Excess Autocorrelation and Mutual Fund Performance

Xi Dong[1] and Massimo Massa[2]

This version: January 2013

Abstract

We develop a new measure to predict mutual fund performance based on the microstructure evidence on stealth trading. We exploit the intuition that strategic stealth trading induces positive autocorrelation in the portfolios of informed investors. The degree of portfolio return autocorrelation of the funds therefore carries information to gauge their skills. We propose an autocorrelation-based measure of mutual fund portfolio returns, termed the excess autocorrelation – the difference between the autocorrelation of actual fund portfolio return and that of the return on a portfolio that invests in the previously disclosed fund holdings. We test our measure using the US mutual fund industry between October, 1998 and December, 2010. The results show that funds with high excess autocorrelation persistently display a net-of-risk performance that ranges between 2 and 3 percent per year. Such performance is predictable up to 12 months ahead. This suggests that the excess autocorrelation predicts fund performance.

Keywords: Autocorrelation, Mutual Fund Performance, Alpha, Skill

JEL Classification: G12, G14

Introduction

Finance literature has extensively analyzed the ability of the mutual funds to deliver "superior performance". The results are mixed. Performance is rare, does not seem to persist, and is limited to a

[1] INSEAD, E-mail: xi.dong@insead.edu.

[2] INSEAD, E-mail: massimo.massa@insead.edu.

We thank Randolph Cohen (AFA discussant), Kent Daniel, Bernard Dumas, Thierry Foucault, Jennifer Huang, Timothy Johnson, Dong Lou, Andrew Metrick, Christopher Polk, Tarun Ramadorai, Clemens Sialm, Richard Sias, Lu Zheng, and seminar participants at the 2014 American Finance Association Meetings, the 2013 China International Conference in Finance, the 3rd Helsinki Finance Summit on Investor Behavior, and INSEAD for valuable comments and discussions.

subset of mutual funds. The key question is therefore how to systematically identify them. In this paper, we address this issue using a novel criterion based on indirect evidence on informed trading.

We start with the fact that if a fund manager is privy to private/superior information, he will try to hide it so as not to affect the price when he trades. The optimal trading strategy is to spread the trades over time across stocks in the portfolios so as to conceal information (e.g., Kyle (1985), Barclay and Warner (1993), Boulatov, Hendershott, and Livdan (2013)). This strategic "stealth" trading is likely to increase the autocorrelation of their daily portfolio returns through serially correlated price impacts. Both anecdotal and empirical evidence also suggest that informed institutional investors indeed spread their trades to conceal information, generating daily return autocorrelation in their portfolios. For example, on November 14, 2011, Warren Buffett announced $10 billion-plus stake in IBM overnight but admitted that he started gradually buying nine months ago.[3] Sias and Starks (1997) also show that informed institutional investors' trading induces positive serial correlation in the daily returns of common stock portfolios.

If informed trading induces positive daily return autocorrelation in the portfolio of the informed managers, we can use the "excess" serial correlation in the portfolio of the fund managers to infer their degree of informativeness. In other words, we can extract skill-relevant information from the daily return autocorrelation of the fund portfolios.

In this paper, we propose a new measure that is based on information contained in portfolio return autocorrelation to predict mutual fund performance. The measure is defined as the difference between the autocorrelation of actual daily fund returns and the autocorrelation of a hypothetical portfolio that invests in the previously disclosed fund holdings. We term this difference: "excess autocorrelation," which measures the additional autocorrelation of the actual fund return that is not revealed in a fund's quarterly or semiannually publicly disclosed holdings. To the extent that informed "stealth trading" increases the informed institutional investor's daily portfolio return autocorrelation and that the purpose of such trading is to conceal private information, funds who often tend to generate higher excess autocorrelation in their actual fund portfolio than other funds are also likely to conduct more private-information-motivated trading and thus be more informed on average than other funds.

We test our approach by focusing on the daily returns of U.S. equity mutual funds over the period between October, 1998 and December, 2010. We document a substantial and persistent cross-sectional variation in the excess return autocorrelation and such a variable seems to consistently predict performance. Funds with high prior 12-month or 24-month excess autocorrelation tend to persistently deliver a better performance in the next one to twelve months than funds with low excess-autocorrelation. Moreover, this effect is stronger if we adjust for differences in the fund risk, style, and liquidity. Specifically, the funds with the highest prior-year excess autocorrelation deliver on

[3] See "One Secret Buffett Gets to Keep," New York Times, November 14, 2011.

average an excess return of 3% per year relative to the market, whereas those with the lowest prior-year excess autocorrelation generate a slightly negative but insignificant excess return. The difference in performance between the two portfolios is statistically and economically significant. This difference allows us to identify mutual funds that significantly outperform net-of-fees various passive benchmarks.

Next, we compare how excess autocorrelation relates to the performance measures that extract performance-relevant information from past returns of a similar horizon, such as the return gap of Kacperczyk, Sialm, and Zheng (2008) and the past 12-month return of Carhart (1997). We find that the excess-autocorrelation effect is not subsumed by these performance measures. In fact, after controlling for them, our measure allows us to better identify persistently outperforming high excess-autocorrelation funds – i.e., funds that delivered high past performance in terms of either return or return gap and can still generate positive alpha in the future. For example, high excess-autocorrelation funds with prior-year performance in the top quartile continue outperforming by a four-factor alpha of 49 basis points per month during the portfolio formation period.

The relative outperformance of high excess-autocorrelation funds, while coming from both stock selection and portfolio rebalancing, is mostly due to stock selection. It is also more driven by the performance of the stocks that these funds consistently buy than by the performance of those that they consistently sell during the recent disclosure periods. The stocks they consistently buy deliver a four-factor alpha of 21 basis point per month, which is 30 basis point higher than that of the stocks that low excess-autocorrelation funds consistently buy, while the stocks they consistently sell do not perform significantly differently from the stocks that low excess-autocorrelation funds consistently sell.

Then, we investigate the link between portfolio excess autocorrelation and performance. Portfolio return autocorrelation could be driven by two different mechanisms related to informed trading: the cross-autocorrelation between stocks in the portfolio and the autocorrelation of individual stocks in the portfolio. A positive excess autocorrelation can arise because a fund's actual portfolio contains stocks with either more autocorrelated or more cross-autocorrelated returns than its disclosed holdings portfolio. We find that the performance consequences of the excess autocorrelation are more likely driven by the excess cross-autocorrelation than by the excess autocorrelation of individual stocks in the fund’s actual portfolios.

The excess autocorrelation of a fund’s actual return could also be related to the autocorrelation of the returns of the actual portfolio that the fund is buying or selling during the disclosure periods. We therefore investigate the contribution of the buy-portfolio and the sell-portfolio autocorrelations to the performance effect of excess autocorrelation separately. Our findings suggest that the high autocorrelation of funds' actual buy and sell portfolios during the recent disclosure periods both partially contribute to the performance effect of high excess autocorrelation.

A fund's excess return autocorrelation is not necessarily only related to the degree of informativeness of a fund. It can simply be due to liquidity management. For example, larger funds may have to spread their trades over longer periods. Funds that trade more illiquid assets over the disclosure period may incur larger price impacts. In both cases, the excess autocorrelation of such funds can be higher than other funds. However, these characteristics are unlikely to lead to after-fee fund outperformance as larger funds generally perform worse (e.g., Chen, Hong, Huang, and Kubik (2004)), and funds that trade more illiquid assets over the disclosure period incur more transaction costs. In a multivariate specification that controls for fund size and illiquidity, as well as other characteristics such as fund flows and investment styles, we confirm the positive relation between a fund's excess return autocorrelation and its subsequent performance.

Our paper contributes to the literature along two dimensions. First, we contribute to the literature on fund performance and its persistence (e.g., Grinblatt and Titman (1993), Brown and Goetzmann (1995), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), and Wermers (2000)). In general, the evidence is that mutual funds on average underperform benchmarks and that only the set of worst-performing funds, even after controlling for the Fama-French factors and momentum, still seem to have persistently bad performance. More recently, the literature has shown new evidence of forecastability of mutual fund performance. In particular, Kosowski, Timmermann, Wermers, and White (2006) find a sizable minority of fund managers have stock picking ability that offset their expenses and the performance of these funds display persistence over time. Avramov and Wermers (2006) form an investment strategy in mutual funds that incorporate predictability in manager skills, fund risk loadings, and benchmark returns. Mamaysky *et al.* (2007a) show that the combined use of an ordinary least square (OLS) and Kalman filter model increases the number of funds with predictable out-of-sample alphas by about 60%, which provides evidence of persistence among fund performance. Kacperczyk, Sialm, and Zheng (2008) use a new measure of performance based on unobserved actions of mutual funds – the return gap – and show that it can predict future fund performance. Other authors have directly tried to identify the source of managerial performance (e.g., Cohen, Coval, and Pastor (2005), Gaspar, Massa, and Matos (2006), Kacperczyk and Seru (2007), and Cremers and Petajisto (2009), Huang, Sialm, and Zhang (2011), Dong, Feng, and Sadka (2013)). Our excess autocorrelation measure provides a separate signal of skill in identifying skilled managers.

Second, we contribute to the literature on microstructure-based return-autocorrelation models of informed trading (e.g., Kyle (1985), Barclay and Warner (1993), Wang (1994), Sias and Starks (1997), Llorente, Michaely, Saar, and Wang (2002), and Boulatov, Hendershott, and Livdan (2013)). In this literature, certain forms of short-term (e.g., daily) return autocorrelation are used as a common mechanism to identify informed trading. However, the empirical evidence on whether there is a linkage between the informativeness of an investor and the autocorrelation of his portfolio return is scarce. We confirm this literature by using the micro-founded measures of return autocorrelation to identify informed mutual funds that indeed outperform in the future.

The rest of this paper is organized as follows. Section 2 lays out the main hypotheses. Section 3 presents the data. Section 4 describes the excess autocorrelation measure. Section 5 analyzes the performance consequences of excess autocorrelation. Section 6 provides further results to understand the mechanisms and robustness of the performance effect of excess autocorrelation. A brief conclusion follows.

2. Testable Hypotheses

We now lay out our main testable restrictions. We start by the main results in the existing microstructure literature (e.g., Boulatov, Hendershott, and Livdan (2013), Barclay and Warner (1993), Kyle (1985)). An investor who has information among many stocks and trades in them will spread his trades across stocks over time to minimize his market impact.

This strategic "stealth" trading is likely to increase the serial return correlation of his portfolio returns through serially correlated price impacts for several reasons. One source of portfolio return autocorrelation is the cross-autocorrelated price impacts arising between the individual stocks in the portfolio of the investor. Such cross-autocorrelation can arise due to the desire of the informed investor to dissimulate his information. For example, in the strategic trading model of Boulatov, Hendershott, and Livdan (2013), an informed institutional investor possesses long-lived private information about multiple assets with positively correlated fundamental values. In each trading period, prices in each asset are functions of trading only in that asset and not trading in the other assets. Market frictions prevent market makers from conditioning their pricing rule on trading in all the other assets continuously and instantaneously. The optimal strategy of the informed institution is to spread its trades over time across assets to conceal information. This induces cross-autocorrelations between the individual stocks in his portfolio and in turn increases the autocorrelation of the portfolio returns.

Consider a general example in the spirit of their model. Suppose D is the disclosed holding portfolio of the investor at the end of the quarter, which includes at least one stock. The investor possesses long-lived private information, which only positively affects the future prices of stocks A, B, and C but not D. This implicitly assumes that the fundamental values of stock A, B, and C are positively related to each other but not to that of D either contemporaneously or in a lead-lag relationship, otherwise the long-lived private information may also affect D's future price. In this example, stock A, B, and C generally represent the portfolio that an informed mutual fund has private information on, while portfolio D represents the portfolio that the fund does not have private information on.

At the beginning of quarter, the investor accumulates the stakes of the three stocks strategically, buying stock A during day t, stock B during day $t+1$, and stock C during $t+2$. At the end of day t, the price of stock A increases following the institution's buying activity and reflecting the positive private information. Similarly, at the end of day $t+1$ and $t+2$, stock prices of B and C also increase, respectively, reflecting the same piece of private information. Thus, the return of A at day t, of B at day $t+1$, and of C at day $t+2$ will end up being correlated (i.e., cross-autocorrelated) due to the same piece of private information. This common price change across the three days increases return autocorrelation in the portfolio made of the three stocks A, B, and C. Such portfolio return autocorrelation arises even in the absence of any individual stock return autocorrelation.

Alternatively, portfolio return autocorrelation can also be generated by autocorrelated price impacts in individual stocks if the informed investors possess private information about an individual stock and spread their trades in the stock over time to hide their information (e.g., Kyle (1985) and Barclay and Warner (1993)). In the above example, the returns of stock A, B, and C could be autocorrelated due to the informed buying trades that are spread over time in each individual stock. Such trades are likely to push up the stock prices of all three stocks gradually over time. Since the private information is common among all three stocks, the return autocorrelations in stock A, B, and C also induce positive return autocorrelation in the portfolio that constitutes A, B, and C.

The investor's actual portfolio during the quarter consists of A, B, C, and D. The return autocorrelation of this portfolio is the sum of the return autocorrelations of A, B, C, and D plus the cross-autocorrelations among A, B and C. Since the fundamental value of portfolio D is assumed to be not related to those of A, B, and C in any contemporaneous and lead-lag relationship, there is no cross-autocorrelation between D and each of the three stocks. In other words, one cannot use the fundamental value of D to predict those of A, B, and C, and vice versa. The return autocorrelation of the disclosed portfolio of this investor is the return autocorrelation of D. The excess autocorrelation of this investor, by our definition, is the difference between the autocorrelation of his actual return and that of his disclosed portfolio return. This excess autocorrelation is equal to the sum of the return autocorrelations of individual stock A, B, and C plus the cross-autocorrelations among A, B and C. Thus, the excess autocorrelation captures the individual stock return autocorrelations and cross-autocorrelations induced by the investor's informed trading in stock A, B, and C, but removes the noise introduced by the autocorrelation of the investor's disclosed portfolio D as in reality, the realized returns of D could be autocorrelated due to various other reasons.

The above example assumes that the informed investor leaves permanent price impacts in the daily closing prices through his strategic "stealth" trading. Excess autocorrelation can also arise when both the informed and the noise traders only generate temporary price impacts during the day, which do not affect the daily closing price. This is consistent with the realistic scenario that the informed trader hides his trades among noise trading well enough by spreading his trades over time such that his trading does not gradually impound any private information into daily closing prices. In this case, the daily return autocorrelation and cross-autocorrelation in the above example are absent because daily closing prices are not affected by the informed investor. Our excess autocorrelation measure can still capture the informed investor's "stealth" trading if he accepts a large and persistent price concession each day when he gradually buys or sells the stock(s) that he has private information on.

Consider the following example. Suppose I is a stock or a portfolio already in the informed investor's disclosed portfolio. The informed investor's residual private information suggests that he should continue buying more I. Given the nature of most private information is time-sensitive, he can accept a large price concession persistently every day in order to build up a large position in I before the information is revealed. Suppose daily closing price represents the fundamental value of the stock on that day. The informed investor is willing to buy at a price Y dollars higher than each day's closing price in order to purchase a large block each day. Then the investor introduces a persistent negative daily return component in his actual return because the stock price will revert back to each day's closing price after his purchase, resulting a Y-dollar loss for every share he bought on that day. This persistent loss induces a positive return autocorrelation component in the investor's daily actual return but does not affect the daily return of portfolio I, which is calculated based on daily closing prices. The excess autocorrelation measure again captures this additional autocorrelation component that is in the investor's actual return but not in its disclosed portfolio return, while removing the noise that may be introduced by the realized return autocorrelation of the investor's disclosed portfolio. In contrast, a random noise trader does not need to trade every day and is not as time pressured even when he needs to trade a large quantity. Therefore, he is less likely to incur a persistent daily loss in his actual return.

Overall, all the above considerations suggest that informed investors are likely to display a stronger daily return autocorrelation in their actual fund return than what it is just entailed by the return of their disclosed portfolio holdings. A positive excess autocorrelation captures that the investor is likely to be conducting informed trading. The more often a fund generates excess autocorrelation in its actual returns, the more often it is likely involved in informed trading, and the more likely the fund is an informed fund on average. We can therefore lay out our main hypothesis.

H1: The more informed the manager is and therefore the higher his performance is, the stronger the degree of the average excess daily return autocorrelation of his portfolio.

In terms of the source of such correlation, we can argue that:

H2: The degree of excess daily return autocorrelation of the portfolio may be due to either the cross-autocorrelations arising between the individual stocks in the portfolio or the return autocorrelations in individual stocks.

Of course, there can be several other reasons that may induce a positive daily portfolio return autocorrelation. The first is the presence of non-information related transaction costs. Funds managers spread their trades across time simply to minimize execution costs. For example, Chan and Lakonishok (1995) find that over half the dollar volume of institutional trades takes at least four days to complete. This trading strategy can induce the daily portfolio return autocorrelation if there is a common component in individual security trading at the fund level or at the fund industry level. For example, a fund or the entire fund industry may increase or decrease most of its positions over short horizons for non-informational reasons such as experiencing net inflows or outflows.

Second, the cross-sectional variation of changes in institutional holdings can be related to systematic momentum trading (Carhart (1997)), while systematic momentum trading may induce portfolio-level return autocorrelation.

Third, nonsynchronous trading, which arises when some stocks in the portfolio are less frequently traded than others, may also induce positive portfolio return autocorrelation (e.g., Lo and MacKinlay (1990), Boudoukh, Richardson, and Whitelaw (1994), and Bernhardt and Davies (2008)).

However, these alternative reasons per se will not be related to better fund performance. First, if return autocorrelation is simply due to order-splitting by every mutual fund on average motivated by transaction cost reduction but not by informational reasons, there should not be any link between it and abnormal future performance. Second, if return autocorrelation is due to momentum trading, once we control for momentum such an extra-return should disappear (e.g., Carhart (1997)). Third, while nonsynchronous trading is not related to performance, yet it may still be that a portfolio with more nonsynchronous trading may contain more illiquid assets. In this case, such an extra-return should disappear as we control for the degree of illiquidity of fund holdings. In short, if these alternative reasons are the main economic reasons for the excess autocorrelation, we should not expect funds with high excess autocorrelation to exhibit any unexplainable superior performance.

Before bringing our hypotheses to the test, we describe the data we use and the way we construct our focus variable.

3. Data

Daily and monthly mutual-fund return data are obtained from the CRSP survivor-bias-free database for the period from October, 1998 to December, 2010 as October 1998 is the first month for CRSP to report fund daily returns. Only funds that report monthly net-of-fee (management, incentive, and other expenses) returns are kept in the sample. Some fund families incubate many private funds and make historical performance available only for those that survive (Elton, Gruber, and Blake (2001) and Evans (2004)). In order to address the incubation bias in the data, we exclude the first 12-month fund monthly returns. The removal of these young funds also alleviates the concern that these funds are more likely to be cross-subsidized by their respective fund families (Gaspar, Massa, and Matos (2006)).

We merge the CRSP Mutual Fund Database with the Thompson Financial CDA/Spectrum holdings database and the CRSP stock price data, following the methodology of Kacperczyk, Sialm, and Zheng (2005). The CRSP mutual fund database includes information on fund returns, total net assets (TNA), different types of fees, investment objectives, and other fund characteristics. The CDA/Spectrum database provides stockholdings of mutual funds. The data are collected both from reports filed by mutual funds with the SEC and from voluntary reports generated by the funds. During most of our sample period, funds are required by law to disclose their holdings semiannually. Beginning from 2004, all funds are required to disclose their holdings quarterly.

We focus our analysis on open-end active domestic equity mutual funds, for which the holdings data are most complete and reliable. To select such funds, we first exclude funds that hold less than 85% or more than 105% in equity. We then eliminate index, balanced, bond, money market, international, and sector funds, as well as funds not invested primarily in equity securities. We also exclude funds that hold fewer than 10 stocks and those which in the previous month managed less than $5 million. For funds with multiple share classes, we eliminate the duplicated funds and compute the value-weighted fund-level variables by aggregating across the different share classes.

Table 1 reports the summary statistics of the main fund attributes. We report summary statistics on expense ratio, turnover, fund flow, flow volatility, load dummy, log total net assets (*TNA*), age, number of stocks, the average Amihud illiquidity measure, the average bid-ask spread, and the average size of individual stocks in a fund portfolio, and the return gap measure of Kacperczyk, Sialm, and Zheng (2008). The percentage net flow to fund *i* during month *t* is measured as:

$$Flow_{i,t}=\frac{TNA_{i,t}-TNA_{i,t-1}(1+R_{i,t})-MergeTNA_{i,t}}{TNA_{i,t-1}},$$

where $TNA_{i,t}$ is measured at the end of month t, $R_{i,t}$ is the fund's return for month *t*, and $Merge\,TNA_{i,t}$ is the increase in the *TNA* due to mergers during month *t*. Since estimated fund flows are very volatile, we winsorize both the top and the bottom parts of the distribution at the 1% level. Flow volatility is calculated using the past 12-month flows.

Overall, the statistics show that our sample is similar to the ones used in the literature. For example, the turnover ratio is 89%, while the expense ratio is 1.28%. These compare to 90% and 1.28% in Huang, Sialm, and Zhang (2011).

4. The Excess Autocorrelation

We now define our measure of excess autocorrelation and describe its main characteristics. To evaluate the skill-relevant information hidden from funds' publicly disclosed holdings, we define a measure of excess autocorrelation of the fund portfolio. This is based on the comparison of the autocorrelation of the actual fund portfolio return (net investor return) and the autocorrelation of the net return of the fund's disclosed holdings. This section describes the computation of the excess autocorrelation.

We start with some notation. We define the daily fund portfolio return as the daily net actual investor return of fund *f* at day *t* (*RF*). Management fees and other expenses (*EXP*) are subtracted from this net return. We define the return of the fund's disclosed holdings (*RH*) as the total return of a hypothetical buy-and-hold portfolio that invests in the most recently disclosed stock positions. The net disclosed holdings return is the difference between *RH* and *EXP*.

The weights of individual stocks ($w_{i,\ t-1}^{f}$) depend on the number of shares held by the fund at the most recent disclosure date at day $t-\tau$ ($N_{i,t-\tau}^{f}$) and the stock price at the end of the previous day ($P_{i,t-1}$). Further, we adjust the number of shares and the stock prices for stock splits and other share adjustments:

$$w_{i,t-1}^{f} = \frac{N_{i,t-\tau}^{f} P_{i,t-1}}{\sum_{i=1}^{n} N_{i,t-\tau}^{f} P_{i,t-1}}$$

We define the excess autocorrelation (*EA*) in month *m* as the difference between the autocorrelation of the daily net actual investor return (*AA*) and the autocorrelation of the daily net disclosed holdings return in that month (*DA*):

$$EA_{m}^{f} = AA_{m}^{f} - DA_{m}^{f} \ ,$$

Thus, the excess autocorrelation measures the extra return autocorrelation of a fund's actual portfolio that cannot be captured by just examining its publicly disclosed holdings. The excess autocorrelation measure *EA* in month *m* is positive if the actual fund portfolio returns exhibit a higher autocorrelation than the returns calculated from its most recently disclosed holdings, and is negative otherwise. To the extent that a skillful/informed fund's information is private and that the purpose of the fund's strategic stealth trading is to hide its true demand of stock positions from the market maker, this measure captures the fund’s degree of informativeness as gauged by its “stealth trading”. The more often a fund generates high excess autocorrelation on a monthly basis, the more likely the fund is an informed fund on average.

We report some summary statistics in Table 1. The first three rows of Table 1 report the excess autocorrelation measure, the autocorrelation of the actual fund portfolio return, and the autocorrelation of the net daily return of the fund's disclosed holdings portfolio. Both the actual portfolio return autocorrelation and the disclosed portfolio return autocorrelation are computed and updated on a monthly basis.

The actual portfolio return autocorrelation and the disclosed portfolio return autocorrelation are negative and statistically significant (-4.80% and -5.13%, respectively) with a correlation of 96%. The negative correlation is likely due to the bid-ask bounce of individual stocks (e.g., Roll (1984)), which induces a negative daily return autocorrelation for both individual stocks and portfolio returns.[5]

The excess-autocorrelation measure has a slightly positive mean of 0.33%, suggesting that mutual funds' portfolio rebalancing ("interim trading") on average increases their daily portfolio return autocorrelation. This result is consistent with the finding of Sias and Starks (1997) that institutional trading is generally more informed than average investors' trading and that their informed trading contributes to positive daily portfolio return autocorrelation. The standard deviation of the EA measure is 4.91%, which is about the same absolute magnitude as the average portfolio return autocorrelation. This suggests that there is a substantial cross-sectional variation in the excess return autocorrelation.

In addition, the excess autocorrelation measure alleviates the impact of market conditions by using overlapping return distributions. The daily portfolio return autocorrelation changes substantially due to the exogenous changes in market conditions. Figure 1 presents the effect of market conditions on the autocorrelations of funds' actual and disclosed holding portfolios over time. Funds are first sorted into deciles according to their lagged average excess autocorrelation over the previous 12 months. The top decile of funds exhibits the most positive excess autocorrelation, while the bottom decile the least. The figure then depicts the 12-month moving averages of the cross-sectional means of the actual portfolio return autocorrelation and the disclosed portfolio return autocorrelation over our sample period. The autocorrelation levels change significantly over time. As the figure illustrates, common market shocks affect the two autocorrelation measures to a similar degree. Therefore, by using overlapping time periods to estimate both the actual autocorrelation and the hypothetical autocorrelation of a fund, our measure filters out the impact of common shocks to both autocorrelations.

[5] If the bid-ask bounce process, which determines whether a given trade occurs at the bid or ask price, were independent across different stocks, bid-ask bounce would produce a slight negative autocorrelation in portfolio returns coming from the negative autocorrelation of the individual stocks in the portfolio. In practice, the bid-ask bounce process may show positive correlation across stocks. For example, stock prices may generally rise (fall) on a day just before the close, then most stocks final trade will be at the ask (bid) price, inducing negative autocorrelation in the daily portfolio return.

5. Predictability of Fund Performance

In this section, we test whether excess autocorrelation contains valuable information about future fund performance.

5.1 Trading strategies based on the excess autocorrelation

Our first predictability test examines the predictability of performance on the basis of excess autocorrelation. Specifically, we sort all the funds in our sample into deciles according to their average monthly excess autocorrelation over the previous 12 or 24 months. The 12- or 24-month moving average reduces the noise in estimating monthly excess autocorrelation. We then compute for each month the average subsequent return by weighting all the funds in a decile equally.

We find that the funds in the middle four deciles exhibit relatively similar excess autocorrelation that are all very close to zero. For example, the average 12-month excess autocorrelations for the middle four deciles are between -0.15% and 0.56%.[6] Therefore in the remainder of the paper, we will aggregate several deciles to economize on space. More specifically, on the basis of the excess autocorrelation deciles, we form five excess autocorrelation portfolios. Portfolios 1 and 5 correspond to deciles 1 and 10, portfolio 3 corresponds to deciles 4 to 7, and portfolios 2 (and 4) correspond to deciles 2 and 3 (and deciles 8 and 9), respectively.

In Table 2, we report the average excess autocorrelation and the risk- and style-adjusted fund returns for the five portfolios. The first row reports the excess autocorrelation. Funds in Decile 1 have an average excess autocorrelation of -2.41% (-1.66%) per month during the 12-month (24-month) ranking period, whereas funds in Decile 10 have an average excess autocorrelation of 4.81% (3.60%) per month during the 12-month (24-month) ranking period. The difference between them is highly statistically significant.

The remaining rows report the performance measures based on the net investor returns. The risk-adjusted returns are the intercepts from a time-series regression based on the one-factor model of CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), the five-factor model of Acharya and Pedersen (2005), which adds an Amihud-based liquidity factor to the Carhart four-factor model, the five-factor model of Pástor and Stambaugh (2003), the four-factor model of CPZ proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P500 index, the returns on the Russell 2000 index minus the return on the S&P500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the

[6] The excess autocorrelation of the decile portfolios are -2.41%, -0.87%, -0.44%, -0.15%, 0.08%, 0.30%, 0.56%, 0.91%, 1.49%, and 4.18%, respectively.

Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the Carhart (1997) four-factor model to measure fund performance.[7]

We observe that funds with the lowest past excess autocorrelation (decile 1) tend to significantly underperform funds with the highest past excess autocorrelation (decile 10). If we sort the funds on the basis of the 12-month moving average excess autocorrelation, we find that investing in decile-10 funds would have generated an additional four-factor alpha of 27 basis points per month (*t-value*=3.55) or about 3.29% per year compared to investing in decile-1 funds. These results are not influenced substantially by the variation in risk or style factors, as well as by the controlling for macroeconomic information following Ferson and Schadt (1996). In addition, all the performance measures for the top-decile funds are positive. They are also statistically significant for the CAPM model (27 basis points with *t-value*=2.59), the CPZ four-factor model (21 basis points with *t-value*=2.19), and the Ferson-Schadt conditional model (17 basis points with *t-value*=2.07).

The results based on funds sorted on the basis of the prior 24-month moving average excess autocorrelation are very similar to the results sorted based on the 12-month moving window. This suggests that the performance-relevant information contained in the EA measure is relatively stable and persistent. Given the similarity between the 12-month and 24-month results, we will focus on the 12-month results in later sections to economize on space.

Since investors cannot short mutual funds, the strategies based on shorting the bottom deciles and being long the top ones are not tradable. However, they provide an intuition on the magnitude of the informativeness of the high excess autocorrelation funds. Also, they show how, conditioning on the excess autocorrelation, investors can avoid potential losses that are related to the excess autocorrelation differences between the deciles.

5.2 Trading strategies with back-testing

In a recent study, Mamaysky, Spiegel, and Zhang (2007b) provide evidence that previous performance studies are plagued by estimation problems. In particular, since many sorting variables are measured with noise, the top and the bottom deciles of a given trading strategy might not be populated by just the best and the worst funds, but also by funds that have the highest estimation errors. To alleviate this problem, they suggest using a back-testing technique in which the statistical sorting variable is required to exhibit some past predictive success for a particular fund before it is used to make predictions in the current period. They show that a strategy that uses modest *ex ante*

[7] To calculate Ferson-Schadt conditional performance alpha, we follow previous studies and include the following demeaned macroeconomic variables in month t-1: the dividend yield of the S&P 500 index, the term spread (the difference between the rates on a 10-year Treasury note and a three-month Treasury bill), the default spread (the difference between the rates on AAA and BAA bonds), and the three-month Treasury bill rate.

filters to eliminate funds whose sorting variables likely derive primarily from estimation errors produces very significant out-of-sample risk-adjusted returns.

Motivated by their study, we eliminate funds for which the demeaned excess autocorrelation has a different sign from the excess fund return in two non-overlapping time periods. In a first step, we sort all funds into deciles according to their average excess autocorrelation over month *t-12* and *t-1*, where *t* is the portfolio formation month. The sorting yields exactly the same decile portfolios as those described in Table 2. In the second step, we only keep funds whose reported excess returns relative to the market during month *t-1* have the same sign as their corresponding lagged demeaned average excess autocorrelation over month *t-12* and *t-2*.[8] Thus, in the trading strategy we consider only funds for which there is a concordance between their lagged demeaned excess autocorrelation and their lagged excess return. In this way, the average monthly excess autocorrelation of a fund is required to exhibit some past predicative success in the spirit of Mamaysky *et al.* (2007b) before it can be used to predict the returns during the portfolio formation month *t*. That is, the sign of the average lagged demeaned excess autocorrelation is consistent with the sign of the fund's excess return right before the portfolio formation period.[9]

The results, summarized in Table 3, show that the performance difference between the top and the bottom decile portfolios widens dramatically for all the performance measures. For example, the difference in the abnormal four-factor Carhart alpha increases from 27 basis points per month to 52 basis points per month (*t-value*=2.82).

After filtering out funds with diverging lagged performance measures, we find that the funds in the top excess-autocorrelation decile perform particularly well. All the alphas are now significantly positive. The outperformance ranges from 19 basis points per month (FF4+PS) to 44 basis points per month (CAPM).

5.3 Persistence of the excess autocorrelation and long-term performance

In this section, we examine the persistence of the excess autocorrelation measure and the long-term performance. To test whether the excess autocorrelation of a fund is persistent, we first sort all funds in our sample into the same five portfolios as in the previous sections according to the average excess autocorrelation during previous 1-, 2-, 3-, 4-, and 5-year intervals and compute the average excess autocorrelation during the subsequent month by weighting all funds in each portfolio equally. Table 4 reports the excess autocorrelations of the five portfolios. The first row shows that funds in the lowest excess autocorrelation portfolio, based on the previous 12 months, generate an average excess autocorrelation of –0.32% in the subsequent month. Funds in the highest excess autocorrelation decile

[8] The excess autocorrelation is demeaned by subtracting its times-series mean.
[9] See Kacperczyk, Sialm, and Zheng (2008) for a similar methodology, where their sorting variable is return gap.

generate an excess autocorrelation of 2.22%. The difference in the return gaps between the two extreme deciles is statistically significant (*t value*=15.69). Furthermore, the average excess autocorrelations line up almost monotonically across the five portfolios. In the remaining rows, we show that the persistence pattern remains similar if we sort funds according to their average excess autocorrelations during the prior 2 to 5 years.

We also examine the long-term performance of the excess autocorrelation. We form mutual fund portfolios in the same way as in Table 2 but hold the portfolio for longer periods. We follow the portfolio construction approach of Jegadeesh and Titman (1993). Specifically, we use average returns of multiple portfolios with the same holding horizon. For example, the January return of a three-month holding period strategy is an average of the January returns of three excess autocorrelation portfolios that are constructed in October, November, and December of the previous year. Table 5 presents the results. The results show that the relative outperformance of funds with high excess autocorrelation is relatively persistent. The high-minus-low excess autocorrelation fund return spread is still highly statistically and economically significant when the holding periods are extended to 12 months.

Overall, these results show that our excess autocorrelation measure and its performance predictability are persistent.

5.4 Excess autocorrelation, return gap, and prior return

Our excess autocorrelation measure is constructed using past 12-month returns. In this section we examine how excess autocorrelation relates to the performance measures that extract performance-relevant information from past returns of a similar horizon. ..

The first measure is the return gap measure of Kacperczyk, Sialm, and Zheng (2008). The return gap measure also extracts information from the recent 12-month difference between the actual fund portfolio and their disclosed holding portfolio. However, the economic mechanisms of the two measures are different. The daily return autocorrelation of a portfolio is not necessarily positively or negatively related to the monthly return of the portfolio. For example, a stock with high daily return autocorrelation can either be a winner (high monthly return) or a loser (low monthly return) as long as the price of the winner or loser stock gradually appreciates or depreciates over the month. Table 1 confirms that the correlation between the return gap and the excess autocorrelation measure is very small (3%).

The second measure is the past 12-month fund return of Carhart (1997). If excess autocorrelation reflects fund informedness or skill, jointly examining fund past performance and excess autocorrelation should help reveal whether such informedness is persistent or due to luck.

In Table 6 Panel A, we perform double sorts by first sorting on the past 12-month return gap and then on the past 12-month excess autocorrelation. In the interest of brevity, we only report the results based on the Carhart four-factor alphas. The results show that our excess autocorrelation effect survives controlling for the return gap. High excess-autocorrelation funds outperform low excess-autocorrelation funds in both large and small return-gap fund portfolios. The average high-minus-low excess-autocorrelation fund performance spread after controlling for the effect of return gap increases to 29 basis points (*t-value*=3.58). In fact, we are able to better identify the high excess-autocorrelation funds with positive alpha after controlling for the return-gap characteristics. The four-factor alpha of the high excess-autocorrelation funds conditioning on large past 12-month return gap is 37 basis points per month (*t-value*=2.23).

In Table 6 Panel B, we perform double sorts by first sorting on the past 12-month return and then on the past 12-month excess autocorrelation. The table shows that past winner funds with high excess-autocorrelation tend to continue outperforming out-of-sample with a four-factor alpha of 49 basis points per month (*t*=2.35). Carhart (1997) shows that the outperformance of past winner funds (in terms of past 12-month returns) is not persistent as they do not outperform in the future once the momentum factor is controlled for. We show that past winner funds can still persistently outperform in the future if they are also funds with high excess autocorrelation.

Overall, these results show that excess autocorrelation captures a dimension not already dealt with by the previous measures of skills. The results also provide further support that the outperformance of high excess-autocorrelation funds is relatively persistent.

5.5 Performance decomposition

To further understand the ability of the excess autocorrelation to predict fund performance, we decompose the total monthly return performance of the fund portfolio into two components: the holdings return and the residual return. The holdings return is the return of the fund based on its most recent reported portfolio holdings. The residual return is the difference between the fund actual total return and the holdings return.

For a stock to appear in a fund's most recent reported holdings, it must have been purchased on or before the most recent report date. Therefore, the holdings return reflects a fund manager's ability to outperform through a buy-and-hold strategy. The residual return reflects the fund manager's ability to outperform through interim trading during the disclosure period. Table 7 presents the results of the decomposition. Funds are sorted in the same way as in Table 2. The table reports the outperformance of the top decile of funds relative to the bottom decile of funds sorted by the excess autocorrelation measure. The results show that high excess autocorrelation funds are able to outperform low excess-autocorrelation funds through both buy-and-hold and interim trading, but more of the relative outperformance comes from the former than the latter. About two thirds (e.g., a four-factor alpha of 18 basis points) of the total outperformance in the portfolio formation period comes from the fund holdings return, while the remaining one third (e.g., a four-factor alpha of 9 basis points) comes from the interim-trading return.

5.6 Consistently buy and sell portfolio performance

We now study how excess autocorrelation predicts the performance of the portfolios of stocks that a fund recently buys and sells. We infer a fund's buy and sell portfolios from its two most recent reported holdings. If the number of shares of a stock increases (decreases) over the most recent disclosure period, we categorize this stock as the stock that the fund buys (sells). The buy (sell) portfolio of the fund is then all the stocks that the fund buys (sells) during the most recent disclosure period. The weight of each stock in the buy (sell) portfolio is proportional to the market value of the shares that have been purchased (sold) during the disclosure period.

Mutual funds not only trade for informational reasons but also for liquidity reasons. For example, fund managers must trade in response to unanticipated investor flows. For liquidity trading, a high skill fund whose stocks on average perform better than those of a low skill fund may have to sell some of these better performing stocks to meet investors' liquidity demands. To reduce the noise introduced by funds' liquidity trading, we focus on funds' consistently buy and sell portfolios. A stock that a fund sells during the most recent disclosure period is categorized into the consistently sell portfolio of the fund if the fund also sells the stock during the disclosure period immediately prior to the most recent disclosure period. Given that investors' liquidity-based buying and selling demands arrive randomly, selling for two consecutive disclosure periods (two quarters or one year) is less likely to be liquidity-based selling. For a similar reason, a stock is categorized into the consistently buy portfolio of the fund if it buys the stock in the most recent disclosure period but does not sell the stock during the disclosure period immediately prior to the most recent disclosure period. Table 8 Panels A and B respectively provide the out-of-sample performance of funds' consistently buy and sell stock portfolios for fund portfolios sorted on the excess autocorrelation in the same way as in Table 2. The results show that the stocks that high excess-autocorrelation funds consistently buy significantly outperform those that high excess-autocorrelation funds consistently buy, while the stocks that high excess-autocorrelation funds consistently sell no longer outperform those that high excess-autocorrelation funds consistently sell. The results suggest that among the stocks that funds consistently buy and sell, high excess-autocorrelation funds have better skill in buying stocks than low excess-autocorrelation funds, while there is no significant difference in the skill of selling stocks between the two types of funds.

The asymmetry between the relative abnormal performance of buy and sell trades is consistent with many previous studies in the literature (e.g., Puckett and Yan (2011) and Fang, Peress, and

Zheng (2012)). In particular, Chan and Lakonishok (1993, 1995) argue that when institutional investors purchase securities, their choice of which security to buy is likely to be unconstrained. As such, the decision to buy a particular security, out of the numerous possibilities that exist, is likely to convey positive firm-specific information. Alternatively, an institutional investor holds a finite number of securities in its portfolio and, when short sales are constrained, faces a limited number of alternatives when deciding to sell. As a result, there are many reasons why institutional sales might not necessarily convey negative firm-specific information.

Overall, these results do provide a strong – both statistically and economically – evidence that the funds that display higher excess portfolio autocorrelation display higher performance. We will now investigate the channel.

6. Analysis of Excess Autocorrelation

In this section we directly focus on the excess autocorrelation to understand the mechanisms that drive such an excess correlation – i.e., cross-autocorrelations among stocks or autocorrelations. The new tests will also provide a further robustness check on the link between fund performance and portfolio excess autocorrelation.

6.1 Individual stock autocorrelation and cross autocorrelation

To further understand the mechanisms of the performance consequence of the excess autocorrelation, we will now introduce some alternative measures of fund portfolio return autocorrelation.

As we argued above, portfolio return autocorrelation could be driven by two different mechanisms: *cross-autocorrelation between stocks* in a portfolio (e.g., Boulatov, Hendershott, and Livdan (2013)) and *serial autocorrelation in individual stock* returns (e.g., Kyle (1985), Barclay and Warner (1993)).

Since the actual daily fund portfolio holdings are not available, we use a fund's disclosed portfolio holdings at the end of the recent disclosure period to proxy for the actual portfolio holdings of the fund during the disclosure period. Thus, the average excess *autocorrelation of individual stocks* in a fund in a particular month is computed as the contemporaneous difference between the average return autocorrelation of individual stock holdings disclosed at the end of the recent disclosure period and the average return *autocorrelation of individual stock* holdings disclosed at the beginning of the recent disclosure period.

We approximate the average cross-autocorrelation of individual stocks in the actual (disclosed) fund portfolio by the average cross-autocorrelation between individual stock return and the fund actual (disclosed) portfolio return minus the average autocorrelation of individual stocks in the fund.

The average cross-autocorrelation between individual stock return and the fund actual (disclosed) portfolio return is calculated as the mean of the correlation between the one-day lagged return of individual stocks and the fund actual (disclosed) portfolio return and the correlation between the return of individual stocks and the one-day lagged actual (disclosed) fund portfolio return. The average excess cross-autocorrelation of individual stocks in a fund in a particular month is then computed as the difference between the average cross-autocorrelation of all the individual stocks in the actual fund portfolio and the average cross-autocorrelation of all the individual stocks in the fund disclosed holdings portfolio. The individual stock holdings in the actual fund portfolio are again proxied by the disclosed holdings at the end of the disclosure period.

Table 9 and 10 report the performance of funds sorted by the average excess cross-autocorrelation of individual stocks in a fund and the average excess autocorrelation of individual stocks in a fund respectively. The results show that the performance predictability of excess-autocorrelation mainly comes from the excess *cross-autocorrelation between individual stocks* rather than the excess *autocorrelation of individual stocks*. Table 9 shows that when the funds are sorted by excess *cross-autocorrelation*, the top decile (high excess cross-autocorrelation) of funds outperforms the bottom decile (low excess cross-autocorrelation) of funds by a four-factor alpha of 15 basis points per month (*t*-value=2.56). The top decile funds can also generate 9 to 10 basis points positive alpha in the CAPM model and in the CPZ model.

In contrast, Table 10 shows that when funds are sorted by excess *autocorrelation of individual stocks,* the top decile (high excess autocorrelation of individual stocks) of funds does not outperform the bottom decile (low excess autocorrelation of individual stocks) of funds. The top decile funds cannot generate a positive alpha in any benchmark model either. Overall the results suggest that the performance consequences of the excess autocorrelation are more likely driven by the *cross-autocorrelatio*n than by the *autocorrelation of individual stocks* in the fund portfolios.

The performance results using either the excess cross-autocorrelation or the excess autocorrelation of individual stocks are weaker than the performance results using our excess autocorrelation measure. This is expected as the information on the true daily holdings of individual stocks in a fund portfolio during the disclosure period is not available and has to be proxied by the holding information at the end of the disclosure period.

6.2 Buy portfolio autocorrelation and sell portfolio autocorrelation

. The excess autocorrelation of a fund's actual return could also be related to the autocorrelation of the returns of the actual portfolio that the fund is buying or selling during the disclosure periods. We now investigate the contribution of buy-portfolio and sell-portfolio autocorrelations to the performance effect of excess autocorrelation separately.

Since the actual daily fund portfolio holdings is not available, we again rely on changes of portfolio positions between two adjacent recent disclosure dates to separate the stocks that a fund trades during the disclosure period into buy and sell portfolios. A stock is categorized into the actual fund buy (sell) portfolio during the disclosure period if the number of its disclosed shares increases (decreases) over that period. The weight of the stock in the buy (sell) portfolio is proportional to the market value of the stock shares increased (decreased) during the period.

Table 11 performs a double-sort analysis based on the buy-portfolio autocorrelation and the excess autocorrelation of individual funds. In Panel A, funds are first sorted into five portfolios by the average return autocorrelation of their buy portfolios in the past 12 months. Within each buy-autocorrelation portfolio, funds are further sorted into five excess-autocorrelation portfolios as in Table 2. The results show that, by conditioning on the actual buy-portfolio autocorrelation, we are better able to identify the high excess-autocorrelation funds are going to outperform – i.e., the high excess-autocorrelation funds that also have high buy-portfolio autocorrelation. Panel B reverses the sorting order and confirms this result. The Carhart four-factor alpha of such outperforming funds can be as high as 43 basis points per month with a t-value of 2.53 (the portfolio in the bottom-right corner of Panel B). The results suggest that the high autocorrelation of funds' actual buy portfolios during the disclosure period contributes to the outperformance of high excess-autocorrelation funds.

However, the results in Table 11 indicate that after controlling for the buy-portfolio autocorrelation, the excess autocorrelation effect is still present in most portfolios with different buy-portfolio autocorrelation(Panel A). In contrast, after controlling for the excess autocorrelation measure, buy-portfolio autocorrelation has no predictive power over future fund performance except in the fund portfolio with the highest excess autocorrelation (Panel B). In unreported results, we also confirm that the top decile of funds do not significantly outperform the bottom decile of funds if funds are sorted solely based on the buy-portfolio autocorrelation. These results suggest that the excess-autocorrelation measure provides a more precise signal on fund future performance than the buy-portfolio autocorrelation. The results are expected as the information about a fund's actual buy portfolio is not available.

Panels C and D perform a similar analysis as in Panels A and B but by focusing on the relation between the sell portfolio autocorrelation and the excess autocorrelation. The results point to a similar conclusion as in Panels A and B. That is, the performance consequence of the excess autocorrelation is partially related to but not solely driven by the autocorrelation of a fund's actual sell portfolio. The performance effect of the sell portfolio autocorrelation is weaker than that of the buy portfolio autocorrelation. The results are consistent with the asymmetry between the relative abnormal performances of buy and sell trades reported in Section 5.6.

6.3 Multivariate regression

In this section, we use a multivariate Fama-Macbeth regression analysis to investigate the relation between excess autocorrelation and subsequent fund performance, controlling for additional fund characteristics. We want to know whether the relation between excess autocorrelation and fund performance is robust after controlling for a battery of fund characteristics that are related to fund performance.

The dependent variable in each cross-section is one of three performance measures: (i) the Carhart four-factor alpha; (ii) the five-factor alpha of Acharya and Pederson (2005); (iii) the five-factor model of Pástor and Stambaugh (2003). The first measure is the common performance measure for domestic equity mutual funds used by many studies. We use it for ease of comparison with other studies. The other two measures specifically control for liquidity risk, as daily return autocorrelation is likely to be associated with liquidity.

The control variables include prior-year return, expense ratio, turnover, prior-year flow volatility, flow, aggregate flow of the fund style, load dummy, log of lag TNA, log of lag family TNA, fund age, number of stocks, and the illiquidity measures of a fund portfolio. To control for the potential relation between fund styles and excess autocorrelation, we also include style fixed effects.

Investors incur higher transaction costs in trading illiquid assets. Thus, they may require higher returns for holding such assets (e.g., Amihud and Mendelson (1986)). Therefore, the outperformance of high excess autocorrelation funds could be due to that these funds buy and hold more illiquid assets, thus earning illiquidity premium for holding (instead of trading) these assets. However, this concern is unlikely to drive our performance effect as findings in other studies (e.g., Massa and Phalippou (2005) and Dong, Feng, Sadka (2013)) document that funds with illiquid stock holdings do not outperform funds with liquid stock holdings. To formally investigate this concern, we use several ways to control for the potential relation between illiquidity and fund performance.

First, consistent with other studies, we use the Amihud illiquidity ratio of fund holdings as our main illiquidity proxy for fund portfolio holdings. Each month, we calculate the Amihud illiquidity ratio for each stock in the fund's most recent reported stock holdings. Then, we aggregate them at the fund-level monthly by taking a value-weighted average of the Amihud ratios of the individual stocks. As alternative measures of illiquidity, we also use the average bid-ask spreads and the size of the stocks in a fund portfolio as two alternative measures of illiquidity of fund holdings.

Second, in addition to the illiquidity of fund disclosed holdings, a fund can buy illiquid stocks and sell liquid ones after it reports its holdings. Although this implies that the fund incurs higher trading costs, we formally investigate whether the difference in illiquidity between a fund's buy and sell portfolios during the disclosure period are related to fund performance. The illiquidity of a fund's buy or sell portfolio is measured by the value-weighted average Amihud illiquidity of the stocks in the portfolio. The buy and sell portfolios are constructed in the same way as in the previous section.[10]

Table 12 reports the multivariate regression estimates. All the specifications indicate a significantly positive relation between excess autocorrelation and the various performance measures. The performance consequences of the excess autocorrelation measure are similar in magnitude to the results reported in Table 2. The results suggest that concerns such as liquidity do not drive the excess autocorrelation effect. In fact, the liquidity of underlying stock holdings is not significantly related to fund future performance, which is consistent with the findings in other studies. The difference in the illiquidity level between a fund's buy and sell portfolios is not significantly related to fund future performance either. Thus, the performance predictability of the excess autocorrelation measure is unlikely to be driven by illiquidity premium and the other fund characteristics in the regression.

In addition, given the possibility that mutual fund sell trades are less informative about fund skills than buy trades and that our measure might less precisely capture the informed selling trades where a manager is selling a highly-autocorrelated portfolio of stocks, which are already in the previously disclosed holding portfolio, the relationship between excess autocorrelation and fund skill is likely stronger in the fund universe where managers' trades are more dominated by buy trades. We hypothesize that buy trades by funds in fund styles that experienced higher style-wide inflows in the past 12 months are likely to be more prevalent on average. The significant positive coefficient on the interaction between style flow and excess autocorrelation in Table 12 suggests the relationship between excess autocorrelation and performance is indeed stronger in fund styles where buy trades are likely to be more prevalent.

Conclusion

In this paper, we analyze the impact of daily portfolio return autocorrelation on fund performance using a large sample of US equity mutual funds from 1998 to 2010. We propose a portfolio autocorrelation-based measure based on the difference between the autocorrelation of actual daily fund portfolio returns and the autocorrelation of a hypothetical portfolio that invests in the previously disclosed fund holdings. We term this autocorrelation difference the excess autocorrelation, which measures the additional autocorrelation of the actual fund portfolio return that cannot be captured by simply examining a fund's publicly disclosed holdings.

Funds differ substantially in the cross-section with respect to the excess autocorrelation. We document that the excess autocorrelation measure has significant predictive power for fund

[10] The results (unreported) are similar if we use the difference in bid-ask spread or in stock size between a fund's buy and sell portfolios.

performance. To the extent that informed stealth trading increases the informed institutional investor's daily portfolio return autocorrelation, and that the purpose of such trading is to conceal private information, funds whose actual portfolios have higher excess autocorrelation are likely to be more skillful or informed than funds whose actual portfolios have lower excess autocorrelation. Thus, our results provide consistent evidence that our excess autocorrelation measure reflects the informedness or skill of fund managers.

References

Acharya, V.V., and L. H. Pedersen, 2005, Asset pricing with liquidity risk, Journal of Financial Economics 77, 375--410.

Avramov, D., and Wermers, R., 2006, Investing in mutual funds when returns are predictable, Journal of Financial Economics 81, 339-377.

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, Journal of Financial Economics 17, 223-249.

Barclay, M.J., Warner, J.B., 1993, Stealth trading and volatility: which trades move prices? Journal of Financial Economics 34, 281-305.

Bernhardt, D., and R. Davies, 2008, The impact of nonsynchronous trading on differences in portfolio cross-autocorrelations, working paper.

Boudoukh, J., Richardson, M.P., Whitelaw, R.F., 1994. A tale of three schools: insights on autocorrelations of short-horizon stock returns. The Review of Financial Studies 7, 539-573.

Boulatov, A., T. Hendershott, and D. Livdan, 2013, Informed Trading and Portfolio Returns, Review of Economic Studies, 80 (1), 35-72.

Brown, S. J., and W. N. Goetzmann, 1995, Performance persistence, Journal of Finance 50, 679--698.

Carhart, M. M., 1997, On persistence in mutual fund performance, Journal of Finance 52, 57--82.

Chan, L. K. C., and J. Lakonishok, 1993, Institutional trades and intraday stock price behavior, Journal of Financial Economics 33, 173--199.

Chan, L.K.C., and J. Lakonishok, 1995, The behavior of stock prices around institutional trade, Journal of Finance 50, 1147-1174.

Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2004, Does fund size erode performance? Liquidity, organizational diseconomies and active money management, American Economic Review 94, 1276--302.

Cohen, R. B., J. D. Coval, and Ľ. Pástor, 2005, Judging fund managers by the company they keep, Journal of Finance 60, 1057--1096.

Cremers, M., and A. Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, Review of Financial Studies 22, 3329--3365.

Cremers, M., A. Petajisto, and E. Zitzewitz, 2008, Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation. Working Paper, Yale School of Management.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, Journal of Finance 52, 1035--1058.

Dong, X., S. Feng, and R. Sadka, 2013, Does liquidity beta predict mutual-fund alpha? Working Paper, INSEAD.

Elton, E. J., M. J. Gruber, and C. R. Blake, 2001, A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases, Journal of Finance 56, 2415--2430.

Evans, R. B., 2004, Does alpha really matter? Evidence from mutual fund incubation, termination, and manager change, Working Paper, University of Pennsylvania.

Fama, E. F., and K. R. French, 1993, Common risk factors in the return on bonds and stocks, Journal of Financial Economics 33, 3—53

Fang, L. H., J. Peress, and L. Zheng, 2012, Does your fund manager trade on the news? Media coverage, mutual fund trading and performance, INSEAD Working Paper.

Ferson, W. E. and R. W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, Journal of Finance 51, 425--461.

Gaspar, J. M., M. Massa, and P. Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, Journal of Finance 61, 73--104.

Grinblatt, M. and S. Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns. Journal of Business 66, 47--68.

Grinblatt, M., S. Titman, R. Wermers, 1995, Momentum investment strategies, portfolio performance and herding: a study of mutual fund behavior. American Economic Review 85, 1088-1105.

Huang, J., C. Sialm, and H. Zhang, 2011, Risk Shifting and Mutual Fund Performance. Review of Financial Studies 24:2575--616.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, Journal of Finance 48, 65--91.

Kyle, A. S., 1985, Continuous auctions and insider trading, Econometrica 53, 1315--1336.

Kacperczyk, M., and A. Seru, 2007, Fund manager use of public information: New evidence on managerial skills, Journal of Finance 62, 485—528

Kacperczyk, M., C. Sialm, and L. Zheng, 2005, On the industry concentration of actively managed equity mutual funds, Journal of Finance 60, 1983--2011.

Kacperczyk, M., C. Sialm, and L. Zheng, 2008, Unobserved actions of equity mutual funds. Review of Financial Studies 21 (6), 2379--2416.

Kosowski, R., A. Timmermann, R. Wermers, and H. White, 2006, Can mutual fund `stars' really pick stocks? New evidence from a bootstrap analysis. Journal of Finance 61, 2551--2595.

Lo, A., and A.C. MacKinlay, 1990, An econometric analysis of nonsynchronous trading, Journal of Econometrics 45: 181-211

Llorente, G., R. Michaely, G. Saar, and J. Wang, 2002, Dynamic volume-return relation of individual stocks, Review of Financial Studies 15, 1005-1047.

Mamaysky, H., M. Spiegel, and H. Zhang. 2007a. Estimating the Dynamic of Mutual Fund Alphas and Betas. Review of Financial Studies 21:233–264.

Mamaysky, H., M. Spiegel, and H. Zhang. 2007b. Improved Forecasting of Mutual Fund Alphas and Betas. Review of Finance 11, 359–400.

Massa, M., and L. Phalippou, 2005, Mutual fund and the market for liquidity, Working Paper, INSEAD.

Pástor Ľ., and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, Journal of Political Economy 111, 642--685.

Wang, J., 1994, A model of competitive stock trading volume, Journal of Political Economy 102, 127–168.

Wermers, R., 1999, Mutual fund herding and the impact on stock prices, Journal of Finance 54, 581-622.

Wermers, R., 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, The Journal of Finance 55, 1655-1703.

Puckett, A., and X. Yan, 2011, The interim trading skill of institutional investors, Journal of Finance 66, 601-633.

Roll, R., 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, Journal of Finance 39(4), 1127--1139.

Sias, R.W., and L.T. Starks, 1997, Return autocorrelation and institutional investors, Journal of Financial Economics 46, 103-131.

Table 1
Summary Statistics

This table summarizes the characteristics of the mutual funds in our sample over the period between October, 1998 and December, 2010.

	Mean	Median	Standard deviation
Panel A. All funds			
Excess Autocorrelation (%)	0.33	0.15	4.91
Actual Autocorrelation (%)	-4.80	-4.89	17.72
Disclosed Autocorrelation (%)	-5.13	-5.26	17.59
Expense Ratio (%)	1.28	1.23	0.44
Turnover Ratio (%)	88.83	69.42	82.36
Flow	-0.15	-0.49	5.54
Flow Volatility	2.91	1.66	3.67
Load Dummy	0.63	1.00	0.48
TNA (Millions)	1,522.53	271.60	5,760.62
Family TNA(Millions)	38,007.38	3,088.50	103,836.87
Fund Age	16.59	11.00	15.42
Number of Stocks	110.32	75.00	138.80
Stock Amihud Illiquidity	0.01	0.00	0.14
Stock Bid-ask Spread	0.31	0.12	0.48
Stock Size (Millions)	25,706.37	21,346.49	23,559.22
Investor Return (%)	0.38	0.84	5.42
Return Gap (%)	0.02	0.00	0.36
Panel B. Full Sample Excess Autocorrelation, by investment style			
Small-Cap Growth Funds (in %)	0.09	0.06	2.84
Small-Cap Core Funds (in %)	0.21	0.11	2.92
Small-Cap Value Funds (in %)	0.34	0.18	2.85
Mid-Cap Growth Funds (in %)	0.06	0.04	3.05
Mid-Cap Core Funds (in %)	0.21	0.09	3.12
Mid-Cap Value Funds (in %)	0.39	0.19	3.29
Large-Cap Growth Funds (in %)	0.17	0.12	3.02
Large-Cap Core Funds (in %)	0.21	0.15	2.79
Large-Cap Value Funds (in %)	0.19	0.11	2.44

Table 1
Summary Statistics

Panel C. Cross Correlation

	Excess Autocorrelation (%)	Actual Autocorrelation (%)	Disclosed Autocorrelation (%)	Expense Ratio (%)	Turnover Ratio (%)	Flow	Flow Volatility	TNA (Millions)	Family TNA(Millions)	Fund Age	Number of Stocks	Stock Amihud Liquidity	Stock Bid-ask Spread	Stock Size (Millions)	Investor Return (%)
Actual Autocorrelation (%)	0.16	1.00													
Disclosed Autocorrelation (%)	-0.11	0.96	1.00												
Expense Ratio (%)	-0.01	0.06	0.06	1.00											
Turnover Ratio (%)	-0.03	0.06	0.07	0.19	1.00										
Flow	0.02	0.02	0.01	0.00	-0.02	1.00									
Flow Volatility	-0.01	0.02	0.03	0.03	0.11	0.10	1.00								
TNA (Millions)	0.03	0.03	0.02	0.16	0.01	-0.02	-0.05	1.00							
Family TNA(Millions)	0.05	0.01	0.00	-0.34	-0.15	0.04	-0.26	0.16	1.00						
Fund Age	0.04	0.01	0.00	-0.18	0.02	0.00	-0.08	0.09	0.44	1.00					
Number of Stocks	-0.01	-0.11	-0.10	-0.13	-0.07	-0.09	-0.10	0.10	0.17	0.06	1.00				
Stock Amihud Illiquidity	0.01	0.00	0.00	-0.12	0.02	0.00	-0.04	-0.07	0.15	0.13	0.01	1.00			
Stock Bid-ask Spread	0.01	0.03	0.02	0.05	0.01	0.01	0.04	0.00	-0.02	-0.04	-0.02	0.06	1.00		
Stock Size (Millions)	0.02	0.06	0.05	0.04	0.05	0.03	0.06	0.07	-0.02	-0.05	-0.44	0.01	0.20	1.00	
Investor Return (%)	0.00	-0.12	-0.12	-0.18	-0.13	-0.03	-0.12	0.01	0.10	0.01	0.03	-0.23	-0.17	-0.18	1.00
Return Gap (%)	0.00	-0.12	-0.12	-0.18	-0.13	-0.03	-0.12	0.01	0.10	0.01	0.03	-0.23	-0.17	-0.18	-0.05

Table 2

Excess-Autocorrelation Sorted Portfolios

This table reports the average monthly returns for deciles of mutual funds sorted according to the past 12-month or 24-month excess autocorrelation. The sample includes the CRSP equity mutual fund universe over the period from October, 1998 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 (24) months of excess autocorrelations during the prior 12 (24) months. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. In the first row, we report the mean past 12- or 24-month excess autocorrelation (in percentage) for the portfolios. We use the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The returns are expressed in percent per month. *T*- statistics are in parenthesis. The *T*-statistics for the 12-month (24-month) excess autocorrelations are computed using Newey-West corrections with 12 (24) lags.

	12-Month Excess Autocorrelation Sorted Portfolios						24-Month Excess Autocorrelation Sorted Portfolios					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
	Decile 1 [low]	Deciles 2-3	Deciles 4-7	Deciles 8-9	Decile 10 [high]		Decile 1 [low]	Deciles 2-3	Deciles 4-7	Deciles 8-9	Decile 10 [high]	
Excess	-2.41	-0.66	0.20	1.20	4.18	6.59	-1.66	-0.42	0.18	0.94	3.60	5.26
Autocorrelation (%)	(-20.98)	(-18.64)	(3.48)	(10.56)	(14.31)	(17.07)	(-18.86)	(-8.98)	(2.87)	(8.44)	(11.28)	(13.82)
Alpha												
CAPM	0.01	0.01	-0.02	0.00	0.27	0.26	0.04	-0.01	-0.02	0.01	0.24	0.20
	(0.13)	(0.18)	(-0.39)	(-0.04)	(2.59)	(3.39)	(0.46)	(-0.10)	(-0.27)	(0.18)	(2.38)	(2.42)
Fama-French	-0.14	-0.13	-0.14	-0.11	0.13	0.27	-0.11	-0.14	-0.14	-0.11	0.12	0.23
	(-1.86)	(-2.25)	(-3.38)	(-2.32)	(1.32)	(3.54)	(-1.59)	(-2.83)	(-3.18)	(-2.02)	(1.27)	(2.80)
Carhart	-0.14	-0.13	-0.14	-0.12	0.12	0.27	-0.12	-0.14	-0.14	-0.11	0.12	0.24
	(-2.09)	(-2.41)	(-3.54)	(-2.40)	(1.36)	(3.55)	(-1.87)	(-3.17)	(-3.33)	(-2.07)	(1.28)	(2.85)
FF4+Amihud	-0.15	-0.14	-0.14	-0.11	0.13	0.27	-0.12	-0.15	-0.14	-0.11	0.13	0.25
	(-2.15)	(-2.57)	(-3.61)	(-2.29)	(1.38)	(3.66)	(-1.95)	(-3.23)	(-3.46)	(-2.04)	(1.41)	(3.12)
FF4+PS	-0.20	-0.16	-0.15	-0.13	0.03	0.24	-0.17	-0.17	-0.15	-0.13	0.05	0.22
	(-3.04)	(-2.96)	(-3.53)	(-2.52)	(0.38)	(3.07)	(-2.82)	(-3.68)	(-3.45)	(-2.40)	(0.53)	(2.57)
CPZ	-0.03	-0.02	-0.02	0.00	0.21	0.24	-0.01	-0.03	-0.02	0.00	0.21	0.21
	(-0.42)	(-0.31)	(-0.54)	(-0.01)	(2.19)	(3.25)	(-0.08)	(-0.56)	(-0.50)	(0.06)	(2.06)	(2.55)
Ferson-Schadt	-0.10	-0.12	-0.14	-0.11	0.17	0.27	-0.09	-0.14	-0.14	-0.10	0.17	0.27
	(-1.46)	(-2.20)	(-3.36)	(-2.19)	(2.07)	(3.52)	(-1.45)	(-2.91)	(-3.10)	(-1.88)	(2.04)	(3.21)

Table 3

Excess-Autocorrelation Sorted Portfolios with Back-Testing

This table reports the average monthly returns for deciles of mutual funds sorted according to the past 12-month month excess autocorrelation. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. In the first row, we report the mean past 12-month excess autocorrelation (in percentage) for the portfolios. We use the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. This table report the results with the back-testing method in the spirit of Mamaysky, Spiegel, and Zhang (2007). Mutual funds are sorted into deciles according to the average excess autocorrelation between 13 and 2 months prior to the portfolio formation. In addition, funds are considered only if the sign of the average excess autocorrelation equals the sign of the excess market reported fund return prior to the portfolio formation.The returns are expressed in percent per month. *T*- statistics are in parenthesis. The *T*-statistics for the 12-month excess autocorrelations are computed using Newey-West corrections with 12 lags.

	Excess Autocorrelation Sorted Portfolios					
	1 [low]	2	3	4	5 [high]	5-1
Excess Autocorrelation (%)	-2.45	-0.65	0.18	1.18	4.20	6.64
	(-20.79)	(-14.98)	(2.84)	(9.13)	(12.35)	(15.83)
Alpha						
CAPM	-0.16	-0.13	-0.05	0.11	0.44	0.60
	(-1.35)	(-1.32)	(-0.63)	(1.07)	(3.23)	(3.29)
Fama-French	-0.26	-0.22	-0.18	-0.05	0.26	0.51
	(-2.35)	(-2.48)	(-2.97)	(-0.61)	(2.02)	(2.81)
Carhart	-0.26	-0.22	-0.18	-0.05	0.26	0.52
	(-2.47)	(-2.60)	(-3.17)	(-0.61)	(2.01)	(2.82)
FF4+Amihud	-0.27	-0.23	-0.19	-0.05	0.27	0.54
	(-2.52)	(-2.70)	(-3.38)	(-0.58)	(2.13)	(2.94)
FF4+PS	-0.31	-0.25	-0.20	-0.07	0.19	0.50
	(-2.92)	(-2.86)	(-3.40)	(-0.76)	(1.95)	(2.64)
CPZ	-0.15	-0.12	-0.06	0.06	0.35	0.50
	(-1.38)	(-1.31)	(-1.01)	(0.69)	(2.60)	(2.79)
Ferson Schadt	-0.20	-0.17	-0.14	-0.09	0.23	0.43
	(-1.91)	(-2.14)	(-2.65)	(-1.05)	(1.97)	(2.25)

Table 4

Persistence of the Excess-Autocorrelation

This table reports the average monthly excess-autocorrelation (in percentage) for deciles of mutual funds sorted according to the past 1, 2, 3, 4, and 5 years excess autocorrelation over the period from October, 1999 to December, 2010. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. The excess-autocorrelations are expressed in percent per month. *T*- statistics are in parenthesis.

	Excess Autocorrelation					
	1 [low]	2	3	4	5 [high]	5-1
1 Year	-0.32	0.01	0.12	0.33	2.22	2.54
	(-3.89)	(0.28)	(3.41)	(6.01)	(14.73)	(15.69)
2 Years	-0.27	0.06	0.08	0.31	2.37	2.64
	(-3.55)	(1.44)	(2.35)	(5.64)	(15.06)	(15.42)
3 Years	-0.25	0.05	0.07	0.32	2.38	2.63
	(-3.51)	(1.43)	(1.85)	(6.34)	(14.50)	(15.24)
4 Years	-0.26	0.04	0.09	0.31	2.37	2.63
	(-3.57)	(0.93)	(2.55)	(5.84)	(14.32)	(15.12)
5 Years	-0.26	0.05	0.08	0.32	2.37	2.63
	(-3.70)	(1.17)	(2.19)	(5.92)	(14.26)	(14.78)

Table 5
Longer Holding Periods

This table reports the monthly returns of the high-minus-low excess-autocorrelation portfolios with longer holding-periods (i.e., more than one month). Each month, mutual funds are first sorted into decile portfolios according to past 12-month excess autocorrelation. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. The monthly returns of longer holding-period strategies are calculated from an equal weighted average of a series of excess-autocorrelation-sorted portfolios. For example, the return of Decile 1 of the 3-month holding-period strategy on January is an equal weighted average of the January returns of the Decile 1 portfolios sorted in December, November, and October of the previous year. The monthly return of the high-minus-low excess-autocorrelation portfolio of a particular holding period is the difference in the monthly return between Decile 10 (high) and Decile 1 (low) of the same holding period. The table reports the returns and alphas for the high-minus-low portfolio for different holding periods. We use the return excess of risk-free rate, the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The returns and alphas are expressed in percent per month. *T*- statistics are in parenthesis.

Holding Period	Monthly Returns of High-Minus-Low Excess-Autocorrelation Portfolios							
	Return	Alpha						
		(CAPM)	(Fama-French)	(Carhart)	(FF4+Amihud)	(FF4+PS)	(CPZ)	(Ferson-Schadt)
1 month	0.26	0.26	0.27	0.27	0.27	0.24	0.24	0.27
	(3.39)	(3.39)	(3.54)	(3.55)	(3.66)	(3.07)	(3.25)	(3.52)
6 months	0.21	0.21	0.23	0.23	0.23	0.21	0.21	0.21
	(2.92)	(2.95)	(3.14)	(3.12)	(3.23)	(2.79)	(2.92)	(2.83)
12 months	0.18	0.18	0.21	0.21	0.22	0.19	0.19	0.20
	(2.73)	(2.68)	(3.13)	(3.14)	(3.41)	(2.77)	(2.87)	(3.01)

Table 6

Excess-Autocorrelation Portfolios controlling for Prior-Year Return Gap and Return

Each month mutual funds are first sorted into five portfolios according to their prior-year return gap or accumulative return and then sorted into five portfolios according to their excess autocorrelation as in Table 2 within each prior-year return-gap or return portfolio. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. The table reports the average monthly alphas (in percent) of double-sorted portfolios, as well as of the high-minus-low excess-autocorrelation portfolios. Alphas are four-factor alphas, where returns are adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). At the bottom of Panel A and B, the high-minus-low excess-autocorrelation portfolio returns are averaged over each of the five prior year return-gap and return portfolios. Hence, they represent the high-minus-low excess-autocorrelation portfolio returns controlling for prior-year return gap and return, respectively. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. The returns are expressed in percent per month. *T*- statistics are in parenthesis.

Panel A. Return Gap and Excess Autocorrelation

Prior-Year Return Gap	Excess Autocorrelation Portfolios					
	1 [low]	2	3	4	5 [high]	High-Low
1 [small]	-0.32	-0.17	-0.21	-0.18	0.16	0.48
	(-3.77)	(-2.79)	(-3.79)	(-2.70)	(0.82)	(2.50)
2	-0.10	-0.12	-0.14	-0.18	0.06	0.16
	(-1.63)	(-2.04)	(-3.80)	(-4.00)	(0.66)	(1.96)
3	-0.13	-0.11	-0.12	-0.15	-0.01	0.12
	(-2.08)	(-1.95)	(-2.80)	(-3.02)	(-0.08)	(1.40)
4	-0.20	-0.13	-0.19	-0.05	-0.01	0.19
	(-2.76)	(-2.94)	(-3.78)	(-0.89)	(-0.13)	(2.22)
5 [large]	-0.13	-0.17	-0.16	-0.02	0.37	0.50
	(-1.56)	(-2.20)	(-2.29)	(-0.33)	(2.23)	(3.04)
					Average	0.29
						(3.58)

Panel B. Prior-Year Return and Excess Autocorrelation

Prior-Year Return	Excess Autocorrelation Portfolios					
	1 [low]	2	3	4	5 [high]	High-Low
1 [losers]	-0.36	-0.31	-0.27	-0.27	-0.07	0.29
	(-3.19)	(-2.96)	(-2.87)	(-2.99)	(-0.48)	(2.14)
2	-0.21	-0.20	-0.18	-0.14	-0.12	0.09
	(-3.13)	(-3.60)	(-3.67)	(-2.90)	(-1.59)	(1.24)
3	-0.21	-0.12	-0.14	-0.13	-0.10	0.11
	(-3.25)	(-2.77)	(-3.23)	(-2.86)	(-1.65)	(1.80)
4	-0.06	-0.12	-0.12	-0.07	0.02	0.08
	(-0.87)	(-1.92)	(-2.08)	(-1.08)	(0.23)	(1.03)
5 [winners]	0.09	-0.06	-0.02	-0.02	0.49	0.41
	(0.76)	(-0.65)	(-0.23)	(-0.23)	(2.35)	(2.23)
					Average	0.20
						(2.65)

Table 7
Performance Decomposition

This table reports the performance decomposition of the monthly returns of the high-minus-low excess-autocorrelation portfolios. Each month, mutual funds are first sorted into decile portfolios according to their past 12-month excess autocorrelation. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. Fund return is decomposed into holdings return and residual return (the difference between fund total return and holdings return). The monthly return of the high-minus-low excess-autocorrelation portfolio is the difference in the monthly return between Decile 10 (high) and Decile 1 (low). We use the return excess of risk-free rate, the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, and the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The returns are expressed in percent per month. *T*- statistics are in parenthesis. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months.

Holding Period	Monthly Returns of High-Minus-Low Excess-Autocorrelation Portfolios							
	Return	Alpha						
		(CAPM)	(Fama-French)	(Carhart)	(FF4+Amihud)	(FF4+PS)	(CPZ)	(Ferson-Schadt)
Total Return	0.26	0.26	0.27	0.27	0.27	0.24	0.24	0.27
(after fee)	(3.39)	(3.39)	(3.54)	(3.55)	(3.66)	(3.07)	(3.25)	(3.52)
Holding Return	0.19	0.18	0.18	0.18	0.18	0.17	0.17	0.19
(after fee)	(2.49)	(2.44)	(2.58)	(2.64)	(2.63)	(2.40)	(2.39)	(2.67)
Total Return Minus	0.08	0.07	0.09	0.09	0.09	0.07	0.08	0.08
Holding Return	(2.43)	(2.37)	(2.79)	(2.79)	(2.94)	(2.17)	(2.64)	(2.57)

Table 8

Consistently Buy and Sell Portfolio Performance

This table reports the average monthly returns of consistently buy portfolio (Panel A) and sell portfolio (Panel B) performance for portfolios of mutual funds sorted according to the past 12-month excess autocorrelation over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. Consistently buy portfolio of a fund is the portfolio of stocks that the fund buys over the most recent disclosure period and does not sell during the disclosure period immediately prior to the most recent disclosure period. Consistently sell portfolio of a fund is the portfolio of stocks that the fund sells over the most recent two consecutive disclosure periods. We use the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The returns are expressed in percent per month. *T*- statistics are in parenthesis.

Panel A. Consistently Buy Portfolio Performance

	Excess Autocorrelation Portfolios					
	1	2	3	4	5	5-1
Alpha	[low]				[high]	
CAPM	0.07	0.12	0.04	0.04	0.40	0.33
	(0.63)	(1.15)	(0.41)	(0.38)	(3.02)	(3.21)
Fama-French	-0.09	-0.05	-0.11	-0.11	0.21	0.30
	(-1.15)	(-0.72)	(-1.63)	(-1.42)	(3.57)	(3.06)
Carhart	-0.09	-0.05	-0.11	-0.11	0.21	0.30
	(-1.19)	(-0.71)	(-1.64)	(-1.48)	(2.72)	(3.21)
FF4+Amihud	-0.09	-0.05	-0.10	-0.10	0.21	0.30
	(-1.11)	(-0.73)	(-1.58)	(-1.38)	(2.67)	(3.14)
FF4+PS	-0.17	-0.08	-0.11	-0.13	0.12	0.30
	(-2.22)	(-1.20)	(-1.64)	(-1.65)	(2.27)	(2.99)
CPZ	0.07	0.11	0.05	0.04	0.36	0.29
	(0.70)	(1.45)	(0.67)	(0.51)	(3.50)	(3.14)
Ferson-Schadt	-0.02	0.02	-0.06	-0.07	0.29	0.31
	(-0.31)	(0.27)	(-1.00)	(-0.94)	(3.20)	(3.13)

Panel B. Consistently Sell Portfolio Performance

	Excess Autocorrelation Portfolios					
	1	2	3	4	5	5-1
Alpha	[low]				[high]	
CAPM	0.18	0.08	0.13	0.07	0.24	0.06
	(1.45)	(0.90)	(1.48)	(0.71)	(2.08)	(0.62)
Fama-French	0.03	-0.04	0.02	-0.04	0.12	0.08
	(0.36)	(-0.60)	(0.25)	(-0.59)	(1.04)	(0.84)
Carhart	0.03	-0.04	0.02	-0.04	0.11	0.08
	(0.35)	(-0.59)	(0.25)	(-0.59)	(1.03)	(0.84)
FF4+Amihud	0.03	-0.04	0.01	-0.04	0.12	0.09
	(0.33)	(-0.61)	(0.22)	(-0.55)	(1.14)	(0.95)
FF4+PS	-0.06	-0.09	-0.02	-0.07	0.07	0.13
	(-0.69)	(-1.32)	(-0.24)	(-0.97)	(0.54)	(1.34)
CPZ	0.18	0.10	0.16	0.11	0.25	0.08
	(1.67)	(1.33)	(2.27)	(1.37)	(2.09)	(0.76)
Ferson-Schadt	0.11	-0.01	0.03	0.00	0.15	0.04
	(1.14)	(-0.17)	(0.44)	(-0.06)	(1.39)	(0.43)

Table 9

Portfolios Sorted by Excess Cross-Autocorrelation of Individual Stocks

This table reports the mean monthly returns for deciles of mutual funds sorted according to the lagged one-year average excess cross-autocorrelation of individual stocks in a fund portfolio. The average excess cross-autocorrelation of individual stocks in a fund portfolio in a particular month is the difference between the average cross-autocorrelations of all the individual stocks in the actual fund portfolio and the average cross-autocorrelations of all the individual stocks in the fund disclosed holdings portfolio, where individual stock holdings in the actual fund portfolio are proxied by the disclosed holdings at the end of the disclosure period. In the first row, we report the mean prior-year excess autocorrelation (in percentage) for each portfolio, as well as difference in excess autocorrelation between the high and low excess-autocorrelation portfolios. We use the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio returns begin from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. The returns are expressed in percent per month. *T*- statistics are in parenthesis.

	Excess Cross-Autocorrelation Sorted Portfolios					
	1	2	3	4	5	5-1
Alpha	[low]				[high]	
CAPM	-0.07	-0.08	-0.03	0.04	0.10	0.17
	(-0.74)	(-1.15)	(-0.47)	(0.55)	(2.13)	(2.64)
Fama-French	-0.18	-0.18	-0.14	-0.08	-0.03	0.15
	(-2.39)	(-3.64)	(-3.98)	(-1.68)	(1.10)	(2.51)
Carhart	-0.18	-0.18	-0.14	-0.08	-0.03	0.15
	(-2.57)	(-3.89)	(-4.34)	(-1.81)	(1.05)	(2.56)
FF4+Amihud	-0.17	-0.17	-0.14	-0.09	-0.03	0.14
	(-2.49)	(-3.85)	(-4.29)	(-1.87)	(1.13)	(2.41)
FF4+PS	-0.20	-0.19	-0.16	-0.13	-0.09	0.12
	(-2.76)	(-3.97)	(-4.71)	(-2.70)	(-1.30)	(1.97)
CPZ	-0.06	-0.05	-0.02	0.04	0.09	0.15
	(-0.71)	(-0.96)	(-0.38)	(0.72)	(1.81)	(2.56)
Ferson-Schadt	-0.13	-0.17	-0.14	-0.06	0.00	0.13
	(-1.85)	(-3.65)	(-4.12)	(-1.32)	(1.34)	(2.29)

Table 10

Portfolios Sorted by the Excess Autocorrelation of Individual Stocks

This table reports the average monthly returns for mutual fund portfolios sorted according to the lagged prior-year average excess auto-correlation of individual stocks in a fund portfolio. The average excess autocorrelation of individual stocks in a fund portfolio in a particular month is computed as the difference between the average return autocorrelation of individual stock holdings disclosed at the end of the disclosure period and the average return autocorrelations of individual stock holdings disclosed at the beginning of the disclosure period. In the first row, we report the mean prior-year excess autocorrelation (in percentage) for each portfolio, as well as difference in excess autocorrelation between the high and low excess-autocorrelation portfolios. We use the one-factor alpha (CAPM), the three-factor alpha of Fama and French (1993), the four-factor alpha of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model, the CPZ Alpha, proposed by Cremers, Petajisto and Zitzewitz (2010), which includes the excess return on the S&P 500 index, the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor, and the Ferson and Schadt (1996) conditional measure based on the four-factor model to measure fund performance. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. The returns are expressed in percent per month. *T*-statistics are in parenthesis.

	Stock-level Excess Autocorrelation Sorted Portfolios					
	1	2	3	4	5	5-1
Alpha	[low]				[high]	
CAPM	0.00	0.01	0.04	0.03	0.06	0.06
	(0.01)	(0.03)	(0.08)	(0.06)	(0.13)	(0.89)
Fama-French	-0.05	-0.04	-0.01	-0.02	0.01	0.06
	(-0.56)	(-0.55)	(-0.16)	(-0.30)	(0.12)	(0.92)
Carhart	-0.14	-0.14	-0.12	-0.14	-0.10	0.04
	(-2.21)	(-2.97)	(-2.90)	(-2.51)	(-1.34)	(0.55)
FF4+Amihud	-0.14	-0.14	-0.12	-0.14	-0.10	0.04
	(-2.34)	(-3.20)	(-3.06)	(-2.63)	(-1.36)	(0.55)
FF4+PS	-0.13	-0.14	-0.12	-0.13	-0.09	0.04
	(-2.31)	(-3.22)	(-3.04)	(-2.67)	(-1.35)	(0.69)
CPZ	-0.17	-0.16	-0.15	-0.17	-0.11	0.06
	(-2.85)	(-3.64)	(-3.73)	(-3.24)	(-1.40)	(0.93)
Ferson-Schadt	-0.01	-0.02	0.01	0.00	0.03	0.05

Table 11
Excess Autocorrelation and Buy/Sell Portfolio Autocorrelation

In Panel A, each month mutual funds are first sorted into five portfolios according to the average return autocorrelation of their buy portfolios in the past 12 months and then sorted into five portfolios according to excess autocorrelation within each buy portfolio. In Panel B, funds are sorted into five excess autocorrelation portfolios and then sorted into five portfolios based on the average return autocorrelation of buy portfolios in the past 12 months within each excess autocorrelation sorted portfolio. In Panel C, each month mutual funds are first sorted into five portfolios according to the average return autocorrelation of their sell portfolios in the past 12 months and then sorted into five portfolios according to excess autocorrelation within each sell portfolio. In Panel D, funds are sorted into five excess autocorrelation portfolios and then sorted into five portfolios based on the average return autocorrelation of sell portfolios in the past 12 months within each excess autocorrelation sorted portfolio. The table reports the returns adjusted by Fama-French three factors (MKT, SMB, and HML) and the momentum factor (UMD) of Carhart (1997). The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio formation period begins from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months. The returns are expressed in percent per month. *T*-statistics are in parenthesis.

Panel A.

Buy Portfolio Autocorrelation		Excess Autocorrelation Sorted Portfolios					
		1 [low]	2	3	4	5 [high]	High-Low
1	[low]	-0.18	-0.15	-0.17	-0.18	-0.01	0.18
		(-2.26)	(-2.26)	(-3.59)	(-3.26)	(-0.07)	(1.73)
2		-0.15	-0.17	-0.18	-0.12	0.02	0.17
		(-1.93)	(-3.57)	(-4.05)	(-2.60)	(0.22)	(1.88)
3		-0.21	-0.17	-0.16	-0.15	0.02	0.22
		(-2.89)	(-3.20)	(-4.05)	(-3.34)	(0.19)	(2.61)
4		-0.07	-0.20	-0.15	-0.12	0.05	0.13
		(-1.01)	(-3.26)	(-3.29)	(-1.92)	(0.46)	(1.05)
5	[high]	-0.08	-0.09	-0.09	-0.05	0.37	0.45
		(-0.93)	(-1.14)	(-1.33)	(-0.67)	(2.26)	(2.85)

Panel B.

Excess Autocorrelation Portfolios		Buy Portfolio Sorted Autocorrelation					
		1 [low]	2	3	4	5 [high]	High-Low
1	[low]	-0.20	-0.11	-0.21	-0.13	-0.08	0.11
		(-2.23)	(-1.48)	(-2.67)	(-1.92)	(-0.87)	(1.09)
2		-0.18	-0.15	-0.14	-0.18	-0.10	0.08
		(-3.06)	(-2.96)	(-2.99)	(-3.25)	(-1.33)	(0.93)
3		-0.16	-0.19	-0.15	-0.16	-0.09	0.07
		(-3.50)	(-4.22)	(-4.00)	(-3.61)	(-1.43)	(0.87)
4		-0.16	-0.15	-0.15	-0.08	-0.10	0.06
		(-2.75)	(-3.12)	(-2.77)	(-1.37)	(-1.33)	(0.68)
5	[high]	-0.02	0.01	0.06	0.10	0.42	0.44
		(-0.20)	(0.12)	(0.57)	(0.95)	(2.53)	(2.77)

Panel C.

Sell Portfolio Autocorrelation		Excess Autocorrelation Sorted Portfolios 1 [low]	2	3	4	5 [high]	High-Low
1	[low]	-0.21	-0.15	-0.19	-0.14	0.15	0.36
		(-2.48)	(-2.36)	(-3.66)	(-2.34)	(1.49)	(3.03)
2		-0.20	-0.18	-0.17	-0.22	-0.04	0.16
		(-2.61)	(-3.52)	(-4.09)	(-3.77)	(-0.38)	(1.35)
3		-0.14	-0.14	-0.15	-0.13	-0.07	0.08
		(-2.04)	(-2.65)	(-3.81)	(-2.04)	(-0.72)	(0.76)
4		-0.22	-0.11	-0.16	-0.08	0.06	0.29
		(-3.06)	(-1.75)	(-3.33)	(-1.30)	(0.58)	(2.95)
5	[high]	-0.05	-0.14	-0.12	-0.08	0.39	0.45
		(-0.57)	(-1.93)	(-1.92)	(-1.27)	(2.27)	(2.98)

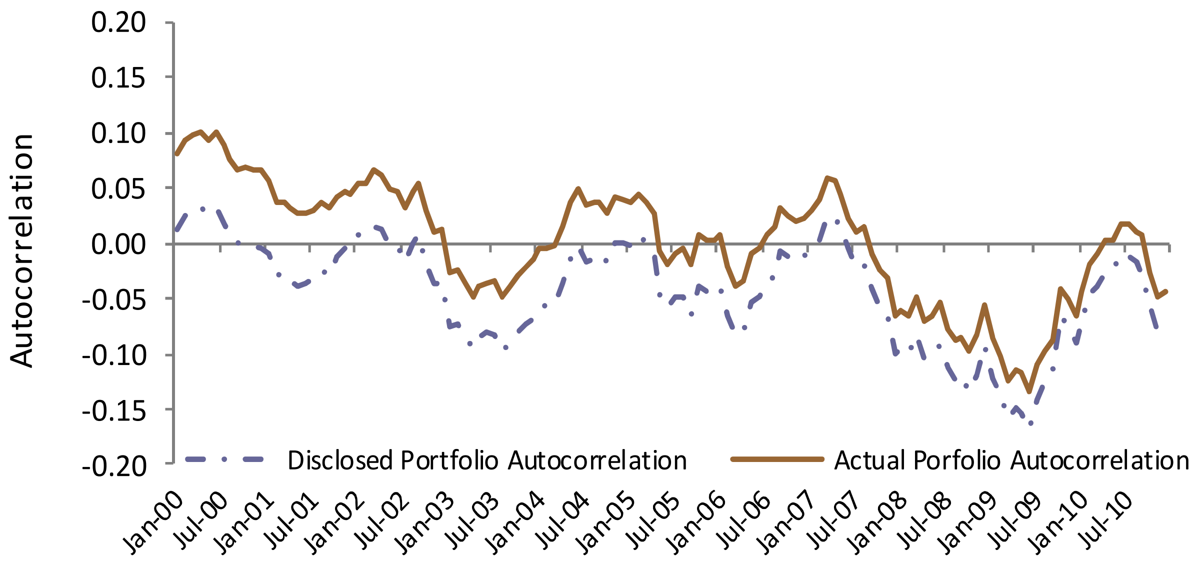
Panel D.

Excess Autocorrelation Portfolios		Sell Portfolio Sorted Autocorrelation 1 [low]	2	3	4	5 [high]	High-Low
1	[low]	-0.20	-0.21	-0.14	-0.13	-0.10	0.10
		(-2.53)	(-2.60)	(-1.99)	(-1.51)	(-1.14)	(0.98)
2		-0.16	-0.18	-0.14	-0.13	-0.14	0.02
		(-2.60)	(-3.55)	(-2.70)	(-2.21)	(-2.09)	(0.22)
3		-0.18	-0.18	-0.15	-0.15	-0.12	0.07
		(-3.70)	(-4.19)	(-3.67)	(-3.05)	(-1.89)	(0.83)
4		-0.20	-0.20	-0.13	-0.06	-0.08	0.12
		(-3.46)	(-3.29)	(-2.23)	(-0.96)	(-1.30)	(1.50)
5	[high]	0.09	0.05	-0.04	0.07	0.37	0.28
		(0.97)	(0.52)	(-0.39)	(0.62)	(2.20)	(1.85)

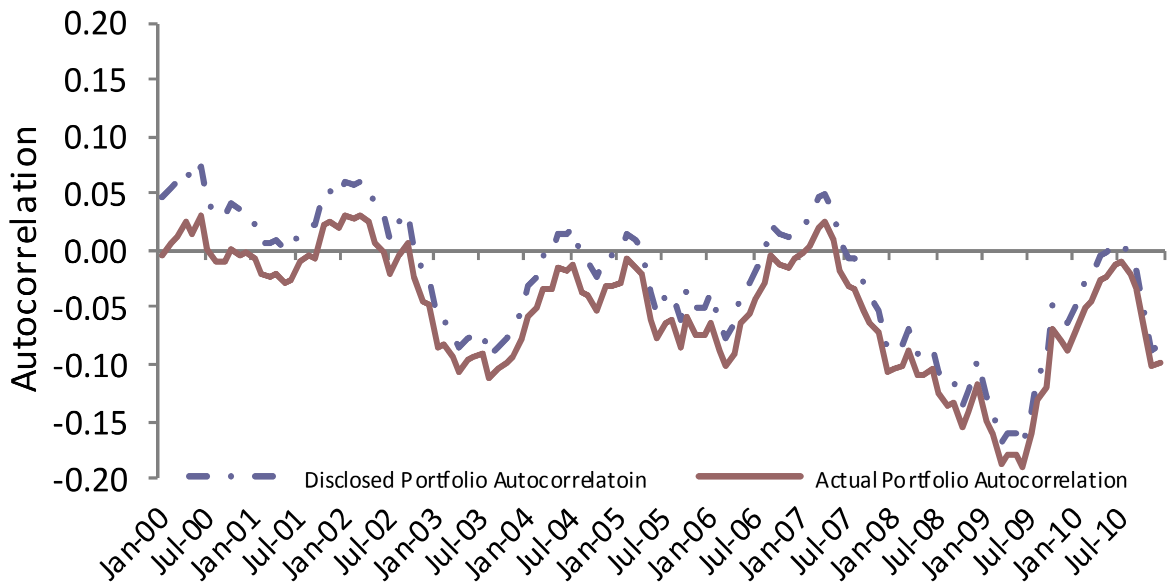
Table 12
Predictive Regression for Fund Performance

This table reports the coefficients of Fama-Macbeth regressions of monthly abnormal returns on various fund attributes. Excess autocorrelation is defined as the difference between the actual fund portfolio return autocorrelation and the previous disclosed holdings portfolio return autocorrelation. The dependent variable is the four-factor abnormal return of Carhart (1997), the Amihud-based five-factor alpha, which follows Acharya and Pederson (2005) by adding an Amihud-based liquidity factor to the Carhart four factor model, and the PS-based five-factor alpha, which adds the liquidity factor of Pástor and Stambaugh (2003) to the Carhart four factor model. All regressions include style fixed effects and are performed at a monthly frequency. *T*-statistics computed using Newey-West standard errors with 12 lags are reported in parenthesis. The sample includes the CRSP equity mutual fund universe over the period from October, 1999 to December, 2010. Portfolio returns begin from November, 2000, using funds with 12 months of excess autocorrelations during the prior 12 months.

	FF4 Alpha				FF4+Amihud Alpha				FF4+PS Alpha			
Excess Autocorrelation	3.600	3.314	3.319	3.582	3.857	3.511	3.620	3.831	3.413	3.094	3.231	3.364
	(2.31)	(2.28)	(2.16)	(2.24)	(3.17)	(3.12)	(2.86)	(3.13)	(2.68)	(2.62)	(2.47)	(2.65)
Excess Autocorrelation*Style Flow	2.730	2.492	2.870	2.870	4.175	3.869	4.374	4.248	3.992	3.692	4.266	4.007
	(2.07)	(1.91)	(2.16)	(2.04)	(3.05)	(2.97)	(3.14)	(3.12)	(2.79)	(2.68)	(2.87)	(2.83)
Style Flow	0.049	0.040	0.018	0.048	-0.020	-0.027	-0.034	-0.021	-0.001	-0.006	-0.021	-0.001
	(0.95)	(0.90)	(0.42)	(0.94)	(-0.35)	(-0.47)	(-0.67)	(-0.36)	(-0.02)	(-0.09)	(-0.34)	(-0.01)
Prior-year Return	0.920	0.922	0.938	0.919	1.635	1.646	1.678	1.647	1.246	1.256	1.298	1.256
	(1.97)	(2.00)	(2.07)	(1.96)	(3.38)	(3.44)	(3.52)	(3.39)	(2.64)	(2.67)	(2.80)	(2.65)
Prior-year Expense Ratio	-4.798	-4.774	-4.621	-4.824	-3.330	-3.277	-3.840	-3.144	-2.673	-2.525	-3.109	-2.478
	(-2.54)	(-2.72)	(-2.39)	(-2.54)	(-1.09)	(-1.16)	(-1.22)	(-1.03)	(-0.93)	(-0.97)	(-1.06)	(-0.87)
Prior-year Turnover Ratio	-0.033	-0.033	-0.036	-0.033	-0.027	-0.026	-0.030	-0.026	-0.036	-0.034	-0.037	-0.035
	(-1.95)	(-1.88)	(-2.27)	(-1.94)	(-1.55)	(-1.48)	(-1.97)	(-1.5)	(-2.07)	(-1.98)	(-2.48)	(-2.01)
Flow	-0.000	0.000	-0.000	-0.000	-0.002	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001
	(-0.04)	(0.01)	(-0.11)	(-0.04)	(-0.72)	(-0.69)	(-0.92)	(-0.75)	(-0.32)	(-0.29)	(-0.53)	(-0.37)
Prior-year Flow Volatility	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003
	(1.24)	(1.16)	(1.24)	(1.21)	(0.89)	(0.79)	(0.73)	(0.91)	(0.95)	(0.84)	(0.85)	(0.98)
Load Dummy	0.018	0.019	0.018	0.019	0.040	0.041	0.045	0.040	0.032	0.032	0.037	0.031
	(1.89)	(1.96)	(1.96)	(1.89)	(3.21)	(3.21)	(3.28)	(3.22)	(2.84)	(2.87)	(3.01)	(2.82)
Log of Lagged TNA	-0.005	-0.005	-0.005	-0.005	-0.011	-0.010	-0.011	-0.010	-0.012	-0.012	-0.012	-0.012
	(-0.81)	(-0.79)	(-0.70)	(-0.80)	(-1.80)	(-1.80)	(-1.80)	(-1.74)	(-1.97)	(-1.98)	(-1.96)	(-1.90)
Log of Lag Family TNA	0.007	0.007	0.006	0.006	0.007	0.007	0.006	0.007	0.005	0.006	0.004	0.005
	(2.43)	(2.52)	(2.07)	(2.34)	(2.29)	(2.45)	(1.85)	(2.22)	(1.84)	(1.98)	(1.55)	(1.76)
Lag Age	-0.004	-0.006	-0.005	-0.005	-0.002	-0.004	-0.003	-0.002	-0.001	-0.003	-0.003	-0.001
	(-0.58)	(-0.69)	(-0.6)	(-0.62)	(-0.5)	(-0.72)	(-0.68)	(-0.52)	(-0.26)	(-0.50)	(-0.48)	(-0.27)
Number of Stocks	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-3.04)	(-2.66)	(-2.70)	(-2.87)	(-2.87)	(-2.54)	(-2.56)	(-2.78)	(-1.88)	(-1.57)	(-1.67)	(-1.79)
Stock Amihud Illiquidity	0.408			0.223	0.357			-0.004	0.259			-0.136
	(1.29)			(0.93)	(1.18)			(-0.02)	(0.92)			(-0.34)
Stock Bid-ask Spread		0.224				0.204				0.142		
		(1.02)				(1.05)				(0.69)		
Stock Size			-0.000				-0.000				-0.000	
			(-1.43)				(-1.46)				(-0.89)	
Buy-Minus-Sell				0.285				-0.035				-0.083
Stock Amihud Illiquidity				(0.59)				(-0.14)				(-0.34)
Style Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes



Panel A. Top Decile of Funds



Panel B. Bottom Decile of Funds

Figure 1 Autocorrelations of Actual Fund Portfolio Returns and Disclosed Holding Portfolio Returns. The figure depicts the average 12-month moving averages of actual fund portfolio return autocorrelation and the disclosed holding portfolio return autocorrelation of the top decile and the bottom decile of funds ranked by the excess autocorrelation between 1999 and 2010.