The Price of Conformism*

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Abstract

There is ample evidence that institutional investors herd. Does this behavior affect asset prices? We formulate a simple theory of institutional conformism, which predicts that assets that have been persistently bought (sold) by institutions are overpriced (underpriced) and will perform poorly (well) in the longer term. Our prediction is tested with data on US institutional onwership from 1983 to 2004. We find a negative relationship between past net trade and future excess returns. For example, a strategy consisting of selling stocks that have been bought by institutions in the last 5+ quarters and buying stocks that have been sold by institutions in the last 5+ quarters generates a cumulative abnormal return of 18% in the following two years. Our findings are statistically significant and survive a number of robustness checks.

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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]

This paper provides some evidence in support of that assertion. We study 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. This is consistent with a model in which institutional investors are keen to behave like their peers, even when this implies buying overvalued assets and selling undervalued ones.

The paper begins with a minimalist model of financial markets with institutional and individual investors. Institutions are characterized by both an informational advantage and a conformist tendency. Suppose that the fundamental value of an asset receives a positive shock. At first, only institutions are aware of the shock and they exploit their informational advantage by becoming net buyers of that asset. After some time, investors revise their valuation and informational symmetry is restored. But then, a second phase begins, in which institutions are still net buyers, not for informational reasons but because of the conformist tendency: they are still keen to acquire what their peers have been buying in the recent past. This causes the asset price to overshoot its long-term value. In this phase, the overpriced asset continues to be sold from individuals to institutions.

[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."

As time passes, the imitational effect runs its course and the price reverts to its correct level. A similar process occurs when the stock is hit by a negative, rather than positive, shock. This theory predicts a negative correlation between net trade and long term returns, which forms the object of the present paper.

Our sample consists of quarterly observations on stock holdings of institutional investors with at least 100 millions 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. We report the following main results:

1. We compute the difference in portfolio returns across positive and negative persistence groups. Our main finding is that these returns exhibit a clear monotonic pattern: stocks that have been persistently sold outperform stocks that have been persistently bought. On average, a strategy of buying stocks that have been persistently sold by institutions for five quarters and selling stocks that have been persistently bought by them for the same period yields a cumulative CAPM-adjusted return of 10% over one year and 18% after two years.

2. In the event-time analysis, the difference in quarterly returns between persistently sold stocks and persistently bought stocks is positive, increasing until four-five quarters after portfolio formation, and declining afterwards. It remains positive even after ten quarters following portfolio formation. The magnitude of the return difference varies with the length of trade persistence and with the type of adjustment used to compute abnormal returns. For a persistence of five or more quarters, the difference in market-adjusted returns between the portfolio of net sells and the portfolio of net buys is about 3% after one year, and 1.67% after two years, and becomes indistinguishable from zero afterwards. When we use size and book-to-market adjusted returns, the difference in quarterly abnormal returns exhibits a similar pattern, although the economic importance of the returns is magnified. The return differential across sell and buy persistence is now 7% after one year and 4% after two years.

3. When we carry out our analysis in calendar time, we compute monthly returns for portfolios

of stocks sorted on trade persistence and rebalanced at a quarterly frequency. Besides allowing for more reliable inference on long-run portfolio performance, this methodology yields results that can be readily interpreted as returns from strategies that are long negative persistence stocks and short positive persistence stocks. We compute raw returns, as well as estimated intercepts from time series regressions of the CAPM model and the Fama-French model inclusive of the Carhart (1997) momentum factor. The results confirm the presence of a significant and positive return differential between stocks persistently sold and stocks persistently bought by institutions.

4. We then relate our findings to the stylized patterns of momentum and reversal in stock returns previously documented by Jegadeesh and Titman [26] and DeBondt and Thaler [12]. We classify stocks on the basis of their relative performance in the past nine months, and identify winners and losers as stocks belonging to the top and bottom terciles of the distribution of past returns. First, we find that the pattern in quarterly abnormal returns related to the persistence of trading is still present after controlling for past performance. The size-B/M adjusted return differential between sell and buy persistence is positive and significant both for winners and for losers. Furthermore, we compute monthly returns to portfolio strategies based on price momentum and trading persistence. The return differential between sell and buy persistence is particularly strong among stocks that have performed poorly in the past. The momentum return is indistinguishable from zero among sell persistence stocks, and becomes significant among stocks that have been persistently bought.

5. Finally, we document that institutions exhibit specific trading patterns that are hard to justify within standard models. We track the weights that individual (persistently bought or sold) stocks represent in the portfolios of institutions after portfolio formation. We find that institutions do not sell (buy) in a timely manner stocks that they have persistently bought (sold), even though these can be identified as underperformers (overperformers).[3] This confirms that institutions engage in conformist behavior even when such behavior is

[3] Dasgupta and Prat (2005) show that when institutions care both about their profits and their reputations, they may sometimes choose to buy (sell) expensive (cheap) stocks to enhance their reputation at the expense of short term profits.

suboptimal when considering trading profits alone.[4]

Our paper is related to a number of recent empirical studies on institutional herding. There is now ample evidence that institutions herd. However, evidence on the impact of such herd behavior on prices is scant. Wermers [35] 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 [32] finds that the fraction of institutions buying a stock is (weakly) positively correlated with returns in the following one to four quarters. Furthermore, Sias [33] 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.[5]

The findings of these two papers may appear to be in contrast with ours. However, this apparent difference can be reconciled on both a theoretical and an empirical level. As our brief theory section will show, the presence of institutional conformism generates a correlation between past net trade and future returns that is positive in the short term (as Wermers and Sias find) and negative in the long term (as we find). In the short term, imitative buying (selling) leads to price increases (decreases), eventually overshooting (undershooting) fundamental value. In the longer term, the price reverts towards fundamentals. Indeed, we find that the sign of the short-term correlation is positive in our dataset too (see Footnote 10)

Two other empirical papers report results that are somewhat complementary to ours. Dennis and Strickland [15] examine stock returns on days of large market movements. They find that stocks with a greater percentage of institutional ownership have higher (lower) returns on days in which the market return increases (decreases) by more than 2%. They also document that, for stocks mostly owned by institutions, cumulative abnormal returns are positive in the 6 months after a market

[4] Brunnermeier and Nagel (2004) find instead that hedge funds were able to predict the mispricing of internet stocks during the bubble period 1998-2000. They show that hedge funds heavily tilted their portfolios towards technology stocks during 1998-2000, and were skillfully able to reduce their exposure to such overpriced stocks just before the crash.

[5] Other papers finding evidence of a positive correlation between institutional demand and future returns include Nofsinger and Sias [29], Sias, Starks and Titman [34], Grinblatt, Titman and Wermers [23]. Cohen, Gompers and Vuolteenaho [10] find a positive relationship between institutional ownership and future stock returns. Chen, Hong and Stein (2003) 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.

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. However, future returns after a market rise are also positive (albeit not strongly significant). Finally, in a contemporaneous paper, Sharma, Easterwood and Kumar [31] examine herding by institutional investors for a sample of internet firms during the bubble and crash period 1998-2001. The authors find evidence of reversals after buy herding in the quarter following institutional trading. They also find evidence of one-quarter reversals after buy and sell herding cumulated during two quarters.

To conclude the introduction, it is worth placing our contribution in the context of some relevant theoretical papers. The phenomenon of institutional herding can be understood in the context of several important classes of theoretical models. The seminal reputational herding model of Scharfstein and Stein [30], which has been recently extended to a general equilibrium setting by Dasgupta and Prat [11], provides theoretical grounding for conformist behavior by institutional traders. In these models the conformist tendency arises as the rational response to an incentive structure that, on average, rewards managers who imitate their predecessors. In equilibrium, fund managers who are concerned about their own reputation for stock-picking ability have an incentive to ignore their own private information and to imitate the trading strategy of the managers who have traded just before them. The celebrated social learning models of Banerjee [2] and Bikhchandani, Hirshleifer, and Welch [5], which have been subsequently extended to a general equilibrium setting by Avery and Zemsky [1], can also be used to justify herding by both individual and institutional traders. In these models, conformism arises because the information inferred from the actions of several predecessors can overwhelm the private information of individuals, thus leading to imitation. Other well-known theories of herd behavior include the investigative herding model of Froot, Scharfstein, and Stein [20] and Hirshleifer, Subrahmanyam, and Titman [24], where herding arises due to strategic complementarities in the acquisition of information, as well as characteristic herding (Falkenstein [17], Del Guercio [13], Gompers and Metrick [22], Bennett, Sias, and Starks [4]). Distinct from the literature on rational herd behavior, De Long, Shleifer, Summers, and Waldmann [14] show that in the presence of exogenous positive feedback trading, rational speculation can destabilize prices and generate temporary mispricing.

The rest of the paper is organized as follows. In the next section we present a simple reducedform model to capture our main hypothesis in the simplest possible framework. Sections 3-4 contains our main empirical results, and section 5 concludes.

2 A Simple Model of Conformism among Institutional Traders

This short section does not attempt to construct a full-fledged theory explaining why institutional traders may engage in conformist behavior. Its much more limited objective is to assume that such behavior may exist and to examine its effect on the dynamics of market variables. The resulting predictions will guide our empirical study.

Consider a financial market with a single asset traded in periods $t = 0, ..., \infty$. The fundamental value of the asset is

$$v_t = v_{t-1} + \varepsilon_t,$$

where ε_t is normally distributed variable with mean 0 and variance σ^2.

Two classes of traders operate on the asset market: regular traders and institutional traders. For simplicity assume that there is a mass 1 of traders in each of the two classes. We think of regular traders as individuals who are investing their own money and of institutional traders as fund managers who invest funds on behalf of other investors (e.g. mutual funds or pension funds). As we shall see, institutional traders differ from regular traders in two aspects: they have more information and they have a tendency to imitate each other.

Let X_t denote the amount of net trade from regular traders to institutional traders. Given that for every buyer there is a seller, the net trade X_t is equal to the number of units bought by any institutional trader minus the number of units sold by any institutional trader.

Regular traders receive stale information. At time t, they know v_{t-1}, but they do not observe the current shock ε_t. They submit demand schedule:

$$D_t^R(p_t) = v_{t-1} - p_t,$$

that is, given price p_t, they demand a (positive or negative) amount of asset $D_t^R(p_t)$.

Institutional traders are better informed. They observe ε_t prior to trading at time t. They submit demand function

$$D_t^C(p_t) = v_t + \beta X_{t-1} - p_t,$$

where $\beta \in [0, 2)$ and it captures a conformism effect among institutional traders.

This term can be understood either in behavioral terms, as a desire on the part of professional investors to imitate their peers, or as the rational response to an incentive structure that, on average, rewards managers who imitate their predecessors. A leading example of such a situation can be found in Scharfstein and Stein's [30] model of herd behavior in financial markets. In equilibrium, fund managers who are concerned about their own reputation for stock-picking ability have an incentive to ignore their own private information and to imitate the trading strategy of the managers who have traded just before them. The same theme is explored in general equilibrium by Dasgupta and Prat [11], who show that the presence of career concerns leads to informational cascades and systematic mispricing.

The market-clearing price $\hat{p}_t$ is the unique value satisfying $D_t^R(\hat{p}_t) + D_t^C(\hat{p}_t) = 0$, that is

$$2v_{t-1} + \varepsilon_t + \beta X_{t-1} - 2p_t = 0.$$

Therefore

$$\begin{aligned} \hat{p}_t &= v_{t-1} + \frac{\varepsilon_t + \beta X_{t-1}}{2}. \\ \hat{p}_t &= v_{t-1} + X_t. \end{aligned}$$

Also, net trade can be expressed in two ways:

$$\begin{aligned} X_t &= -D_t^R(\hat{p}_t) = \hat{p}_t - v_{t-1} \\ X_t &= D_t^C(\hat{p}_t) = \frac{\varepsilon_t + \beta X_{t-1}}{2} \end{aligned}$$

This simple model provides a series of predictions. First, the price process satisfies these conditions:

Proposition 1 *The autocorrelation of returns is positive in the short term and negative in the long term. Formally,*

$$cov\left[\hat{p}_t - \hat{p}_{t-1}, \hat{p}_{t-1} - \hat{p}_{t-2}\right] > 0;$$

and for $s \geq 3$,

$$cov\left[\hat{p}_t - \hat{p}_{t-1}, \hat{p}_{t-s} - \hat{p}_{t-s-1}\right] < 0.$$

Proof. See Appendix. ■

These results represent standard findings in the empirical literature (Jegadeesh and Titman [26] and DeBondt and Thaler [12]). The first captures price momentum and the second represents mean-reversion.

However, our model provides a novel relationship between net trade and prices. Let over-pricing be defined as the difference between the market price and the fundamental value of the asset: $\hat{p}_t - v_t$. We have:

Proposition 2 *Over-pricing is positively correlated to past net trade if and only if the conformism effect is present. Formally, if $\beta > 0$,*

$$cov\left[\hat{p}_t - v_t, X_{t-1}\right] > 0.$$

If $\beta = 0$, the covariance if zero.

Proof. Note that

$$\begin{aligned} cov\left[p_t - v_t, X_{t-1}\right] &= cov\left[v_{t-1} + \frac{\varepsilon_t + \beta X_{t-1}}{2} - v_t, X_{t-1}\right] \\ &= cov\left[\frac{\beta X_{t-1}}{2} - \frac{\varepsilon_t}{2}, X_{t-1}\right] \\ &= \frac{\beta}{2} var\left[X_{t-1}\right] > 0. \end{aligned}$$

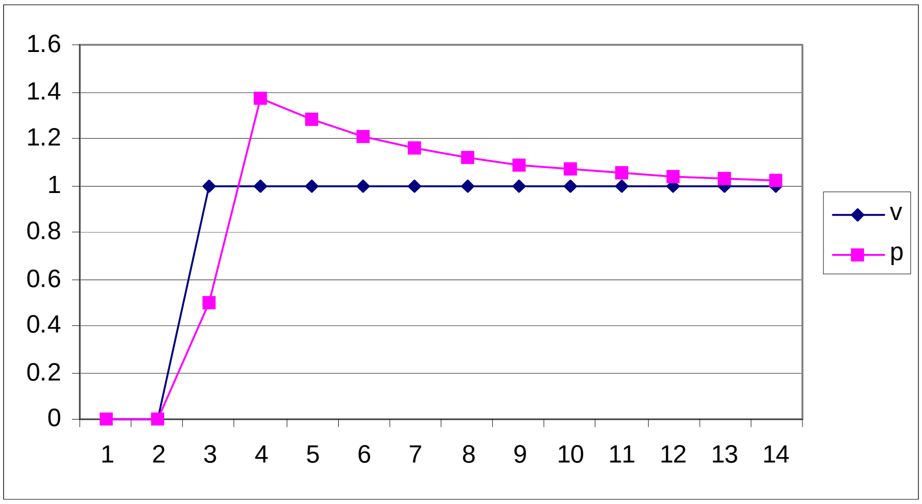
■

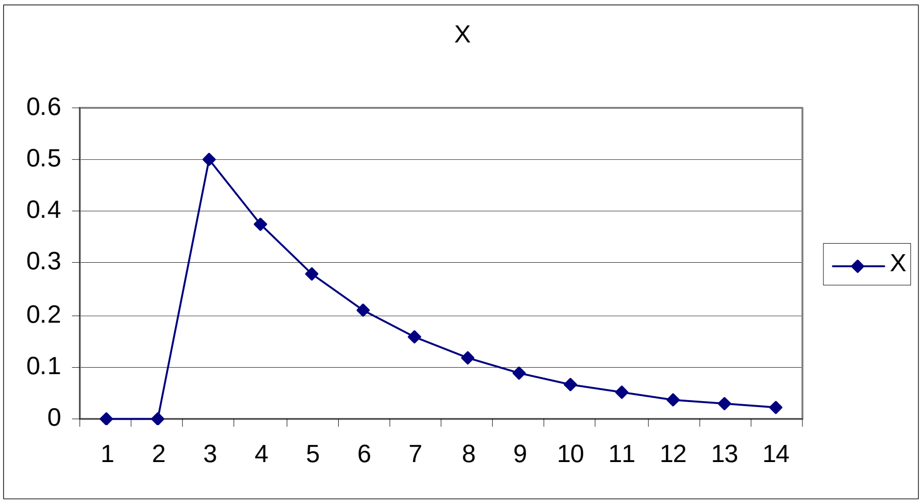
The intuition behind this finding is simple. If institutional traders have tendency towards conformism, a positive net trade in the recent past – whether it was for informational or for imitational reasons – generates additional positive conformist trade today: the price rises without there being an increase in the fundamental value of the asset. This result represents the core prediction of the model, which will guide our empirical analysis.[6]

For example, suppose that there is a positive shock at a certain time. The figures below depict the reaction of price and net trade to a positive shock at time $t = 3$ ($\varepsilon_3 = 1$, while all the other ε_t's are zero). We set the conformism parameter $\beta = 1.5$. At $t = 3$, there is an informational

[6] Our model also predicts that net trade is positively auto-correlated, namely that $cov\left[X_t, X_{t-1}\right] > 0$. However, this prediction is also consistent with models of asymmetric information such as Glosten and Milgrom [21].

asymmetry: institutional traders are aware of the positive shock and they are net buyers: the price begins to increase. At $t = 4$, informational symmetry is restored because regular traders are now aware of the positive shock. If there were no conformism effect ($\beta = 0$), the price would reach the true value 1 and it would stay there: no net trade would occur. If instead there is conformism, as we assume, the price overshoots the true value of the asset, in this case by 40%. There is still positive net trade, which is due to the conformism effect only. The positive net trade persists in the following periods, albeit at a decreasing level. The price slowly reverts to the true value of the asset.





The model is ambiguous with regards to expected returns. If β is low, career traders make higher expected returns than regular traders (this is immediate to see when $\beta = 0$). If β is high, the opposite is true. In the example discussed above, career traders buy $X_3 = \frac{1}{2}$ at $p_3 = \frac{1}{2}$, which generates an informational profit of $\frac{1}{4}$ but then they buy in the following periods at an excessive price, generating a non-discounted cumulative loss of

$$\sum_{t=4}^{\infty} \hat{p}_t X_t \simeq 0.33,$$

which is greater than the initial informational profit.

Clearly, our model predicts a long-run negative correlation between net trade and future returns. For s sufficiently large, $Cov\,[p_{t+s} - p_t, X_t] < 0$ (this is a consequence of Proposition 2). However, it is important to note that the same correlation is positive in the short run:

Proposition 3 *In the short-run, net trade is positively correlated with future returns:*

$$cov\,[\hat{p}_t - \hat{p}_{t-1}, X_{t-1}] > 0.$$

Proof. See Appendix. ■

This result brings under one theoretical roof both the empirical results presented here and the findings of Wermers [35] and [32].

This extremely stylized model could be extended in several directions. For instance, the conformism effect could be more general: it may depend not only on X_t but also on previous net trades. This would make the graphs above smoother and more realistic. Or we could consider a more complex form of informational asymmetry, for instance assuming that fund career traders observe heterogenous signals. However, the goal of this section is just to provide the most parsimonious setting to yield the core prediction that we shall test in the remaining of the paper.

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.

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.[7]

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 1,130 managers each 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: $Turnover_t^j = \frac{\sum_i |n_t^{i,j} - n_{t-1}^{i,j}| p_t^i}{\sum_i n_t^{i,j} p_t^i}$. 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:

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

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.[8] 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.

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

[8] The results of the paper do not change if we classify net buys and net sells according to the sign of $d_{i,t}$. We choose the median in order to have an equal number of stocks in the two subgroups.

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. The portfolio with persistence -5 (5) includes stocks that have been sold (bought) for *at least* five consecutive quarters.

4 Trading persistence and the cross-section of stock returns

In this section, we examine the return patterns associated with differences in trading persistence between individual investors and institutions. We first form portfolios based on institutions' net trades, and track their returns in the future. We also test whether quarterly portfolio returns are significantly different across persistence categories in event time. We next present our results in calendar time, so that they can be easily interpreted as average monthly returns from investment strategies based on the persistence of institutional trading.

We study the trading behavior of institutional managers after portfolio formation to test whether trading persistence can predict future trades, and to understand the extent to which managers exploit possible mispricing related to previous trading patterns.

Finally, we investigate the relation between trading persistence and price momentum, by computing future returns to persistence portfolios conditional on a stock's past performance.

4.1 Portfolio returns

At the end of each quarter t, we form portfolios based on the persistence of net trading by institutional investors. Table II, Panel A, 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 exchanges.[9] The findings show that size tends to increase across persistence portfolios, although the variation is small. Turnover increases with net buy persistence,

[9] 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.

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 [33]). As expected, the frequency of net buys 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.

Panel B of Table II reports market-adjusted portfolio returns in event time, for ten quarters after portfolio formation. The returns are equal-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) is long stocks that have been sold for 5 quarters and short stocks that have been bought for 5 quarters. We form analogous hedge 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 (not statistically significant), and becomes larger and significant in the subsequent quarters, reaching 3% one year after portfolio formation. It then starts to slowly decline afterwards, but is still positive and significant after 8 quarters. The returns of the hedge portfolios based on shorter persistence (-4,4 and -3,3) are smaller in magnitude but follow similar patterns. We plot the sum of these quarterly excess returns in Figure 1, to illustrate the pattern in returns after portfolio formation.[10]

[10] Wermers [35] 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.

To check that these results are not driven by stock characteristics possibly associated with long-run stock performance, we compute size and book-to-market adjusted returns. Each quarter, we form size and book-to-market reference portfolios as in Barber, Lyon and Tsai [3]. We first form decile size portfolios based on NYSE cutoff points, and further divide the smallest decile into quintiles, without distinction by stock exchange. Each size portfolio is further partitioned into book-to-market quintiles, to form a total of 70 portfolios. We match every stock in our institutional trading sample to its size and B/M portfolio of reference, and subtract the reference portfolio buy-and-hold return from each stock's quarterly buy-and-hold return.[11] With these size and B/M adjusted returns, we form equal weighted portfolios based on the persistence of trading by institutions. The results are shown in Table II, Panel C, and are illustrated graphically in Figure 2. The predictability of trading persistence is again striking, and the difference in characteristic-adjusted portfolio returns across trading persistence is even stronger than before. Returns from persistence hedge portfolios are large and still significant after 10 quarters from portfolio formation.

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.[12] For robustness, we compute average monthly returns from overlapping persistence portfolios formed at the end of each quarter t. In this manner, we can interpret the results as returns from an investment strategy that buys negative persistence stocks and shorts positive persistence stocks. We calculate returns from these strategies for different holding periods. This approach implies that, for a k quarters holding period, $1/k$ of the portfolio is rebalanced every quarter. In Table III 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 guarantee that the results are not driven by the covariance of portfolio returns with risk, we estimate one-factor and multi-factor regressions for the time-series of the strategy monthly raw returns. We consider the CAPM model and a four-factor model including the Fama-French [18]

[11] We also compute abnormal returns with respect to a different set of reference portfolios. Specifically, we rank all stocks in the sample by size quintiles and B/M quinitiles, and form 25 reference portfolios from their intersection. The results do not change if we use these in-sample cutoff points.

[12] It is well known that long-run event study tests can be problematic because of sample selection biases, model misspecifications, and cross-sectional correlation (Kothari and Warner [27], Barber et al. [3]). Simulations generally show a strong tendency to find positive abnormal performance.

three-factors and Carhart [7] momentum factor. In Table III we report the estimated intercepts for the hedge portfolios of low minus high trading persistence; the t-statistics for zero intercept tests are obtained from Newey-West autocorrelation consistent standard errors.

4.2 Can trading persistence predict future trading behavior?

In this section, we examine the evolution of net trading by institutional managers in the quarters that follow portfolio formation. Are institutional investors able to predict mispricing related to previous trading patterns? Brunnermeier and Nagel [6] show that hedge funds anticipated price peaks 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 institutional managers in our sample, instead, continue to buy stocks that have been persistently bought in the past and are thus overpriced, and continue to sell underpriced stocks.

Figure 3 shows the percentage of stocks in a specific trading persistence portfolio that are bought by institutional investors in the quarters after portfolio formation. Figure 4 shows the median change of a stock's weight in the portfolio of institutional investors, classified according to the persistence of institutional trading.[13] Both figures indicate that institutional investors do not sell (buy) in a timely manner stocks that they have persistently bought (sold), even though these can be identified as underperformers (overperformers). This confirms that institutions engage in conformist behavior even when such behavior is suboptimal when considering trading profits alone.

4.3 Price momentum and trading persistence

To the extent that institutions consistently buy winners and sell losers, the observed patterns in returns could be driven by the reversal phenomenon previously documented in the literature (Jegadeesh and Titman, 1993 and 2001, DeBondt and Thaler, 1985). How are momentum returns related to the persistence of institutional trading?[14]

We form momentum portfolios on the basis of a stock's relative performance in the past nine

[13] The median weight is calculated as the time-series average of the cross-sectional median for each persistence portfolio.

[14] Our theoretical model predicts *both* a net trade effect and price momentum effect. So there is no incosistency between the two. The empirical question that is asked in this section is as follows: What is the magnitude of the net trade effect once we control for momentum?

months.[15] Winners and losers are defined as stocks belonging to the top and bottom terciles of the distribution of past returns. In Table IV we present quarterly size and B/M adjusted returns for persistence portfolios, separately for past winners and past losers. The findings show that returns of stocks that have been persistently sold outperform stocks that have been persistently bought even within the sub-samples of past winners and past losers. These results suggest that the trading persistence differential is not explained away by price persistence.

We then compute calendar-time returns for portfolios formed from the intersection of momentum and trading persistence sorts, rebalanced at a quarterly frequency. Table V shows average monthly returns for winners and losers classified by persistence, as well as returns for the hedge portfolios based on persistence (low-high persistence) separately for past winners and past losers. The Table presents monthly returns for a selected number of holding periods, varying from 6 to 30 months. The returns to these two-sorts strategies suggest that persistence maintains its predictive power even conditional on a stock's past performance, although the returns are larger and significant for losers. On the other hand, momentum strategies do well among stocks that have been persistently bought and lose significance when implemented among stocks that have been persistently sold.

5 Conclusion

Following the seminal contribution of Milton Friedman [19], the conventional view of rational speculation has been that speculators stabilize prices, buying on average when prices are (too) low, and selling when prices are (too) high. As potentially well-informed and ostensibly rational speculators, institutional traders would naturally be thought to be price stabilizing. However, the empirical finding of extensive herding and momentum trading by institutions has generated a discussion in the literature on whether institutions help or hinder price stabilization. This paper lends empirical backing to the view that institutions, through mimetic trading, destabilize prices.

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 the analysis is carried out in event time or in calendar time, and even after separately considering "winners" and "losers" based on price momentum. We interpret this as evidence that institutions

[15] We obtain very similar results by using 12 months as a ranking period to form momentum portfolios.

move prices away from fundamentals, acting in the short term as a destabilizing influence on the market.

In addition, we find that institutions do not sell (buy) in a timely manner stocks that they have persistently bought (sold), even though these can be clearly identified as underperformers (overperformers). This apparently irrational behavior can be interpreted to mean that institutions care about more than just their financial returns. Our results thus provide empirical support for the need to model the non-standard incentives faced by institutional traders, arising, for example, out of reputational concerns engendered by agency conflicts (e.g. Scharfstein and Stein [30] and Dasgupta and Prat [11]). It remains of clear interest, though beyond the scope of the current exercise, to more closely integrate the theory of reputational herding with the empirical mispricing identified here.

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

Year	Number of managers	Holdings per mgr Mean ($mill)	Holdings per mgr Median ($mill)	Aggregate stock holdings ($mill)	Mkt share	Portf turnover Mean	Portf turnover 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				

Table II - Panel A
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. Size is the market capitalization 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 tot portfolio formation.

Persistence	**Size**		**B/M**		**Turnover**		**Ownership**		**Past Ret**
	Avg	Med	Avg	Med	Avg	Med	Avg	Med	Avg
-5	855397	37381	1.06	0.91	0.45	0.28	0.21	0.14	-0.001
-4	1041765	60422	1.08	0.79	0.49	0.31	0.23	0.18	-0.014
-3	1065765	72142	0.97	0.72	0.52	0.32	0.25	0.19	-0.019
-2	1039411	85867	0.88	0.65	0.53	0.32	0.26	0.21	-0.028
0	1021318	90738	0.74	0.57	0.53	0.32	0.28	0.22	0.037
2	953024	130213	0.63	0.50	0.58	0.37	0.30	0.26	0.107
3	882471	151822	0.56	0.45	0.63	0.40	0.31	0.28	0.109
4	933862	177346	0.53	0.42	0.69	0.44	0.33	0.30	0.111
5	1037566	220110	0.47	0.36	0.76	0.49	0.36	0.34	0.111

Table II - Panel B
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, 1 to 10 quarters after portfolio formation. The returns are market-adjusted. Portfolio (-5,5) is long stocks that have been persistently sold and short stocks tha 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	1.23	1.31	2.05	1.77	1.11	1.39	1.15	0.85	1.00
	(1.33)	(1.90)	(2.15)	(3.27)	(2.67)	(1.95)	(2.67)	(2.32)	(1.72)	(2.48)
-4	0.06	0.28	1.30	0.44	2.26	1.32	0.92	1.42	1.07	0.69
	(0.10)	(0.62)	(2.91)	(0.92)	(3.93)	(2.58)	(1.77)	(2.99)	(2.03)	(1.23)
-3	-0.16	0.18	0.60	1.16	0.47	1.61	1.22	0.48	0.99	0.90
	-(0.54)	(0.37)	(1.77)	(3.42)	(1.22)	(3.79)	(3.00)	(1.35)	(2.70)	(2.33)
-2	-0.39	0.07	0.37	0.60	0.76	0.25	0.95	0.87	0.49	0.78
	-(1.56)	(0.29)	(1.04)	(2.29)	(3.25)	(0.86)	(2.72)	(2.80)	(1.85)	(2.82)
0	-0.17	-0.08	-0.01	0.19	0.22	0.17	0.13	0.28	0.49	0.42
	-(2.02)	-(0.81)	-(0.13)	(1.44)	(1.55)	(1.07)	(0.80)	(1.62)	(2.71)	(2.15)
2	0.11	-0.03	-0.11	-0.32	-0.24	0.08	0.15	0.11	0.10	0.17
	(0.57)	-(0.14)	-(0.52)	-(1.38)	-(1.03)	(0.34)	(0.68)	(0.47)	(0.39)	(0.84)
3	0.26	-0.23	-0.30	-0.30	-0.32	0.12	0.21	-0.36	-0.02	-0.08
	(0.75)	-(0.75)	-(0.87)	-(1.04)	-(1.16)	(0.39)	(0.68)	-(1.15)	-(0.06)	-(0.33)
4	-0.04	-0.36	-0.66	-0.57	-0.55	-0.24	-0.62	-0.63	-0.52	0.37
	-(0.10)	-(0.78)	-(1.63)	-(1.56)	-(1.31)	-(0.61)	-(1.35)	-(1.91)	-(1.41)	(0.90)
5	-0.63	-0.43	-0.83	-0.93	-0.92	-1.14	-0.73	-0.51	0.10	0.07
	-(1.26)	-(0.92)	-(1.85)	-(2.12)	-(2.20)	-(2.55)	-(1.65)	-(1.33)	(0.24)	(0.18)
-5,5	1.47	1.66	2.15	2.98	2.69	2.25	2.12	1.67	0.75	0.92
	(1.40)	(1.67)	(2.30)	(3.24)	(2.89)	(2.48)	(2.67)	(2.29)	(1.16)	(1.55)
-4,4	0.10	0.64	1.96	1.01	2.81	1.55	1.54	2.05	1.59	0.33
	(0.11)	(0.81)	(2.78)	(1.42)	(3.45)	(2.08)	(1.86)	(3.31)	(2.32)	(0.47)
-3,3	-0.42	0.41	0.89	1.46	0.79	1.48	1.00	0.85	1.01	0.98
	-(0.75)	(0.57)	(1.50)	(2.89)	(1.44)	(2.38)	(1.71)	(1.58)	(2.09)	(2.15)

Table II - Panel C
Size and Book-to-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, 1 to 10 quarters after portfolio formation. The returns are size and book-to-market adjusted. We first form decile size portfolios based on NYSE cutoff points, and further divide the smallest decile into quintiles, without distinction by stock exchange. Each size portfolio is further partitioned into book-to-market quintiles, to form a total of 70 portfolios. We then subtract the reference portfolio buy-and-hold return from each stock's quarterly buy-and-hold return. Portfolio (-5,5) is long stocks that have been persistently sold and short stocks tha 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	4.53	4.63	4.14	4.25	3.92	3.27	3.34	2.84	2.39	2.18
	(9.69)	(9.54)	(8.79)	(8.81)	(6.48)	(6.68)	(6.60)	(5.88)	(4.86)	(5.57)
-4	2.42	2.36	3.60	2.47	3.39	2.69	2.28	2.63	2.10	1.59
	(5.50)	(6.24)	(8.60)	(6.11)	(6.49)	(5.43)	(5.08)	(5.57)	(3.92)	(3.16)
-3	1.67	1.79	1.86	2.78	1.85	2.55	2.02	1.48	1.91	1.61
	(5.61)	(4.87)	(6.48)	(7.56)	(5.43)	(7.25)	(5.46)	(4.68)	(5.18)	(4.50)
-2	0.83	1.07	1.32	1.34	1.74	1.20	1.51	1.46	1.22	1.42
	(4.41)	(4.84)	(4.77)	(6.22)	(6.53)	(4.42)	(5.64)	(5.24)	(5.13)	(5.50)
0	-0.28	-0.06	0.10	0.33	0.39	0.38	0.40	0.55	0.68	0.65
	-(2.77)	-(0.60)	(0.96)	(2.61)	(3.05)	(2.83)	(2.68)	(3.40)	(4.26)	(3.93)
2	-1.18	-1.05	-0.96	-1.00	-0.82	-0.43	-0.05	-0.09	-0.14	0.17
	-(6.07)	-(5.49)	-(5.27)	-(5.50)	-(4.20)	-(2.09)	-(0.26)	-(0.49)	-(0.64)	(0.93)
3	-1.54	-2.00	-1.62	-1.59	-1.27	-0.61	-0.47	-1.03	-0.30	-0.30
	-(5.42)	-(8.53)	-(6.28)	-(6.23)	-(5.29)	-(2.41)	-(1.80)	-(3.85)	-(1.14)	-(1.16)
4	-2.57	-2.37	-2.40	-2.08	-1.67	-1.42	-1.49	-1.05	-0.97	0.05
	-(6.86)	-(6.60)	-(6.97)	-(5.55)	-(4.82)	-(4.35)	-(3.95)	-(3.40)	-(2.90)	(0.15)
5	-3.74	-3.18	-3.12	-2.81	-2.62	-2.38	-1.67	-1.26	-0.53	-0.61
	-(9.77)	-(7.22)	-(7.57)	-(8.36)	-(7.65)	-(6.35)	-(4.23)	-(3.97)	-(1.40)	-(1.55)
-5,5	8.26	7.81	7.26	7.06	6.54	5.65	5.02	4.10	2.92	2.79
	(11.81)	(10.68)	(10.60)	(10.23)	(8.59)	(8.12)	(7.16)	(6.46)	(4.84)	(5.00)
-4,4	4.99	4.73	6.00	4.55	5.06	4.11	3.77	3.68	3.07	1.54
	(7.53)	(8.35)	(9.84)	(7.72)	(7.51)	(6.48)	(5.77)	(6.12)	(4.55)	(2.62)
-3,3	3.21	3.80	3.48	4.36	3.13	3.16	2.49	2.51	2.20	1.90
	(7.38)	(7.86)	(8.39)	(8.64)	(6.99)	(6.99)	(5.08)	(5.57)	(4.80)	(4.17)

Table III

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

This table presents average monthly returns from portfolios that are long 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 (H1) to 30 months (H10). 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. Autocorrelation-consistent t-statistics are in parentheses.

Holding period	**H 1**	**H 2**	**H 3**	**H 4**	**H 5**	**H 6**	**H 7**	**H 8**	**H 9**	**H 10**
Raw returns										
Pers -5,5	0.56	0.56	0.60	0.65	0.67	0.66	0.65	0.63	0.60	0.56
	(1.81)	(1.99)	(2.23)	(2.51)	(2.67)	(2.74)	(2.80)	(2.85)	(2.82)	(2.82)
Pers -4,4	0.18	0.19	0.38	0.36	0.43	0.43	0.42	0.42	0.42	0.38
	(0.68)	(0.82)	(1.83)	(1.89)	(2.40)	(2.49)	(2.52)	(2.66)	(2.80)	(2.70)
Pers -3,3	0.02	0.10	0.15	0.23	0.22	0.25	0.26	0.26	0.26	0.26
	(0.08)	(0.53)	(0.90)	(1.60)	(1.67)	(1.98)	(2.13)	(2.19)	(2.33)	(2.44)
CAPM alphas										
Pers -5,5	0.80	0.80	0.84	0.88	0.90	0.89	0.87	0.85	0.80	0.76
	(2.49)	(2.81)	(3.11)	(3.39)	(3.72)	(3.89)	(4.02)	(4.17)	(4.23)	(4.26)
Pers -4,4	0.33	0.35	0.53	0.52	0.59	0.58	0.57	0.57	0.56	0.51
	(1.17)	(1.33)	(2.37)	(2.61)	(3.01)	(3.18)	(3.31)	(3.50)	(3.78)	(3.75)
Pers -3,3	0.09	0.20	0.26	0.34	0.34	0.37	0.38	0.37	0.37	0.36
	(0.49)	(1.12)	(1.43)	(2.21)	(2.54)	(2.75)	(2.92)	(3.13)	(3.33)	(3.49)
Fama-French + Momentum alphas										
Pers -5,5	0.77	0.63	0.60	0.54	0.52	0.52	0.50	0.48	0.46	0.44
	(2.45)	(2.30)	(2.28)	(2.30)	(2.38)	(2.46)	(2.47)	(2.55)	(2.55)	(2.59)
Pers -4,4	0.40	0.29	0.41	0.33	0.36	0.31	0.32	0.34	0.34	0.31
	(1.43)	(1.28)	(1.97)	(1.80)	(2.01)	(1.88)	(1.96)	(2.15)	(2.34)	(2.18)
Pers -3,3	0.44	0.36	0.28	0.29	0.26	0.26	0.24	0.24	0.25	0.25
	(1.59)	(1.63)	(1.58)	(1.92)	(1.88)	(1.89)	(1.86)	(1.95)	(2.11)	(2.18)

Table IV

Size and B/M adjusted quarterly returns to momentum and persistence portfolios

This table presents time-series averages of equal-weighted quarterly returns for portfolios of stocks ranked on institutional trading persistence. The returns are size and book-to-market adjusted. We first form decile size portfolios based on NYSE cutoff points, and further divide the smallest decile into quintiles, without distinction by stock exchange. Each size portfolio is further partitioned into book-to-market quintiles, to form a total of 70 portfolios. We then subtract the reference portfolio buy-and-hold return from each stock's quarterly buy-and-hold return. Portfolio (-5,5) is long stocks that have been persistently sold and short stocks tha 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. Past winners (losers) are stocks in the top (bottom) tercile of the distribution of past nine-month returns. Returns are reported in percent per quarter. t-statistics are in parentheses.

Persistence	**q1**	**q2**	**q3**	**q4**	**q5**	**q6**	**q7**	**q8**	**q9**	**q10**
	Past winners									
(-5,5)	7.95	8.34	9.51	8.43	7.42	6.90	6.56	5.36	3.73	4.80
	(9.45)	(9.60)	(9.40)	(9.92)	(7.26)	(6.22)	(6.33)	(5.04)	(3.63)	(5.36)
(-4,4)	4.86	5.25	7.15	6.49	7.10	5.12	5.41	5.61	2.23	1.97
	(4.86)	(6.32)	(8.35)	(6.54)	(4.70)	(5.35)	(5.18)	(5.20)	(2.30)	(2.30)
(-3,3)	3.89	5.76	4.44	4.11	4.24	5.66	3.42	3.07	3.94	1.90
	(6.60)	(7.30)	(7.23)	(5.28)	(6.66)	(6.19)	(4.02)	(4.31)	(4.81)	(2.27)
	Past losers									
(-5,5)	9.70	8.86	7.12	7.46	7.91	6.57	4.69	3.40	0.99	0.66
	(8.08)	(8.60)	(6.75)	(6.56)	(6.56)	(5.85)	(4.48)	(3.27)	(0.90)	(0.59)
(-4,4)	6.82	5.07	6.95	3.79	5.62	3.82	4.81	3.55	4.03	0.27
	(6.37)	(5.37)	(6.93)	(3.62)	(5.82)	(3.23)	(5.27)	(3.42)	(3.50)	(0.25)
(-3,3)	5.19	4.73	3.33	5.47	2.40	2.02	3.21	1.61	0.51	1.45
	(7.34)	(6.50)	(4.70)	(6.47)	(3.10)	(2.47)	(3.49)	(2.11)	(0.57)	(2.03)

Table V

Average monthly returns to portfolio strategies based on momentum and trading persistence

This table presents average monthly returns to portfolios of different institutional trading persistence. Holding periods are 6 months to 30 months. Past winners (losers) are stocks in the top (bottom) tercile of the distribution of past nine-month returns. Returns are reported in percent per month. t-statistics are in parentheses.

Holding Period	**Past ret Portf.**	**Trading Persistence**								
		-5	**-4**	**-3**	**3**	**4**	**5**	**[-5,5]**	**[-4,4]**	**[-3,3]**
6 months	Win	1.61	1.55	1.57	1.46	1.42	1.29	0.32	0.13	0.12
		(3.97)	(3.77)	(3.84)	(3.36)	(3.10)	(2.71)	(1.01)	(0.43)	(0.50)
	Los	1.40	1.09	0.85	0.00	0.08	0.01	1.37	1.02	0.85
		(2.56)	(2.13)	(1.75)	(0.00)	(0.16)	(0.02)	(4.07)	(3.51)	(4.06)
	W-L	0.21	0.45	0.72	1.45	1.34	1.27			
		(0.80)	(1.25)	(2.13)	(4.62)	(3.76)	(3.20)			
9 months	Win	1.58	1.60	1.63	1.35	1.27	1.20	0.38	0.33	0.28
		(3.96)	(3.88)	(4.11)	(3.11)	(2.82)	(2.54)	(1.25)	(1.27)	(1.37)
	Los	1.40	1.27	0.93	0.35	0.14	-0.05	1.43	1.13	0.57
		(2.73)	(2.63)	(2.03)	(0.79)	(0.31)	-(0.12)	(4.52)	(4.44)	(3.21)
	W−L	0.18	0.32	0.70	1.00	1.13	1.25			
		(0.84)	(1.03)	(2.59)	(3.48)	(3.55)	(3.82)			
12 months	Win	1.53	1.47	1.45	1.26	1.15	1.08	0.45	0.31	0.19
		(3.84)	(3.75)	(3.70)	(2.92)	(2.59)	(2.29)	(1.53)	(1.32)	(1.06)
	Los	1.48	1.23	1.10	0.56	0.35	0.19	1.28	0.87	0.53
		(3.01)	(2.68)	(2.50)	(1.27)	(0.82)	(0.45)	(4.39)	(3.96)	(3.37)
	W−L	0.05	0.24	0.35	0.69	0.80	0.89			
		(0.40)	(0.95)	(1.53)	(2.66)	(2.92)	(2.93)			
18 months	Win	1.41	1.45	1.43	1.16	1.09	0.97	0.45	0.35	0.28
		(3.68)	(3.67)	(3.85)	(2.73)	(2.50)	(2.07)	(1.63)	(1.59)	(1.67)
	Los	1.66	1.44	1.21	0.79	0.49	0.42	1.21	0.95	0.42
		(3.48)	(3.31)	(2.84)	(1.86)	(1.20)	(1.06)	(4.56)	(4.93)	(3.42)
	W−L	-0.25	0.00	0.22	0.37	0.60	0.54			
		-(0.88)	(0.01)	(1.24)	(1.74)	(2.53)	(2.04)			
24 months	Win	1.36	1.42	1.38	1.14	1.06	0.98	0.38	0.36	0.23
		(3.57)	(3.76)	(3.79)	(2.73)	(2.46)	(2.13)	(1.46)	(1.80)	(1.50)
	Los	1.69	1.42	1.26	0.83	0.57	0.59	1.06	0.85	0.43
		(3.68)	(3.38)	(3.01)	(2.03)	(1.40)	(1.51)	(4.59)	(5.12)	(4.02)
	W−L	-0.33	0.00	0.11	0.31	0.50	0.38			
		-(1.43)	(0.00)	(0.73)	(1.68)	(2.32)	(1.64)			
30 months	Win	1.40	1.34	1.36	1.14	1.09	1.00	0.40	0.25	0.22
		(3.73)	(3.57)	(3.81)	(2.77)	(2.57)	(2.22)	(1.64)	(1.30)	(1.49)
	Los	1.69	1.44	1.31	0.94	0.74	0.82	0.84	0.70	0.36
		(3.79)	(3.46)	(3.15)	(2.33)	(1.80)	(2.07)	(4.11)	(4.90)	(3.78)
	W−L	-0.30	-0.11	0.05	0.20	0.35	0.18			
		-(1.42)	-(0.63)	(0.38)	(1.18)	(1.71)	(0.80)			

Figure 1

Quarterly market-adjusted returns to trading persistence portfolios

One to ten quarters after portfolio formation

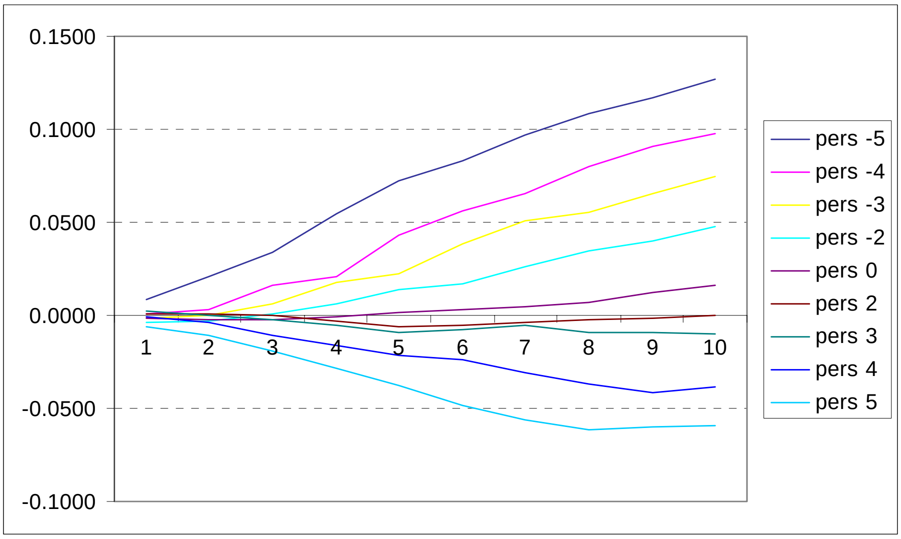


Figure 2

Quarterly size and Book-to-market adjusted returns to trading persistence portfolios

One to ten quarters after portfolio formation

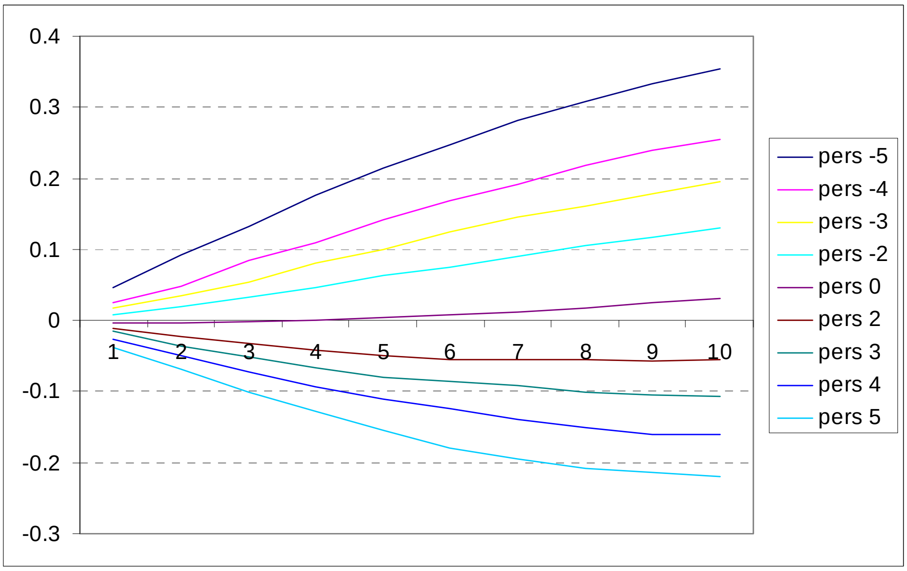


Figure 3

Proportion of stocks that are net buys, by trading persistence

One to ten quarters after portfolio formation

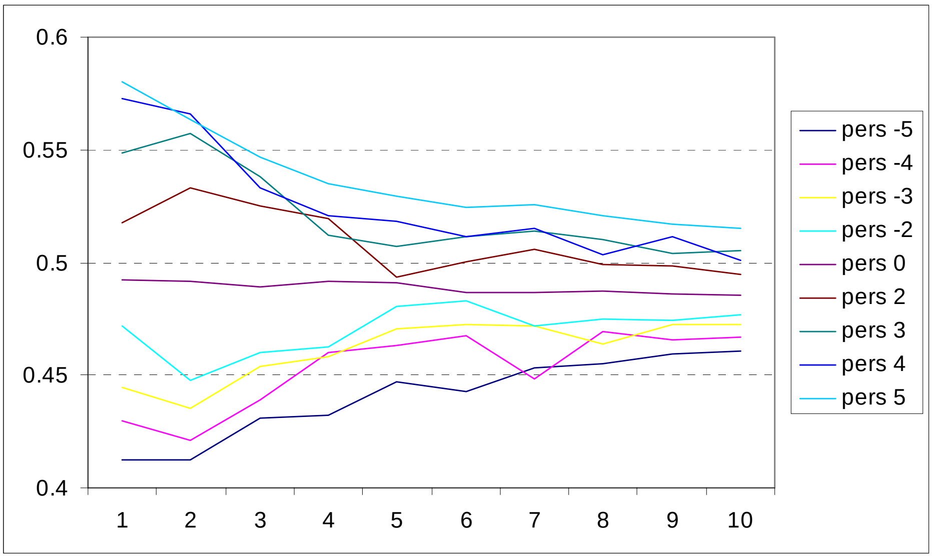


Figure 4

Median change in institutional portfolio weights (d_{it}), by trading persistence

One to ten quarters after portfolio formation

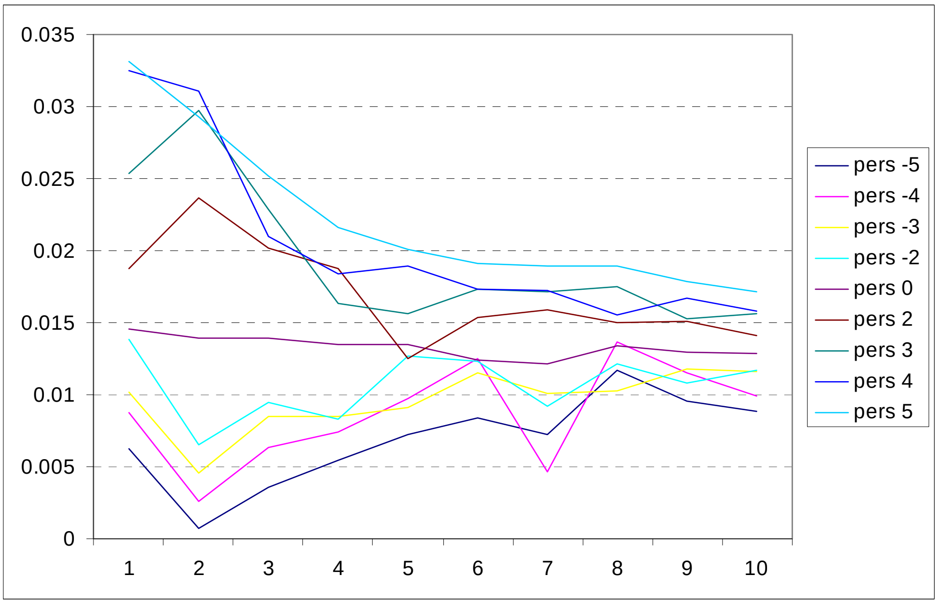
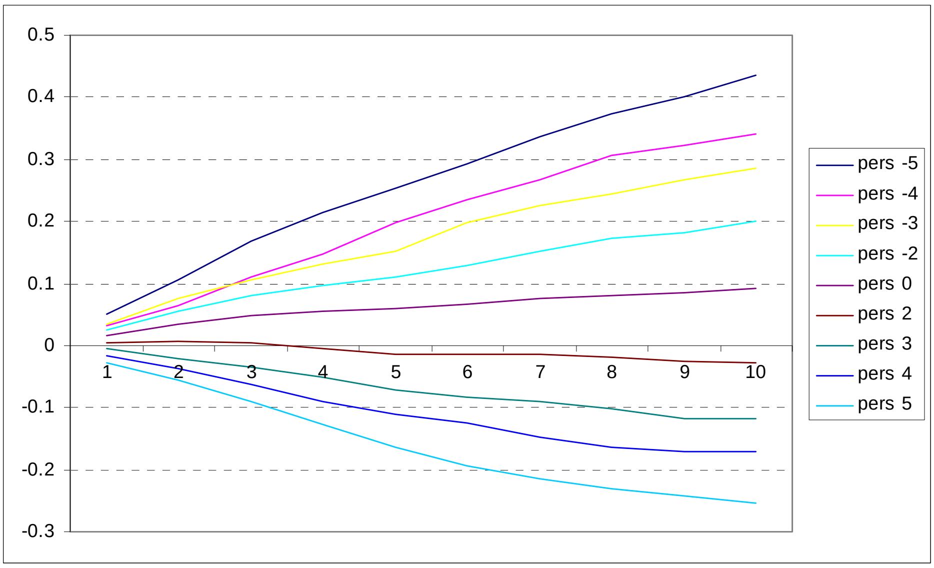


Figure 5

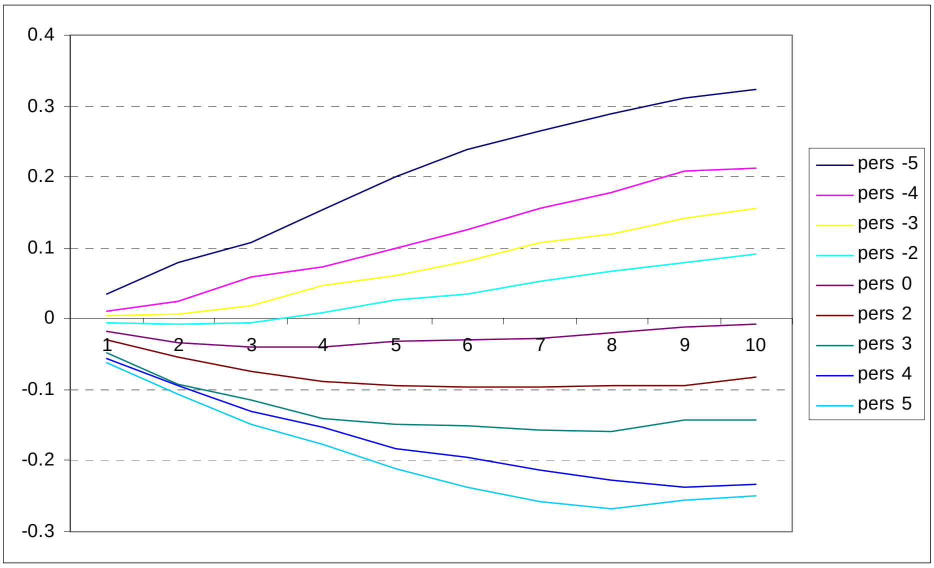
Quarterly size and Book-to-market adjusted returns to trading persistence portfolios

One to ten quarters after portfolio formation

A: Past winners



B: Past losers



6 Appendix: Proofs

6.1 Proof of Proposition 1

The process that generates the price is

$$\begin{aligned}
\hat{p}_t &= v_{t-1} + X_t = v_{t-1} + \frac{\varepsilon_t + \beta X_{t-1}}{2} = v_{t-1} + \frac{\varepsilon_t + \beta\left(\hat{p}_{t-1} - v_{t-2}\right)}{2} \\
&= v_{t-1} + \left(\frac{1}{2}\varepsilon_t + \frac{1}{2}\beta\left(\hat{p}_{t-1} - v_{t-2}\right)\right)
\end{aligned}$$

Hence,

$$\begin{aligned}
& \hat{p}_t - \hat{p}_{t-1} \\
&= v_{t-1} - v_{t-2} + \left(\frac{1}{2}\left(\varepsilon_t - \varepsilon_{t-1}\right) + \frac{1}{2}\beta\left(\left(\hat{p}_{t-1} - \hat{p}_{t-2}\right) - \left(v_{t-2} - v_{t-3}\right)\right)\right) \\
&= \varepsilon_{t-1} + \left(\frac{1}{2}\left(\varepsilon_t - \varepsilon_{t-1}\right) + \frac{1}{2}\beta\left(\left(\hat{p}_{t-1} - \hat{p}_{t-2}\right) - \varepsilon_{t-2}\right)\right) \\
&= \frac{1}{2}\varepsilon_t + \frac{1}{2}\varepsilon_{t-1} - \frac{1}{2}\beta\varepsilon_{t-2} + \frac{\beta}{2}\left(\hat{p}_{t-1} - \hat{p}_{t-2}\right)
\end{aligned}$$

Let $r_t = \hat{p}_t - \hat{p}_{t-1}$. We have and ARMA(1,2) process:

$$\begin{aligned}
r_t &= \frac{1}{2}\left(\varepsilon_t + \varepsilon_{t-1} - \beta\varepsilon_{t-2} + \beta r_{t-1}\right) \\
&= \frac{1}{2}\left(\varepsilon_t + \varepsilon_{t-1} - \beta\varepsilon_{t-2} + \frac{\beta}{2}\left(\varepsilon_{t-1} + \varepsilon_{t-2} - \beta\varepsilon_{t-3} + \beta r_{t-2}\right)\right) \\
&= \frac{1}{2}\left(\varepsilon_t + \varepsilon_{t-1} - \beta\varepsilon_{t-2} + \frac{\beta}{2}\left(\varepsilon_{t-1} + \varepsilon_{t-2} - \beta\varepsilon_{t-3} + \frac{\beta}{2}\left(\varepsilon_{t-2} + \varepsilon_{t-3} - \beta\varepsilon_{t-4} + \beta r_{t-3}\right)\right)\right) \\
&= \frac{1}{2}\varepsilon_t + \frac{1}{2}\left(1 + \frac{\beta}{2}\right)\varepsilon_{t-1} + \frac{1}{2}\left(-\beta + \frac{\beta}{2} + \frac{\beta}{2}\frac{\beta}{2}\right)\varepsilon_{t-2} + \ldots \\
&= \frac{1}{2}\varepsilon_t + \frac{1}{2}\left(1 + \frac{\beta}{2}\right)\varepsilon_{t-1} + \frac{1}{2}\left(-\frac{\beta}{2} + \left(\frac{\beta}{2}\right)^2\right)\varepsilon_{t-2} + \ldots \\
&= \frac{1}{2}\varepsilon_t + \frac{1}{2}\left(1 + \frac{\beta}{2}\right)\varepsilon_{t-1} + \frac{1}{2}\frac{\beta}{2}\left(\frac{\beta}{2} - 1\right)\varepsilon_{t-2} + \ldots \\
&= \frac{1}{2}\left(\varepsilon_t + \left(1 + \frac{\beta}{2}\right)\varepsilon_{t-1} + \left(\frac{\beta}{2} - 1\right)\sum_{s=2}\left(\frac{\beta}{2}\right)^{s-1}\varepsilon_{t-s}\right)
\end{aligned}$$

$$R_t = \varepsilon_t + A\varepsilon_{t-1} + B\sum_{s=2} C^{s-1}\varepsilon_{t-s}$$

where $R_t = 2r_t$, $A = 1 + \frac{\beta}{2} > 0$, $B = \frac{\beta}{2} - 1 < 0$, and $C = \frac{\beta}{2} \in (0, 1)$. Let $d \geq 3$:

$$
\begin{aligned}
& cov\left(R_t, R_{t-d}\right) \\
= \; & cov\left(\varepsilon_t + A\varepsilon_{t-1} + B\sum_{s=2} C^{s-1}\varepsilon_{t-s}, \varepsilon_{t-d} + A\varepsilon_{t-d-1} + B\sum_{s=2} C^{s-1}\varepsilon_{t-d-s}\right) \\
= \; & cov\left(B\sum_{s=d} C^{s-1}\varepsilon_{t-s}, \varepsilon_{t-d} + A\varepsilon_{t-d-1} + B\sum_{s=2} C^{s-1}\varepsilon_{t-d-s}\right) \\
= \; & cov\left(BC^{d-1}\varepsilon_{t-d}, \varepsilon_{t-d}\right) + cov\left(BC^{d}\varepsilon_{t-d-1}, A\varepsilon_{t-d-1}\right) \\
& + cov\left(B\sum_{s=d+2} C^{s-1}\varepsilon_{t-s}, B\sum_{s=2} C^{s-1}\varepsilon_{t-d-s}\right) \\
= \; & cov\left(BC^{d-1}\varepsilon_{t-d}, \varepsilon_{t-d}\right) + cov\left(BC^{d}\varepsilon_{t-d-1}, A\varepsilon_{t-d-1}\right) \\
& + cov\left(BC^{d}\sum_{s=2} C^{s-1}\varepsilon_{t-d-s}, B\sum_{s=2} C^{s-1}\varepsilon_{t-d-s}\right) \\
= \; & BC^{d-1}\sigma^2 + ABC^{d}\sigma^2 + B^2C^{d} var\left(\sum_{s=2} C^{2(s-1)}\varepsilon_{t-d-s}\right) \\
= \; & \left(BC^{d-1} + ABC^{d} + B^2C^{d}\frac{C^2}{1-C^2}\right)\sigma^2 \\
= \; & BC^{d-1}\left(1 + AC + BC\frac{C^2}{1-C^2}\right)\sigma^2
\end{aligned}
$$

Note that

$$
1 + AC + BC\frac{C^2}{1-C^2} > 0
$$

But, because $B < 0$, we have that $cov\left(R_t, R_{t-d}\right) < 0$.

Now, consider

$$\begin{aligned}
& cov\left(R_t, R_{t-1}\right) \\
= \ & cov\left(\varepsilon_t + A\varepsilon_{t-1} + B\sum_{s=2} C^{s-1}\varepsilon_{t-s}, \varepsilon_{t-1} + A\varepsilon_{t-2} + B\sum_{s=2} C^{s-1}\varepsilon_{t-1-s}\right) \\
= \ & cov\left(A\varepsilon_{t-1}, \varepsilon_{t-1}\right) + cov\left(BC\varepsilon_{t-2}, A\varepsilon_{t-2}\right) \\
& + cov\left(B\sum_{s=3} C^{s-1}\varepsilon_{t-s}, B\sum_{s=2} C^{s-1}\varepsilon_{t-1-s}\right) \\
= \ & A\sigma^2 + ABC\sigma^2 + cov\left(BC\sum_{s=2} C^{s-1}\varepsilon_{t-1-s}, B\sum_{s=2} C^{s-2}\varepsilon_{t-1-s}\right) \\
= \ & A\sigma^2 + ABC\sigma^2 + B^2C\sum_{s=2} C^{2(s-1)}\sigma^2 \\
= \ & \left(A + ABC + B^2\frac{C^3}{1-C^2}\right)\sigma^2 > 0, \text{ since } 1 + BC = 1 - \frac{\beta}{2} + \frac{\beta^2}{4} > 0
\end{aligned}$$

6.2 Proof of Proposition 3

From the proof of Proposition 1, we know that

$$\hat{p}_t - \hat{p}_{t-1} = \frac{1}{2}\left(\varepsilon_t + \left(1 + \frac{\beta}{2}\right)\varepsilon_{t-1} + \left(\frac{\beta}{2} - 1\right)\sum_{s=2}\left(\frac{\beta}{2}\right)^{s-1}\varepsilon_{t-s}\right).$$

Note that

$$X_{t-1} = \frac{\varepsilon_{t-1} + \beta X_{t-2}}{2} = \frac{1}{2}\left(\varepsilon_{t-1} + \sum_{s=2}\left(\frac{\beta}{2}\right)^{s-1}\varepsilon_{t-s}\right).$$

Hence,

$$\begin{aligned}
& Cov\left[\hat{p}_t - \hat{p}_{t-1}, X_{t-1}\right] \\
= \ & \frac{1}{4}\left(\left(1 + \frac{\beta}{2}\right) + \left(\frac{\beta}{2} - 1\right)\sum_{s=2}\left(\left(\frac{\beta}{2}\right)^2\right)^{s-1}\right)\sigma^2
\end{aligned}$$

Defining $b = \frac{\beta}{2}$,

$$\begin{aligned}
& \left(1 + \frac{\beta}{2}\right) + \left(\frac{\beta}{2} - 1\right)\sum_{s=2}\left(\left(\frac{\beta}{2}\right)^2\right)^{s-1} \\
= \ & 1 + b - (1-b)\sum_{s=2}\left(b^2\right)^{s-1} \\
= \ & 1 + b - (1-b)\frac{b^2}{1-b^2} = 1 + b - \frac{b^2}{1+b} = \frac{1+2b}{1+b} > 0.
\end{aligned}$$

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