.35	0.42	0.41	0.44	0.43	0.42
	(0.98)	(1.73)	(2.42)	(3.33)	(3.59)	(4.04)	(4.45)	(4.81)
Fama-French alphas								
Pers (-5,5)	0.59	0.62	0.66	0.68	0.68	0.69	0.67	0.61
	(2.21)	(2.56)	(2.95)	(3.25)	(3.47)	(3.68)	(3.91)	(3.98)
Pers (-4,4)	0.16	0.19	0.38	0.36	0.45	0.44	0.44	0.42
	(0.69)	(0.94)	(2.13)	(2.28)	(2.98)	(3.06)	(3.48)	(3.75)
Pers (-3,3)	0.11	0.14	0.16	0.24	0.24	0.28	0.29	0.29
	(0.50)	(0.80)	(1.11)	(1.95)	(2.22)	(2.71)	(3.09)	(3.49)
Four-factor alphas								
Pers (-5,5)	1.03	0.91	0.85	0.78	0.74	0.72	0.65	0.58
	(4.31)	(3.95)	(3.88)	(3.72)	(3.68)	(3.75)	(3.73)	(3.67)
Pers (-4,4)	0.53	0.49	0.58	0.49	0.53	0.47	0.47	0.43
	(2.47)	(2.62)	(3.42)	(3.16)	(3.50)	(3.23)	(3.63)	(3.74)
Pers (-3,3)	0.54	0.47	0.41	0.41	0.38	0.38	0.34	0.33
	(3.21)	(3.30)	(3.31)	(3.68)	(3.57)	(3.65)	(3.61)	(3.92)
Five-factor alphas								
Pers (-5,5)	1.04	0.92	0.86	0.79	0.75	0.73	0.66	0.59
	(4.34)	(3.97)	(3.89)	(3.73)	(3.71)	(3.79)	(3.79)	(3.72)
Pers (-4,4)	0.52	0.50	0.60	0.50	0.54	0.48	0.48	0.44
	(2.43)	(2.65)	(3.49)	(3.22)	(3.53)	(3.27)	(3.71)	(3.81)
Pers (-3,3)	0.52	0.46	0.41	0.42	0.38	0.38	0.34	0.34
	(3.09)	(3.22)	(3.33)	(3.71)	(3.58)	(3.63)	(3.65)	(3.93)

Table IV: Panel B
Value-weighted return differentials between portfolios of negative and positive institutional trade persistence

This table reports average monthly return differentials between portfolios of stocks persistently sold by institutions for n quarters and portfolios of stocks persistently bought by institutions for n quarters $(-n, n)$. Portfolios are value-weighted. Institutional trade persistence is measured over 3, 4, and 5 or more quarters. Holding periods are 3 months to 30 months. Return differentials are estimated as intercepts (alphas) from the following multifactor models: the CAPM model; the three-factor Fama-French (1993) model; the four-factor model represented by the Fama-French model augmented by Carhart (1997) momentum factor; the five-factor model represented by the four-factor model augmented by Pastor and Stambaugh (2003) liquidity factor. Estimates are reported in percent per month. t-statistics are in parentheses.

Holding period	**3 m**	**6 m**	**9 m**	**12 m**	**15 m**	**18 m**	**24 m**	**30 m**
CAPM alphas								
Pers (-5,5)	0.40	0.64	0.63	0.58	0.53	0.55	0.54	0.57
	(1.31)	(2.29)	(2.40)	(2.24)	(2.08)	(2.24)	(2.31)	(2.59)
Pers (-4,4)	0.09	0.18	0.36	0.31	0.36	0.32	0.38	0.38
	(0.32)	(0.82)	(1.91)	(1.76)	(2.21)	(2.10)	(2.78)	(3.09)
Pers (-3,3)	0.34	0.26	0.30	0.46	0.41	0.38	0.31	0.29
	(1.36)	(1.48)	(1.87)	(3.23)	(3.02)	(3.13)	(2.90)	(2.89)
Fama-French alphas								
Pers (-5,5)	-0.03	0.19	0.17	0.10	0.03	0.04	0.01	0.06
	-(0.10)	(0.77)	(0.79)	(0.47)	(0.13)	(0.21)	(0.08)	(0.38)
Pers (-4,4)	-0.16	-0.06	0.14	0.07	0.15	0.10	0.17	0.18
	-(0.57)	-(0.29)	(0.74)	(0.44)	(0.97)	(0.70)	(1.42)	(1.72)
Pers (-3,3)	0.16	0.10	0.12	0.28	0.23	0.23	0.15	0.14
	(0.68)	(0.61)	(0.81)	(2.18)	(1.92)	(2.09)	(1.73)	(1.81)
Four-factor alphas								
Pers (-5,5)	0.32	0.46	0.38	0.26	0.14	0.15	0.09	0.11
	(1.22)	(1.94)	(1.75)	(1.20)	(0.70)	(0.80)	(0.51)	(0.67)
Pers (-4,4)	0.07	0.12	0.26	0.17	0.21	0.13	0.20	0.22
	(0.23)	(0.59)	(1.39)	(1.02)	(1.39)	(0.95)	(1.67)	(2.12)
Pers (-3,3)	0.51	0.33	0.30	0.40	0.32	0.27	0.17	0.18
	(2.42)	(2.21)	(2.23)	(3.14)	(2.69)	(2.48)	(1.91)	(2.22)
Five-factor alphas								
Pers (-5,5)	0.32	0.46	0.39	0.27	0.16	0.17	0.10	0.13
	(1.22)	(1.92)	(1.79)	(1.26)	(0.77)	(0.90)	(0.62)	(0.81)
Pers (-4,4)	0.10	0.15	0.28	0.20	0.24	0.16	0.23	0.24
	(0.34)	(0.71)	(1.48)	(1.20)	(1.59)	(1.17)	(1.92)	(2.36)
Pers (-3,3)	0.53	0.36	0.33	0.43	0.35	0.31	0.20	0.21
	(2.53)	(2.41)	(2.46)	(3.46)	(3.08)	(2.88)	(2.36)	(2.72)

Table V
Predicting institutional trading

This table reports estimates from a probit model that predicts the likelihood that institutions buy stock i in quarter $t+1$, conditional on the persistence of institutional net trades and on various stock characteristics measured at the end of quarter t. The dependent variable is an indicator that equals one if stock i is an institutional net buy in quarter $t+1$ and zero otherwise. Institutional net trade in security i is defined as the percentage change in the number of shares owned by institutions as an aggregate ($S_{i,t}$), taking place between quarter $t-1$ and quarter t: $d_{i,t}=\frac{S_{i,t}-S_{i,t-1}}{S_{i,t-1}}$. Each quarter, we rank stocks on the basis of $d_{i,t}$ and define as net buys those stocks with a value of $d_{i,t}$ above the cross-sectional median, and as net sells those stocks with a value of $d_{i,t}$ below the median. PANEL A: $dP_{i,t,p}$ 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, $R_{i,t:t-12+1}$. $cap_{i,t}$ 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. PANEL B: All independent variables in Panel B are standardized with respect to their quarterly cross-sectional distribution. $P_{i,t}$ is the standardized persistence measure, $R_{i,t:t-m}$ is the past (m+1)-quarter return, $cap_{i,t}$ is market capitalization, $bm_{i,t}$ is Book-to-Market, $own_{i,t}$ is institutional ownership, and $turn_{i,t}$ is stock i's turnover. Est. are estimates from a probit model. t-statistics are in parentheses. The marginal effect is calculated as the marginal probability that stock i is bought by institutions, averaged over the entire sample.

Panel A					Panel B				
Indep. Variable	Est.	Marg. effect	Est.	Marg. effect	Indep. Variable	Est.	Marg. effect	Est.	Marg. effect
$dP_{i,t,1}$	-0.0934	-0.0363	-0.0868	-0.0339	$P_{i,t}$	0.0267	0.0104	0.0237	0.0093
	-(9.25)		-(7.55)			(10.68)		(8.17)	
$dP_{i,t,2}$	-0.0035	-0.0014	-0.0045	-0.0018	$R_{i,t:t-3}$	0.1493	0.0582		
	-(0.51)		-(0.57)			(53.32)			
$dP_{i,t,4}$	0.0358	0.0139	0.0310	0.0121	$R_{i,t:t-11}$			0.0990	0.0389
	(5.11)		(3.88)					(30.94)	
$dP_{i,t,5}$	0.1405	0.0546	0.1564	0.0612	$cap_{i,t}$	0.1358	0.0530	0.1129	0.0444
	(14.79)		(13.84)			(41.15)		(29.71)	
$dR_{i,t:t-3,1}$	-0.2162	-0.0840			$bm_{i,t}$	-0.0376	-0.0147	-0.0369	-0.0145
	-(26.05)					-(11.75)		-(9.97)	
$dR_{i,t:t-3,2}$	-0.0411	-0.0160			$own_{i,t}$	-0.1573	-0.0614	-0.1542	-0.0606
	-(5.27)					-(46.26)		-(38.55)	
$dR_{i,t:t-3,4}$	0.0644	0.0250			$turn_{i,t}$	0.0248	0.0097	0.0274	0.0108
	(8.26)					(9.19)		(8.30)	
$dR_{i,t:t-3,5}$	0.1638	0.0636							
	(19.98)								
$dR_{i,t:t-11,1}$			-0.1305	-0.0510					
			-(13.59)						
$dR_{i,t:t-11,2}$			-0.0291	-0.0114					
			-(3.23)						
$dR_{i,t:t-11,4}$			0.0338	0.0132					
			(3.76)						
$dR_{i,t:t-11,5}$			0.0864	0.0338					
			(9.00)						
$cap_{i,t}$	0.1145	0.0445	0.1091	0.0427					
	(44.04)		(36.37)						
$bm_{i,t}$	-0.0179	-0.0070	-0.0188	-0.0074					
	-(8.52)		-(7.23)						
$own_{i,t}$	-0.1351	-0.0525	-0.1369	-0.0535					
	-(51.96)		-(44.16)						
$turn_{i,t}$	0.0408	0.0158	0.0379	0.0148					
	(19.43)		(15.16)						

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

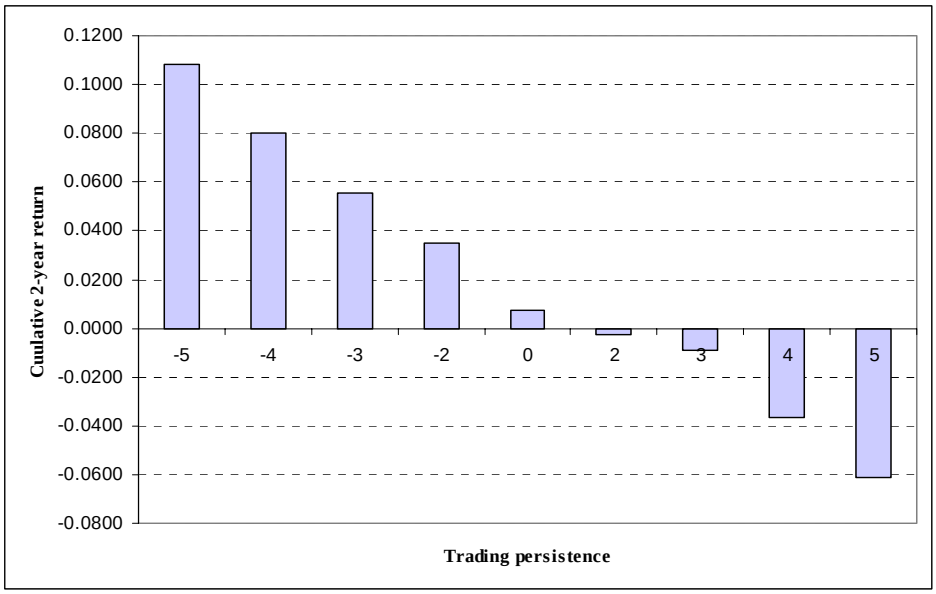


Figure 3
Cumulative market-adjusted returns to trading persistence portfolios
One to ten quarters after portfolio formation

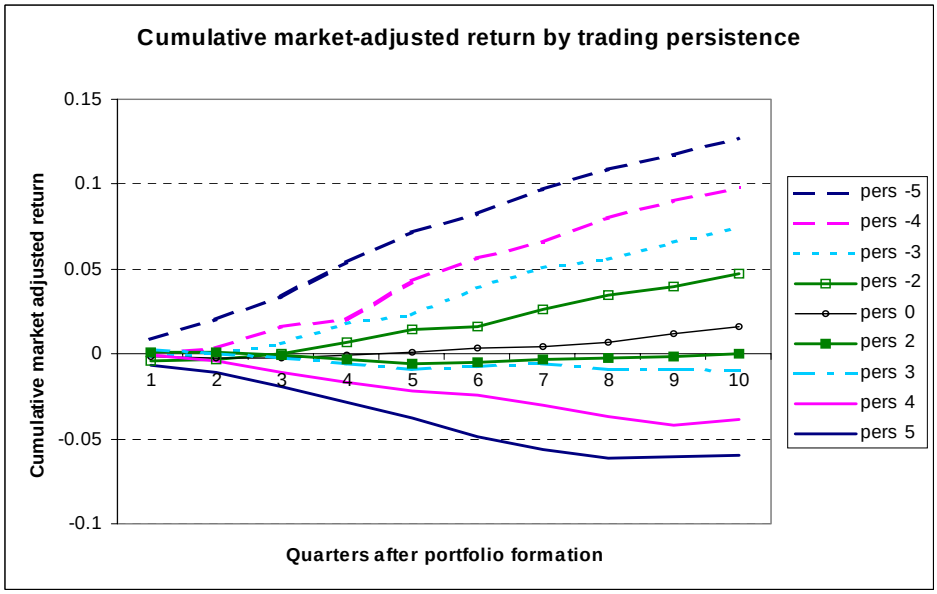


Figure 4A
Cumulative two-year return differential between persistence (-5) and (+5)
By NYSE market capitalization quintiles

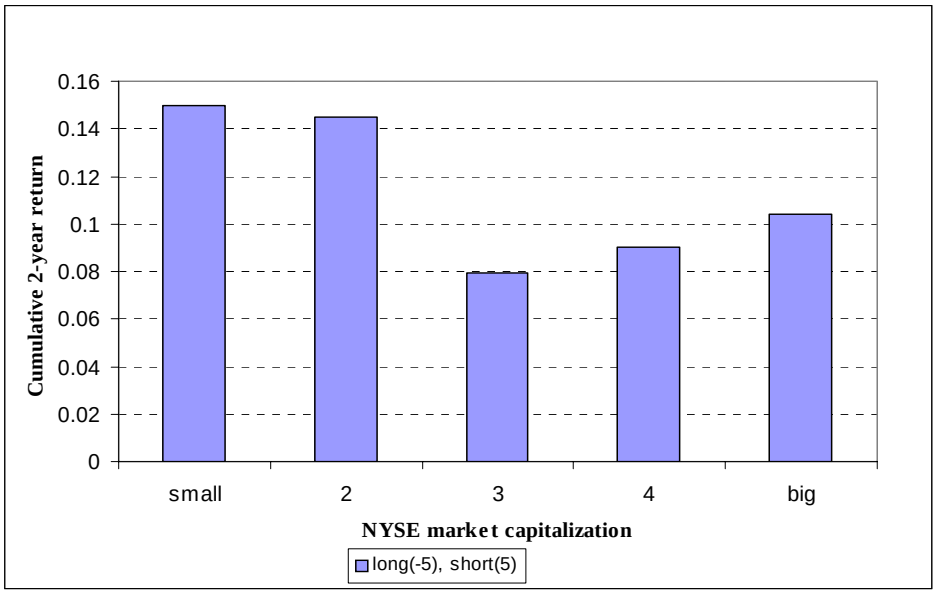


Figure 4B
Cumulative two-year return differential between persistence (-5) and (+5)
By Book-to-Market quintiles

Figure 4C
Cumulative two-year return differential between persistence (-5) and (+5)
By past one-year return quintiles

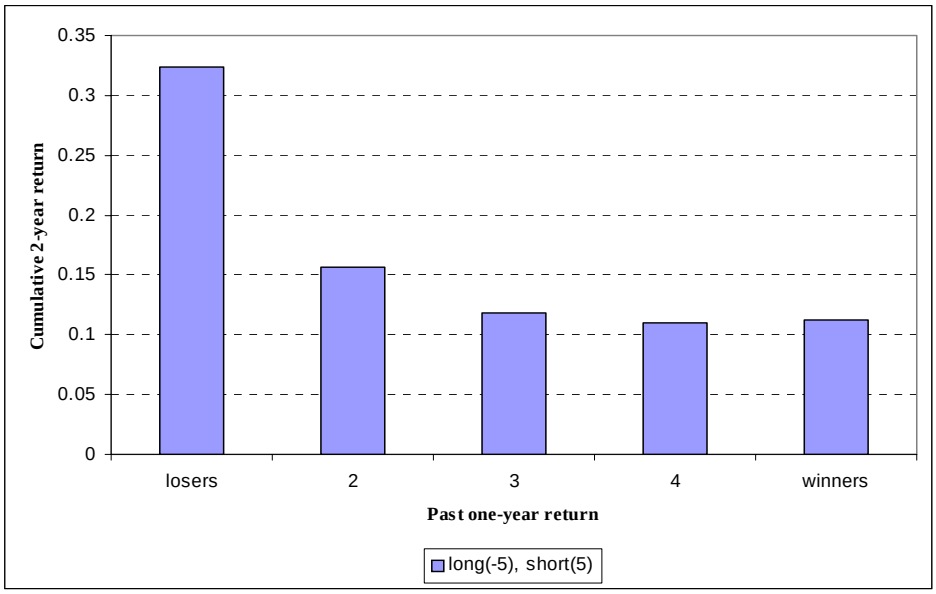
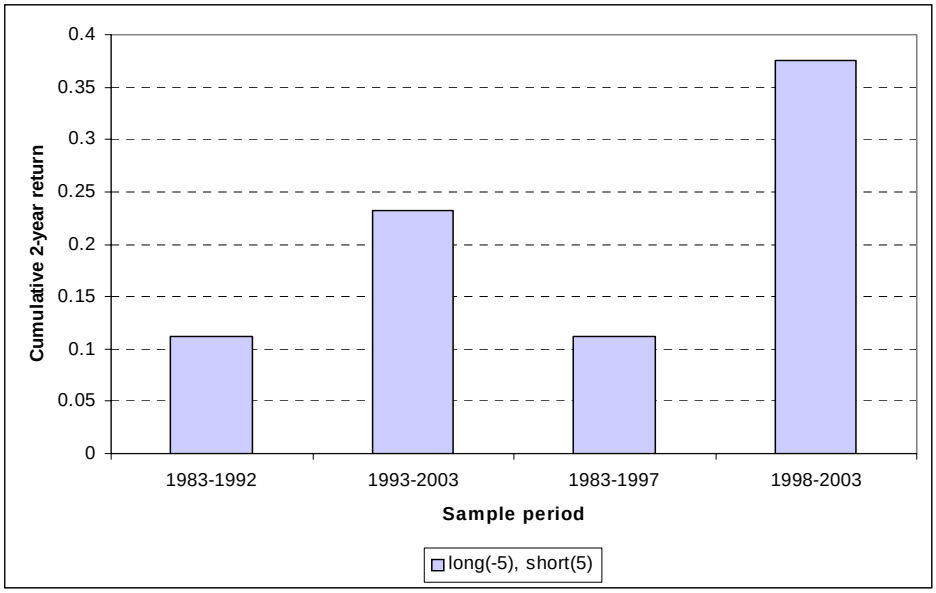


Figure 4D
Cumulative two-year return differential between persistence (-5) and (+5)
By sub-periods



References

[1] Allen, Franklin, and Gary Gorton, 1993, Churning Bubbles, *Review of Economic Studies* 60(4): 813-36.

[2] Barber, Brad M., and Terrance Odean, 2006, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, Working Paper.

[3] Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavioral finance, Handbook of Economics and Finance, Elsevier Science B.V.

[4] Braverman, Oded, Shmuel Kandel, and Avi Wohl, 2005, The (Bad?) Timing of Mutual Fund Investors. Working paper, Tel Aviv University.

[5] Brunnermeier, Markus K., 2001, Asset pricing under asymmetric information, Oxford University Press.

[6] Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge Funds and the Technology Bubble, *Journal of Finance*, 59, 2013-2040.

[7] Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance*, 52, 57-82.

[8] Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171-205.

[9] Chevalier, Judith, and Glenn Ellison, 1999, Career Concerns of Mutual Fund Managers. *Quarterly Journal of Economics*, 114: 389-432.

[10] Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409-462.

[11] Copeland, Thomas, and Dan Galai, 1983, Information Effects on the Bid-Ask Spread. *Journal of Finance* 38, 1457-1469.

[12] Coval, Joshua, and Erik Stafford, 2006, Asset fire sales (and purchases) in equity markets, Working Paper.

[13] Dasgupta, Amil, and Andrea Prat, 2005, Asset Price Dynamics When Traders Care About Reputation, CEPR Discussion Paper No. 5372.

[14] Dasgupta, Amil, and Andrea Prat, 2006, Financial Equilibrium with Career Concerns, *Theoretical Economics* 1, 67-93.

[15] Dass, Nishant, Massimo Massa, and Rajdeep Patgiri, 2005, Mutual Funds and Bubbles: The surprising role of contractual incentives. Working paper, INSEAD.

[16] DeBondt, Werner, and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

[17] Dennis, Patrick, and Deon Strickland, 2002, Who Blinks in Volatile Markets, Individuals or Institutions? *Journal of Finance* 57, 1923-1950.

[18] Dow, James, and Gary Gorton, 1997, Noise trading, delegated portfolio management, and economic welfare. *Journal of Political Economy* 105(5): 1024–1050.

[19] Fama, Eugene, and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[20] Fama, Eugene, and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

[21] Financial Times, 2006, Lessons from a cheerful copycat, Jonathan Davis, 4 September.

[22] Frazzini, Andrea, and Owen Lamont, 2006, Dumb money: Mutual fund flows and the cross-section of stock returns, Working Paper.

[23] Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics* 14, 71-100.

[24] Gorton, Gary, Ping He, and Lixin Huang, 2005, Asset Prices When Agents are Marked-to-Market. Working paper, Wharton School.

[25] Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior, *American Economic Review* 85, 1088-1105.

[26] He, Zhiguo, and Arvind Krishnamurthy, 2006, Intermediation, Capital Immobility, and Asset Prices, Working paper, Northwestern University.

[27] Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533-1597.

[28] Hirshleifer, David, James N. Meyers, Linda A. Meyers, and Siew Hong Teoh, 2005, Individual investor and Post-Earnings Announcement Drift: Direct evidence from personal trades, Working Paper.

[29] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

[30] Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

[31] Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2006, Individual investor trading and stock returns, Working Paper.

[32] Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992, The Impact of Institutional Trading on Stock Prices, *Journal of Financial Economics* 32, 23-43.

[33] Massa, Massimo, and Rajdeep Patgiri, 2005, Compensation and Managerial Herding: Evidence from the Mutual Fund Industry. Working paper, INSEAD.

[34] Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

[35] Nofsinger, John, and Richard Sias, 1999, Herding and feedback trading by institutional and individual investors, *Journal of Finance* 54, 2263-2295.

[36] Ou-Yang, Hui, 2005, An Equilibrium Model of Asset Pricing with Moral Hazard, *Review of Financial Studies* 18, 1253-1303.

[37] Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

[38] Scharfstein, David, and Jeremy Stein, 1990, Herd behavior and investment. *American Economic Review* 80, 465–479.

[39] Sharma, Vivek, John Easterwood, and Raman Kumar, 2006, Institutional Herding and the Internet Bubble. Working paper.

[40] Sias, Richard, 2003, Are Institutions Momentum Traders?, Working paper.

[41] Sias, Richard, 2004, Institutional Herding, *Review of Financial Studies* 17, 165-206.

[42] Sias, Richard, Laura Starks, and Sheridan Titman, 2001, The Price Impact of Institutional Trading, Working Paper.

[43] Wermers, Russ, 1999, Mutual Fund Herding and the Impact on Stock Prices, *Journal of Finance*, 54, 581-622.