Stale Prices and the Performance Evaluation of Mutual Funds

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Abstracts

Staleness in measured prices imparts a positive statistical bias and a negative dilution effect on mutual fund performance. First, evaluating performance with nonsynchronous data generates a spurious component of alpha. Second, stale prices create arbitrage opportunities for high-frequency traders whose trades dilute the portfolio returns and hence fund performance. This paper introduces a model that evaluates fund performance while controlling directly for these biases. Empirical tests of the model show that alpha net of these biases is on average positive although not significant and about 40 basis points higher than alpha measured without controlling for the impacts of stale pricing. The difference between the net alpha and the measured alpha consists of three components: a statistical bias, the dilution effect of long-term fund flows, and the dilution effect of arbitrage flows. Whereas the two former are small, the latter is large and widespread in the fund industry.

JEL Classifications: G12, G14.

Key Words: Performance evaluation, stale pricing, timing arbitrage, flows.

I. Introduction

Mutual fund performance evaluation has long been an important and interesting question to finance researchers as well as practitioners. The evidence of negative alpha (Jensen 1968) for the actively managed U.S. equity funds on average is particularly puzzling, given these funds receive billions of new money flow each year and control trillions of assets. Further studies show that measures of alpha are sensitive to sample periods (Ippolito 1989), benchmark indices (Lehmann and Modest 1987, Elton et al. 1992), and trading dynamics (Ferson and Schadt 1996, etc). This paper explores whether measures of alpha are impacted by fund return properties.

Studies of mutual fund performance typically use monthly return data without controlling for the issue of stale pricing, an inequality between the current price of fund shares and the current value of the underlying assets. This discrepancy occurs when the share price set by funds at the end of each day fails to reflect the most current market information on the assets, because the underlying securities are thinly traded or traded in a different time zone. In funds with stale pricing, observed returns differ from true returns. Scholes and William (1977) and Dimson (1979) show that when data are nonsynchronous, estimates of beta and alpha are biased and inconsistent. In addition, stale prices in mutual fund shares create arbitrage opportunities for short-term traders who purchase shares when the fund's net asset value (NAV) is lower than the value of the underlying securities and sell shares after the true value is incorporated into the NAV. The round trip transactions can be as quick as overnight. Chalmers, Edelen, and Kadlec (2001) call this opportunity a "wild card" option. Greene and Hodges (2002) show that arbitragers take advantage of such opportunities and their trades can dilute fund returns up to 0.5% annually[1].

This paper proposes a performance evaluation model that estimates alpha based on true returns of underlying assets picked by fund managers rather than observed returns that capture price changes of fund shares and that are stale and diluted. The key element of the model is the incorporation of stale pricing and return dilution relative to the true return process. Because the evaluation model directly controls for statistical bias and dilution effects, the estimated managerial picking ability depends only on the true return process of the portfolio and is independent of these biases. The model gives two alpha measures: true alpha that is based on true returns of portfolios and reflects the actual picking ability of managers and observed alpha that is based on observed returns of fund shares.

Empirical tests show that true alpha is about 40 basis points higher than observed alpha and on average positive although not significant. Moreover, true alpha does not correlate with stale pricing of fund shares, while observed alpha, just like performance evaluated using various traditional models, is negatively influenced by stale pricing. As this paper illustrates, for each one standard deviation increase in stale pricing, traditionally evaluated performance decreases by about 10 to 70 basis points. Given an average expense ratio of 0.78% for the sample funds, this magnitude is economically important.

These empirical findings have important implications on the existence of picking abilities among mutual fund managers. Positive alpha in the after-expense returns implies

[1] However, Goetzmann, Ivković and Rouwenhorst (2001) report a much lower dilution and propose an alternative "fair pricing" mechanism to alleviate the stale pricing problem.

that fund managers have superior information/abilities to pick investments and that these abilities are higher than the fees they have charged. In contrast, observed alpha in previous studies measures values remaining for long-term shareholders after covering arbitragers' profits, management fees, liquidity costs, and any other costs not fully compensated through other charges. Therefore, observed alpha underestimates the actual picking ability of fund managers.

The model also generates an interesting industry application -- performance decomposition. The difference between observed alpha and true alpha consists of three components: statistical bias, dilution by long-term flows and dilution by arbitrage flows. The model derives both alphas and bias components and estimates them simultaneously. According to the empirical evidence, the statistical bias from stale pricing is positive but has little economic significance, while the dilution effect, mainly due to arbitrage flows, is negative and significant at the 1% level for most fund style groups. The dilution effect increases with the staleness in pricing, with funds in the stalest quintile having an average dilution of 98 basis points annually and those in the lowest quintile, a dilution of only 18 basis points. This evidence provides a measure of potential gains to mutual fund investors from fund management actions to reduce stale pricing.

The model fits into the literature on nonsynchronous data issue[2]. Chen, Ferson, and Peters (2009) and this paper are the first few to address this issue in mutual fund evaluation models. Whereas the former considers the impact of stale pricing on fund

[2] In addition to Scholes and William (1977) and Dimson (1979) mentioned earlier, Brown and Warner (1985) show when and how the non-synchronous trading data can affect the estimation of abnormal performance in the case of event studies. Lo and MacKinlay (1990) show that nonsynchronous trading could be more evident in portfolios than in individual stocks. A more recent study by Getmansky, Lo, and Makarov (2004) reveals that hedge fund managers can purposely smooth returns to achieve higher measured performance.

managers' timing ability, the latter - this paper- examines their picking ability instead. Correspondingly, the two studies model stale pricing differently. The former assumes a systematic and time-varying component of stale pricing that causes a bias in estimating fund managers' timing ability. This paper assumes stale pricing constant but analyzes the arbitrage timer's response to stale pricing, thereby controlling for the arbitrage dilution effect on fund performance.

This paper contributes to the literature on fund return dilution due to stale pricing arbitrage[3] in the following three dimensions. First, it takes a model-based approach to directly estimate dilution. The model is applicable to both individual funds and group portfolios. Whereas previous studies treat flows as exogenous, by modeling the arbitrage timer's decision, this approach also allows flows to be endogenous to stale pricing. Second, it uses a larger and more convenient data sample than those in previous studies. Whereas previous investigations cover about 20% of U.S. open-end mutual funds from 1998 to 2001, this present analysis covers all U.S. domestic equity open-end mutual funds from 1973 to 2007. It also uses monthly rather than daily observations. Although stale pricing arbitrage happens on a daily basis and is based on daily returns, dilution effect is accumulative and the approach here allows for a monthly aggregation. Using monthly data not only avoids the reporting problems with daily flow data but also makes alpha estimation comparable to those in the performance evaluation literature. Last and most important, empirical analysis in this paper reveals that the arbitrage dilution is indeed a problem for domestic funds just as it is for international funds. This finding is important to investors and fund managers. It also reconciles Chalmers, Edelen, and

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[3] Chalmers et al. (2001), Bhargava et al. (2001), Goetzmann et al. (2001), and Bouroukh et al. (2002) show that stale pricing provides a profitable arbitrage opportunity. Green and Hodge (2002) and Zitzewitz (2003) empirically document return dilutions resulting from the arbitrage behavior.

Kadlec (2001)'s finding that arbitrage opportunity allows 10–20% profits in both U.S. equity funds and international equity funds with Green and Hodge (2002)'s documentation of dilution in international funds only.

The rest of the paper proceeds as follows. Section II introduces the model, Section III describes the data, and Section IV presents the empirical results. Section V then compares the alpha from the proposed model with those from various traditional models, and Section VI presents robustness checks and discusses possible extensions of the model. Section VII concludes the paper.

II. The Model

There are two meanings of "market timing" in the literature on mutual funds. In one definition, fund managers increase fund beta by changing portfolio holdings when they expect the market to rise (hereafter, market timing); in the other, daily timers trade in and out of funds frequently (hereafter, arbitrage timing). This paper focuses only on arbitrage timing and refers to the arbitragers as arbitrage timers.

A. Stale Pricing

Nonsynchronous trading (Sholes and William 1977, Lo and MacKinlay 1990) and naïve methods for determining the fair market value or "marks" for underlying assets (Chalmers, Edelen, and Kadlec 2001, Getmansky, Lo, and Makarov 2004) yield serially correlated observed returns. Thus, assuming that information generated in time t is not fully incorporated into prices until one period later,[4] the observed fund return becomes a weighted average of true returns in the current and last periods:

(1a) $r_t = \alpha + \beta\, r_{mt} + \varepsilon_t\,,$

(1b) $r_t^* = \eta\, r_{t\text{-}1} + (1\text{-}\ \eta)\, r_t\,,$

where r_{t} denotes the true excess return of the portfolio with mean $\mu,$ and variance σ^2, r_{mt} denotes the excess market return with mean $\mu_{m},$ and variance $\sigma_m^{\,2}$. Both r_t and r_{mt} are i.i.d, and the error term ε_t is independent of r_{mt}. r_t^* is the observed excess return of the portfolio with zero flows, while η is the weight on the lagged true return. That is, the higher the η, the staler the prices. Assumedly, arbitrage traders can earn the return r_t^*, by trading at the fund's reported net assets values.

This form can be extended to a variety of more complicated models; for example, to estimate market timing ability by assuming Cov($r_t,\ r_{mt}^2$) is nonzero or to incorporate time-variant stale pricing by specifying the form taken by the parameter η (Chen, Ferson, and Peters 2009). In this paper, for simplicity, η is constant over time.

B. Analysis of Mutual Fund Flows

The new money flows into the mutual funds consist of two components. The arbitrage timers' actions imply a short-term flow component. Nonetheless, the timer faces a choice between fund shares and risk-free assets. By choosing the optimal weights in fund shares, the timer maximizes a utility function that depends on the expected excess return conditional on observations of past fund returns. The change in weights from one period to the next forms flows in and out of the funds. Following Admati et al. (1986),

[4] This assumption can be verified empirically. I apply Getmanky, Lo, and Makorov (2004)'s measure to mutual fund data and show that, on average, fund returns smooth over the current and one previous period (table 4, panel B).

Becker et al. (1999), and Stein's (1973) Lemma, I find that the optimal weights equal the conditional expected fund excess return over its conditional variance and Rubinstein (1973) risk aversion.[5] Therefore, the change in weights from period t-1 to period t equals $\eta(r_{t-1} - r_{t-2}) / \gamma(1 - \eta)^2\sigma^2$, where γ is risk aversion, η measures stale pricing, r_{t-1} is the true portfolio excess return in period t-1, and σ^2 is its volatility.

In addition, the model assumes a long-term flow component C_{t-1}, measured as a fraction of the fund total net assets and occurring at the end of period t-1. This long-term flow component responds to past long-run returns and is uncorrelated with stale pricing or the short-term returns, r_{t-1}. For simplicity, it follows a normal distribution:

(2a) $$C_{t-1} \sim N(c, \sigma_c), \text{ i.i.d.},$$

where c is the mean and σ_c is the standard deviation of the long-term flows.

The total fund flow at the end of period t-1, measured as a percentage of the fund's total net assets, is the sum of the long-term flows and the short-term flows from arbitrage timers:

(2b) $$f_{t-1} = C_{t-1} + \eta(r_{t-1} - r_{t-2}) / \lambda(1 - \eta)^2\sigma^2$$

where λ equals γ TNA $_{\text{fund}, t-1}$ / ASSETS $_{\text{timer}, t-1}$ and f_{t-1} represents flow as a percentage of the fund's TNA.

C. The Impact of Fund Flows

As Greene and Hodge (2002) show, daily flows by active mutual fund traders cause a dilution of returns, which results from the lag between the time that money comes in and the time that fund managers purchase risky assets. Edelen and Warner (2001) note

[5]The optimal weights equal $\gamma^{-1}E(r_t^*|I_{t-1}^o)$ / $Var(r_t^*|I_{t-1}^o)$, where I_{t-1}^o includes all the information in past returns $\{r_{t-1}^o, r_{t-2}^o, - - - r_1^o\}$, r_{t-1}^o is the observed return in period t-1.Given equations (1a) and (1b), the conditional mean and variance are $E(r_t^*| I_{t-1}^o) = \eta r_{t-1} + (1 - \eta)\mu$ and $Var(r_t^*| I_{t-1}^o) = (1-\eta)^2\sigma^2$.

that fund managers typically do not receive a report of the day's fund flow until the morning of the next trading day, by which time the prices of underlying risky assets have changed. For simplicity, this model assumes that the fund manager reacts immediately on seeing the flows so that the response lags by only one day.

The flow occurring at the end of the previous trading day is $f_{t\text{-}1} = CF_{t\text{-}1} / (N_{t\text{-}1}P_{t\text{-}1})$, where $CF_{t\text{-}1}$ is the dollar amount of flows, $N_{t\text{-}1}$ is the number of shares, and $P_{t\text{-}1}$ is the observed share price, $P_{t\text{-}1} = \mathrm{TNA}_{t\text{-}1} / N_{t\text{-}1}$. By the end of the current trading day t, the observed share price is $P_t = \mathrm{TNA}_t / N_t$. Because of the lag in investment, the new money flow overnight earns only a risk-free rate return, $\mathrm{TNA}_t = \mathrm{TNA}_{t\text{-}1}(1 + r_t^* + R_f) + CF_{t\text{-}1}(1 + R_f)$. As noted earlier, r_t^* is the measured TNA excess returns with zero flows. The number of shares also increases when money flows in, $N_t = N_{t\text{-}1} + CF_{t\text{-}1} / P_{t\text{-}1}$.

The observed excess fund return with flows, r_t^0, is the change in the share prices from trading day t-1 to t, in excess of the risk free rate: $r_t^0 = (P_t - P_{t\text{-}1}) / P_{t\text{-}1} - R_f$. Given the relations specified above, simple algebra shows that[6]

(3) $$r_t^0 = r_t^* / (1 + f_{t\text{-}1})$$

Equation (3) indicates that r_t^0 differs from r_t^* and the dilution, $r_t^0 - r_t^* = r_t^0 f_{t\text{-}1}$, depends on the covariance between fund flows and observed returns on the subsequent trading day.

D. The System

The model is now fully defined by equations (1a), (1b), (2a), (2b), and (3). The following are the moment conditions.[7]

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[6] $r_t^0 = (P_t - P_{t\text{-}1}) / P_{t\text{-}1} - R_f = (\mathrm{TNA}_t / N_t) / P_{t\text{-}1} - 1 - R_f = [N_{t\text{-}1}P_{t\text{-}1}(1 + r_t^* + R_f) + CF_{t\text{-}1}(1 + R_f)] / [N_{t\text{-}1}P_{t\text{-}1} + CF_{t\text{-}1}] - 1 - R_f = [1 + r_t^* + R_f + f_{t\text{-}1}(1 + R_f)] / (1 + f_{t\text{-}1}) - 1 - R_f = r_t^* / (1 + f_{t\text{-}1})$

(4a) $E[r_t^o(1 + f_{t-1})] = \mu$,

(4b) $Cov[r_t^o(1 + f_{t-1}),\ r_{mt}] = (1 - \eta)\ Cov(r, r_m)$,

(4c) $Cov[r_t^o(1 + f_{t-1}),\ r_{mt-1}] = \eta\ Cov(r, r_m)$,

(4d) $Var[r_t^o(1 + f_{t-1})] = [\eta^2 + (1 - \eta)^2]\sigma^2$,

(4e) $E(f_t) = c$,

(4f) $Cov(f_{t-1}, f_t) = - \eta^2 / \lambda^2(1 - \eta)^4\sigma^2$,

Combining these equations with

(4g) $E(r_m) = \mu_m$,

(4h) $Var(r_m) = \sigma_m$,

produces a system with eight parameters [μ_m, σ_m^2, μ, Cov(r, r_m), σ^2, η, c, λ] by which fund performance can be estimated. The notations follow definitions from the model: r_t^o is the observed fund excess return in period t, r_{mt} is the excess market return in period t, f_t is fund total flows in period t, and r is the true excess fund return. Parameters μ_m and σ_m^2 are the mean and variance of excess market returns, μ and σ^2 are the mean and variance of fund excess returns, Cov(r, r_m) is the covariance between fund excess returns and market returns, η measures the extent of stale pricing, c is the mean of long-term fund flows, and λ is the multiple of risk aversion and relative assets size between the timer and the fund.

E. Components of Performance and Biases

I define the "true alpha" or true performance as the alpha estimated with the true but unobserved returns. It measures fund managers' picking ability without the influence of stale pricing or arbitrage timing.

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[7] Formulating moment conditions involves simple mean and variance-covariance transformation. Details are available upon request.

(5a) $$\alpha = \mu - \mathrm{Cov}(r_t, r_{mt})\mu_m / \sigma_m .$$

In contrast, I define the observed alpha or observed performance as the traditionally measured alpha, which treats the observed returns as if they were the true returns: $\alpha^o = E(r_t^o) - \mathrm{Cov}(r_t^o, r_{mt})\, \mu_m/\sigma_m^{\,2}$. Thus,

(5b) $$\alpha^o = [\mu - \mathrm{Cov}(f_{t\text{-}1}, r_t^o)] / (1 + c)$$

$$-\{[(1 - \eta)\mathrm{Cov}(r, r_m) - \mathrm{Cov}(r_t^o r_{mt}, f_{t\text{-}1}) + \mathrm{Cov}(f_{t\text{-}1}, r_t^o)\mu_m] / (1 + c)\}\mu_m / \sigma_m^{\,2}.$$

In an ideal situation, one in which there is neither stale pricing nor flows—that is, $\eta = 0$, $c = 0$, and $f_{t\text{-}1} = 0$ — the observed performance is the true performance.

The difference between the observed alpha and the true alpha has the following three components:

(6a) $$B_1 = \eta\mathrm{Cov}(r, r_m)\mu_m / \sigma_m^{\,2} ,$$

(6b) $$B_2 = [- c / (1+c)]\, [\mu - (1 - \eta)\mathrm{Cov}(r, r_m)\, \mu_m / \sigma_m^{\,2}] ,$$

(6c) $$B_3 = [-1 / (1+c)]\, \{\mathrm{Cov}(f_{t\text{-}1}, r_t^o) - [\mathrm{Cov}(r_t^o r_{mt}, f_{t\text{-}1}) - \mathrm{Cov}(f_{t\text{-}1}, r_t^o)\mu_m]\, \mu_m / \sigma_m^{\,2}\}.$$

Specifically, B_1 is the statistical bias in the performance measurement resulting from the nonsynchronicity in the returns data; that is, there is stale pricing, $\eta \neq 0$, but no influence of flows, $c = 0$ and $f_{t\text{-}1} = 0$. If $\eta = 0$, then $B_1 = 0$. B_2 is the dilution bias from long-term flows; that is, $c \neq 0$ but $\mathrm{Cov}(f_{t\text{-}1}, r_t^o) = 0$ and $\mathrm{Cov}(r_t^o r_{mt}, f_{t\text{-}1}) = 0$. If $c = 0$, then $B_2 = 0$. B_2 is nonzero as long as c is nonzero, disregarding whether η is zero or not. As Edelen (1999) shows, the unexpected flows dilute fund performance because of liquidity motivated trading. If c is completely predictable, fund managers can avoid this dilution through certain cash budget arrangements. Finally, B_3 is the dilution effect from arbitrage flows; that is $f_{t\text{-}1} \neq 0$ and it is correlated with subsequent fund returns. The higher the correlation between arbitrage flows and fund returns, the larger the bias (downward). In addition, as

Ferson and Warther(1996) argue, flows also reduce performance through a decrease in the portfolio beta when Cov($r_t^o r_{mt,}, f_{t-1}$) < 0.

The relation among the observed alpha, true alpha, and these biases is as follows:

(6d) $$\alpha^o = \alpha + B_1 + B_2 + B_3,$$

where α^o is the observed alpha; α, the true alpha; B_1, the statistical bias; B_2, the dilution of long-term flows; and B_3, the dilution of arbitrage flows, all defined as above. Appendix A1 presents the details of performance and its decomposition.

III. Data

Both Lipper and Trimtab currently have datasets of daily fund flows. However, it is widely recognized that mutual funds have no accurate day-end TNA figures because they do not know how much money has been received on the current day. Therefore, some funds report TNA on day *t* including the current day's flows, some report it excluding day *t* flows, and some report a mixture that includes part but not all of day *t* flows. In addition, funds may report one way one day and another, the next. In other words, as Edelen and Warner (2001) and Greene and Hodges (2002) argue, the reported daily flows may sometimes lag the true flows by one day, without it being clear when or for which funds. Furthermore, the data cannot be checked against another source because all daily fund flow databases suffer from this problem. The SEC's NSARs include the current day's flow in TNA by requirement, but because they aggregate all share classes, these data cannot be merged with other data either. As a result, it is currently infeasible to calculate the true day-by-day flows.

Practically, a monthly return dilution is the aggregation of daily return dilutions within the month. In addition, it is favorable to use monthly returns for estimation in order to make comparisons with traditionally measured performance. Therefore, based on equation (3), I aggregate the daily return dilution by month to give a measure of the monthly return dilution. Appendix A2 presents the details of the aggregation. It turns out that modifying the flow measure to be a daily average flow of the contemporary month is not only an intuitive approximation but also a safe one that has a downward rather than upward bias.[8]

Therefore, I use monthly data on U.S. equity funds in the CRSP Mutual Fund Database from January 1973 to December 2007, excluding observations during incubation periods and funds with less than one year observations of monthly returns or TNAs smaller than $5 million. The final sample has 3,545 fund portfolios and 7,423 in term of fund share classes. I sort these funds into eight style groups based on the Wiesenberger objective codes, Strategic Insight codes, and Lipper objective codes. They are Small Company Growth, Other Aggressive Growth, Maximum Capital Gain, Growth, Income, Growth and Income, Sector, and Timing funds.[9]

(Insert table 1 here.)

Panel A of table 1 summarizes fund returns by style group during the sample period. The Small Company Growth funds show the highest mean in returns (1.15% per

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[8] The sum of daily flow dilutions, if documentable, is larger than the monthly dilution documented here with monthly flows. At the monthly frequency, the relation between the observed returns with and without flows becomes $r_p^o \approx r_p^* /(1+f_p/D)$. Intuitively, the monthly return is diluted by the flows of that month.

[9] Denoting the objective codes from Wiesenberger as OBJ, those from Strategic Insight as SI, and those from Lipper as LP, I classify the styles as following: Small Company Growth funds = OBJ SCG, SI SCG, or LP SCGE or SG; Other Aggressive Growth funds = OBJ AGG, SI AGG, or LP LCGE or MCGE; Growth funds = OBJ G, G-S, S-G, GRO or LTG or LP G; Income funds = OBJ I, I-S, IEQ, or ING or LP EI, EIEI or I; Growth and Income funds = OBJ GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, or GRI or LP GI; Maximum Capital Gains funds = OBJ MCG or LP CA; Sector funds = OBJ ENR, FIN, HLT, TCH, or UTL or LP UI, FS, TK or TL; and Timing funds = OBJ BAL, SI BAL, or LP B.

month), while the Income funds show the lowest mean in returns (0.72% per month). Panel B of table 1 summarizes fund flows computed as the percentage change of total net assets after fund returns are controlled for.

(7) $$FLOW_{it} = (TNA_{it} - TNA_{it-1}(1 + R_{it})) / TNA_{it-1},$$

where $R_{i,t}$ is the return of fund i in period t. The Income funds exhibit more flows than any other group (1.20% of the TNA monthly), while the Other Aggressive Growth funds exhibit the least flows (-0.02% of the TNA monthly). Except for the Growth funds, fund flows are persistent with first-order autocorrelations about 0.46~0.75.

Section V compares the proposed performance evaluation model with traditional models. The benchmarks used there include market returns, style index (Sharpe 1988 & 1992), Carhart (1997) four factors, and Pastor Stambaugh (2003) liquidity factor. Style index returns are constructed with returns of the following eight asset classes[10]: 90-day treasury bills, one-year treasury bonds, 10-year treasury bonds, BAA corporate bonds, a broad equity index, value stocks, growth stocks, and small-cap stocks. The conditional model (Ferson and Schadt 1996) uses eleven economy instruments as conditional variables. They are short-term interest rate, term structure slope, term structure concavity, interest rate volatility, stock market volatility, credit spread, dividend yield, inflation, industrial output growth, short-term corporate illiquidity, and stock market liquidity.[11] Data of these variables are accessible through the WRDS.

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[10] The style-matched benchmark portfolio has weighted average returns of the eight asset classes. The weights are obtained by minimizing the tracking error between the fund returns (for all funds of the same style) and the style benchmark.

[11] These variables take the same definitions as in Ferson and Qian (2004). The short-term interest rate = the bid yield to maturity on a 90-day treasury bill; term structure slope = the difference between and five-year and a three-month discount treasury yield; term structure concavity = $y_3 - (y_1 + y_5) / 2$, where y_j is the j-year fixed maturity yield from the Federal Reserve; interest rate volatility = the monthly standard deviation of three-month treasury rates, computed from the days within the month. Stock market volatility = the monthly standard deviation of daily returns for the Standard and Poor's 500 index within the month;

IV. Empirical Results

Empirical specifications for the model require transformations of the moment conditions in system (4) into pricing errors.[12] In response to the modification in using monthly data, the flows are contemporary and take the daily average of each month. Estimation employs Generalized Method of Moments (GMM Hansen 1982, Hansen and Singleton 1982) that searches for parameter values to minimize the weighted average of pricing errors using the inverse of their covariance matrix as a weighting matrix. Once the parameters are estimated, I can compute the true alpha (equation 5a), the observed alpha (equation 5b), the statistical bias (equation 6a), the dilution effect of long-term flows (equation 6b), and the dilution effect of arbitrage flows (equation 6c). The following discussion presents the estimation results at the style group and the individual fund level with particular attention to the relation between stale pricing and the performance components.

(Insert table 2 here.)

Table 2 gives the estimation results by style group for the style-group portfolios. Returns of each style portfolio are equally weighted, month by month, average returns of funds within that investment style. As the table indicates, the estimated true alpha is on average positive but not significant. The spurious bias is small for the style portfolios, but the dilution effects of flows are significant. For example, the dilution effect for short-term

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dividend yield = the annual dividend yield of the CRSP value-weighted stock index; inflation = the percentage change in the consumer price index, CPI-U; industrial production growth = the monthly growth rate of the seasonally adjusted industrial production index; short-term corporate illiquidity = the percentage spread of three-month high-grade commercial paper rates over three-month treasury rates; and stock market liquidity = the liquidity measure from Lubos and Stambaugh (2003) based on price reversals.

[12] For example, the moment condition (4a), transformed into a GMM-convenient pricing error, becomes $g_t = r_t^o\,(1+f_t) - \mu$.

flows is 38 basis points for Maximum Capital Gain funds, 31 for Small Company Growth, 22 for Other Aggressive Growth, and 14 for Sector funds. These results are striking, since stale pricing should be quickly diversified away when aggregating individual fund returns to style group average.

(Insert Figure 1 (Graphs A-D) here.)

I also estimate the model for each individual fund. Figure 1 plots the empirical distributions of the *t*-statistics of the true alpha and the bias components for individual funds by style group. The distributions are based on estimations that use before-expenses returns at the fund portfolio level. The returns for the fund portfolios are generated by adding back expenses and value-weighting them by TNA of share classes. Distributions based on after-expenses returns at the fund share class level are similar. These distributions suggest that fund managers generally have no significant picking ability (although the distribution of the *t*-statistics of alpha is centered above zero). In addition, there is little spurious bias or dilution effect of long-term flows; however, the dilution effect due to short-term flows is significant and widespread. Not surprising, the dilutions, while mostly negative, are positive for some funds, which may result, at least partly, from a net outflow causing the cash balance to shift downward or, in a downturn market, from a higher cash balance making the return look better.

(Insert table 3 here.)

I next examine the relation between stale pricing and performance components. Table 3 summarizes the fund-level estimates of true alpha and biases by the extent of stale pricing. Funds are sorted into five quintiles according to stale pricing. Panel A presents the means of the true alpha estimated with after-expenses returns at the fund share class level, while panel B presents the means of the true alpha estimated with before-expenses returns at the fund portfolio level. In both panels, neither the estimated true alpha nor the dilution effect of long-term flows differs significantly across groups; however, the statistical bias is significantly larger in the top quintile than in the bottom quintile. The dilution effect of arbitrage flows is also larger (in a negative direction) in the top quintile than in other quintiles. Since the magnitude of the dilution effect is larger than that of the spurious bias, the observed alpha is therefore significantly smaller in the top quintile. Specifically, in panel B, the true alpha is about 40 basis points higher than the observed alpha in the sample average, the dilution effect of arbitrage flows is -0.98 in the top quintile and -0.18 in the lowest quintile for fund portfolios. These results are consistent with the theoretical derivation that the statistical bias is linearly and positively related with stale pricing, whereas the dilution effect of arbitrage flows is negatively related with arbitrage flows, hence stale pricing. Most important, the true alpha is independent of stale pricing and flows.

(Insert Figure 2 here)

One interesting question is how the magnitude and significance of stale pricing and arbitrage dilution have changed over time. To address this issue, for each year, I pool the monthly return and flow observations of all funds existing in that year and apply GMM procedure. This approach forces the parameters to be identical across all funds in the same year, and searches for values that minimize the moments' estimation errors both in time series and cross section. The yearly estimation of stale pricing and dilution effects are then plotted in figure 2, in which the *x*-axis represents year, the left-hand *y*-axis represents stale pricing and the estimated values are designated by columns, and the right-hand y-axis denotes the arbitrage dilution measured in annualized percentage and the estimated values are designated by line-connected dots.

As the graph illustrates, stale pricing fluctuates only a little, no more than a 0.1 difference from year to year without any trend. Arbitrage dilution, however, exhibits a clear pattern: from a small negative around -0.20 in 1991, it increases in magnitude until reaching the largest negative of -0.65 in 1998 and then reverses to the smallest negative of -0.10 in 2006. This pattern of differences is not surprising given that the magnitude of dilution depends on the amount/frequency of both arbitrage flows and degree of stale pricing. Dilution peaks in years 1998-2001 with a magnitude of more than -0.50 persistently. This finding is consistent with the SEC litigations claiming that during this time period, mutual funds allowed hedge funds to time and late trade mutual fund shares widely and frequently. In all years, estimations are significant at the 1% level for arbitrage dilution but weak for stale pricing.

The overall results indicate that the true alpha estimated with the proposed model is positive although not significant and free of stale pricing biases, while the observed alpha is negatively impacted by stale pricing. The negative impact results primarily from the arbitrage flow dilution effect, while the statistical bias and the dilution effect of long-term flow are small. Moreover, the arbitrage activities vary over time in spite of relatively stable stale pricing level.

V. Comparison: Traditional Performance Measures and Stale Pricing

The previous section shows that alpha estimated with the proposed model is uncorrelated with stale pricing. As a comparison, this section examines the relation between alpha estimated with traditional models and stale pricing.

A. Measures of Performance and Stale Pricing

I compute fund performance using six conventional alpha estimates from the following equations:

(8a) $$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it},$$

(8b) $$r_{it} = \alpha_i + \beta_i r_{st} + \varepsilon_{it},$$

(8c) $$r_{it} = \alpha_i + \beta_i r_{mt} + c_i r_{m,} Z_{t-1} + \varepsilon_{it},$$

(8d) $$r_{it} = \alpha_i + \beta_i r_{st} + c_i r_{st} Z_{t-1} + \varepsilon_{it},$$

(8e) $$r_{it} = \alpha_i + \beta_i r_{mt} + c_i \mathrm{SMB}_t + d_i \mathrm{HML}_t + e_i \mathrm{MOM}_t + \varepsilon_{it},$$

(8f) $$r_{it} = \alpha_i + \beta_i r_{st} + c_i \mathrm{PREMLIQ}_t + \varepsilon_{it},$$

where r_{it} is fund i's return in period t, r_{mt} is the market return, r_{st} is the style benchmark return, and Z_{t-1} are lagged economic instruments[13]. The first four alphas are Jensen's (1968) alpha and the conditional alpha of Ferson and Schadt (1996) estimated with a market benchmark or style benchmarks.[14] The fifth one controls for Carhart (1997) four factors, and the last, Pastor and Stambaugh (1999) liquidity factor.

I use four measures of stale pricing. The first, introduced by Lo and MacKinlay (1990), is designed for a nontrading scenario:

[13] I use average alpha alone in the conditional model, because it is well specified in large samples and unaffected by problems of data mining and persistent lagged regressors. The time-variant alpha, however, has a spurious bias (Ferson, Sarkissian, and Simin 2003 & 2008).
[14] Tables on the style benchmark weights and returns are available from the author upon request.

(9a) $\pi = -\,\text{Cov}(r_t^o, r_{t+1}^o) / \mu^2;$ *if* $\text{Cov}(r_t^o, r_{t+1}^o) < 0$, otherwise 0,

where r_t^o is the observed returns, μ is the mean of the true return. The true return follows a one-factor linear model. In each period, the security has π, the probability of nontrading; the larger the π, the staler the price.

The second measure, the smooth index (Getmansky, Lo, and Makorov 2004), is designed for thin trading scenarios in which trades are not deep enough to absorb all information:

(9b) $\xi = \Sigma\theta_j^2$; where $r_t^o = \Sigma\theta_j r_{t-j}^o$; $\Sigma\theta_j = 1$; $\theta_j \in [0,1]$; and $j = 1, 2, \text{--} k$,

where r_t^o is again the observed returns, θ_j is the autoregressive coefficient of observed returns up to j periods, and the true return follows a one-factor linear model. The value of smooth index ξ is confined: $1 / (1 + k) \leq \xi \leq 1$. The wider the distribution of θ_j, the smaller the ξ; the more concentrated the θ_j, the larger the ξ. Indeed, Getmansky, Lo, and Makorov (2004) show that smoothing increases the Sharpe ratio of the observed returns of hedge funds.

In addition to π and ξ, stale pricing can also be measured by the covariance beta of fund returns and lagged market returns or the autocovariance beta of fund returns:

(9c) $\text{BETA}(r_t, r_{mt-1}) = \text{Cov}(r_t, r_{mt-1}) / \text{Var}(r_m)$

(9d) $\text{BETA}(r_t, r_{t-1}) = \text{Cov}(r_t, r_{t-1}) / \text{Var}(r)$

where r represents fund returns, r_t is the fund return in period t, r_m represents market returns, and $r_{m,t-1}$ is the market return in period t-1.

(Insert table 4 & 5 here)

Table 4 summarizes the estimated stale pricing by fund style with each measure separated out by panel. Less than half the funds display nontrading properties. Among the funds with $\pi > 0$, the probability of nontrading is as high as 0.52. The minimum smoothing index ξ is 0.17 for all style groups, implying that the return can smooth up to five periods, $k = 5$. The average smoothing index ξ is about 0.5, implying that prices on average smooth back only one period, $k = 1$. Both BETA(r_t, r_{mt-1}) and BETA(r_t, r_{t-1}) are on average highest in the Growth funds and lowest in the Timing funds. All the stale pricing measures display wide variations in cross section.

Table 5 presents the joint probability of a fund's stale pricing being high or low in period t and $t + \tau$, $\tau = 1,2, - - 5$, with each block in the table summing up to one. As is apparent, except for BETA(r_t, r_{t-1}) and $\tau = 2$ or 3, whose diagonal sums only to 0.45, the sum of the diagonal in most blocks is larger than the sum of the off-diagonal, even when $\tau > 2$. BETA(r_t, r_{mt-1}) particularly never switching between high and low subsamples from one period to another. These results imply that stale pricing is widespread and persistent in the mutual fund industry.

B. Explanatory Relation between Measured Performance and Stale Pricing

I examine the relation between performance and stale pricing in a two-step process. First, I estimate each fund's performance α and stale pricing π, ξ, BETA(r_t, r_{mt-1}) and BETA(r_t, r_{t-1}) with a rolling window of three years (36 months), in which each rolling moves observations forward one year (12 months). In the second step, I apply the Fama-MacBeth method to examine their cross-sectional relation. Because the rolling window approach causes the estimated coefficient to follow a MA(2) process, I adjust the standard errors of the coefficients on stale pricing with Newey and West (1987) approach.[15] The controlling variables in the second stage regression include log(TNA), expense ratio, log(age of the fund), portfolio turnover, income distributed, capital gains distributed (CAP_GNS), net flows, total loads, and fund style. All explanatory variables are studentized, and fund styles are controlled for with dummies.

(Insert table 6 here)

Table 6 presents the Fama-MacBeth mean and *t*-statistics of the coefficients on stale pricing and other fund characteristics, with each panel addressing one measure of stale pricing. Overall, the results indicate that the traditionally estimated alpha is negatively associated with stale pricing. The results are consistent and significant for all six measures of alpha when stale pricing is measured with smooth index ξ and BETA(r_t, r_{mt-1}). For each one standard deviation increase in ξ, α decreases by 11 to 42 basis points with significance at the 1% level. For each one standard deviation increase in BETA(r_t, r_{t-1}), α decreases by 18 to 73 basis points with significance at a 5% or 1% level. The coefficients on π are negative on average but significant only when performance is evaluated with the Carhart Four Factor model. The results for BETA(r_t, r_{t-1}), however, are puzzling in that the coefficients switch signs and are sometimes significant on positive side. Nonetheless, this outcome is not intuitively surprising. Traditional performance evaluation suffers from a missing variable problem when the returns are partially explained by a lagged pricing factor. The mean of the missing component goes into the estimated alpha and is positively associated with the importance of lagged pricing factor, which can be proxied by BETA(r_t, r_{t-1}).[16] Overall, these results suggest that the cross-

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[15]Denoting γ_1 as the coefficient of stale pricing on alpha, I compute $\sigma(\gamma_1)$ as follows: $\sigma(\gamma_1) = \{(1 / T)*[\Sigma_{t=1:T} g_t g_t + (4/3)\Sigma_{t=2:T} g_t g_{t-1} + (2/3)\Sigma_{t=3:T} g_t g_{t-2}]\}^{1/2}$, where $g_t = \gamma_{1t}$ - Mean(γ_1).

[16] I also examine the role of loads in impeding opportunistic trading by imposing high transaction costs and find that high loads reduce the dilution of returns in funds with stale pricing. In addition, I examine the

sectional differences in conventional alphas are largely explained by stale pricing even after various fund characteristics have been controlled for.

VI. Robustness

A. Two-Stage Approach with the Proposed Measure of Performance

Section IV shows that the true performance derived from the proposed model is free of biases from stale pricing. In contrast, section V shows that performance measures from traditional models are affected by stale pricing. However, performance and stale pricing are estimated separately in section V but simultaneously in section IV using the proposed model. Therefore, it is necessary to check whether or not the true alpha from the proposed model is correlated with stale pricing estimated separately as in section V. As is apparent from table 7, the true alpha estimated using the proposed model is also free of the stale pricing bias when the two-stage approach is used.

(Insert table 7 here.)

B. Errors in Variables

The procedure for estimating the relation between traditional performance measures and stale pricing consists of two stages: estimation of both performance and stale pricing for each fund with time series data and regression of the estimates from the first stage on each other in cross section. As a result, the second stage regression is likely to suffer from an errors-in-variables problem. This section addresses the issue by calculating the bias caused by this problem.

predictive relation between stale pricing and future performance and find that staleness has a weak predictive power. Tables of these results are available upon request.

Two biases are involved here. The first is the attenuation bias, A = Var(a_2) / [Var(a_2) + (x_2'x_2)$^{-1}$Var(ε_2)], where a_2 is the explanatory variable in the second stage, x_2 and ε_2 are respectively the explanatory variable and the observation error in the first stage where a_2 are estimated. This is the bias studied in a traditional errors-in-variables problem, in which only the explanatory variable, a_2, is observed with an error. The second bias is caused by the correlated errors in the dependent and explanatory variables, Φ = (x_1'x_1)$^{-1}$(x_1'x_2)(x_2'x_2)$^{-1}$Cov(ε_1,ε_2) / [Var(a_2) + (x_2'x_2)$^{-1}$Var(ε_2)], where a_1 is the dependent variable in the second stage, x_1 and ε_1, respectively, are the explanatory variable and the observation error in the first stage in which a_1 is estimated. The problem now becomes the calculation of A and Φ, whose values are determined by Cov(ε_1, ε_2) and Var(ε_2).[17]

To estimate the cross sectional variance and covariance of ε_1 and ε_2, the equations in the first stage must be regressed simultaneously for all funds. However, this procedure is plausible only if the number of funds in the cross section is much smaller than the number of periods in the time series. Assuming Cov(ε_1, ε_2) and Var(ε_2) the same for all funds within the same style group enables a random selection of one fund from each style to form a 16 equation system and compute A and Φ. This procedure is repeated 10 times, each time with eight funds randomly redrawn.

(Insert table 8 here.)

Table 8 presents the 10 pairs of estimated A and Φ. It shows that the attenuation bias A ranges from 0.888 to 0.997, while the bias caused by correlated errors is smaller than 0.005. The last column illustrates the implied relation between performance and stale pricing, i.e., the true coefficient g, if the estimated coefficient $\hat{g}$ is 40 basis points in the second stage, where $\hat{g} = g\,A + \Phi$. According to the estimation, the overall bias due to

[17] Details of errors-in-variables issue are available upon request.

the errors-in-variable is minimal in 9 out of 10 cases. Therefore, it is safe to conclude that the relation between traditionally estimated performance and stale pricing is robust.

C. Staleness in Indices

The estimation of the proposed model uses the S&P 500 index returns as benchmark returns, a favorable choice given that other benchmark returns, even style indices, can be stale. I empirically test this assumption with a simplified version of the model that involves zero flows. Applying the simplified model to 12 portfolios—NYSE, AMEX, NASDAQ equally weighted indices, value, growth, small stock indices and the six Fama-French portfolios—shows that most of them are stale relative to the S&P 500 index.[18]

D. Endogenously Chosen Stale Pricing

Getmansky, Lo, and Makarov (2004) document that some hedge fund managers smooth prices on purpose to boost the measured Sharpe ratio. This opportunistic behavior is beneficial to hedge fund managers because flows in and out of hedge funds are far less frequent than those in and out of open-end mutual funds. As a result, they are less concerned with the negative dilution effect. This present analysis shows that the negative dilution effect on the measured mutual fund performance is larger and more significant than the positive statistical effect. Therefore, as regards fund performance, the argument that stale pricing is endogenously chosen by mutual fund managers is unconvincing. To explore the possibility of endogenously chosen stale pricing, the analysis needs to be extended into other areas, such as fund governance.

[18] Results are available from the author upon request.

VII. Conclusion

Stale pricing is prevalent in the mutual fund industry and impacts fund performance through two channels: a statistical bias and an arbitrage dilution. This paper introduces a performance evaluation model that accounts for stale prices and endogenous fund flows. Specifically, it differentiates true performance from observed performance that ignores stale pricing and treats the observed returns as true returns, and attributes the difference to these effects. Compared to the true alpha, the observed alpha has a positive spurious bias that is small, but a negative dilution bias that is large and significant. Such decomposition is particularly interesting for performance attribution studies and applications.

The true picking ability of fund managers should not be explained by stale pricing of fund shares. Alpha estimates from the proposed model meet this standard. Empirical test of the model also shows that the true alpha is on average positive, although not significant, and higher than the observed alpha. Comparative component analysis shows that fund performance evaluated with conventional methods is negatively associated with stale pricing. Overall, these results suggest that reducing stale pricing through fair-value pricing to impede arbitrages may not only protect long-term investors but also benefit portfolio managers.

Appendix

A1: Derivation of the Observed Alpha and Components of the Biases

The main elements of the observed alpha are $E(r_t^o)$ and $Cov(r_t^o, r_{mt})$. Since

(A1.1) $$E(r_t^o(1 + f_{t-1})) = Cov(r_t^o, f_{t-1}) + E(r_t^o)(1 + c),$$

combining with equation (4a), it gives:

(A1.2) $$E(r_t^o) = [\mu - Cov(f_{t-1}, r_t^o)] / (1 + c).$$ Since

(A1.3) $$Cov(r_t^o(1 + f_{t-1}), r_{mt}) = E(r_t^o(1 + f_{t-1})r_{mt}) - E(r_t^o(1 + f_{t-1}))E(r_{mt})$$

$$= Cov(r_t^o r_{mt}, f_{t-1}) + E(r_t^o r_{mt})E(1 + f_{t-1}) - E(r_t^o(1 + f_{t-1})) E(r_{mt})$$

$$= Cov(r_t^o r_{mt}, f_{t-1}) + (1+c)[Cov(r_t^o, r_{mt}) + E(r_t^o)E(r_{mt})] - E(r_t^o(1+f_{t-1}))E(r_{mt})$$

$$= Cov(r_t^o r_{mt}, f_{t-1}) + (1+c)Cov(r_t^o, r_{mt}) - E(r_{mt})Cov(f_{t-1}, r_t^o),$$

combining with equation (4c), it gives:

(A1.4) $$Cov(r_t^o, r_{mt}) = [(1-\eta) Cov(r, r_m) – Cov(r_t^o r_{mt}, f_{t-1}) + Cov(f_{t-1}, r_t^o)u_m]/(1+c).$$

With $E(r_t^o)$ and $Cov(r_t^o, r_{mt})$ derived, α^o can be derived. It gives equation (5b).

When η is nonzero, $c = 0$ and $f_{t-1} = 0$, the observed alpha becomes $\alpha' = \mu - (1-\eta)Cov(r, r_m)\mu_m / \sigma_m^2$. The difference between α' and the true performance is purely due to stale pricing. Denote this bias as B_1, $B_1 = \alpha' - \alpha$. It gives equation (6a).

When c is nonzero but $Cov(f_{t-1}, r_t^o) = 0$ and $Cov(r_t^o r_{mt}, f_{t-1}) = 0$, the observed alpha becomes $\alpha'' = [1/(1+c)] [\mu - (1- \eta)Cov(r, r_m)\mu_m / \sigma_m^2]$. The difference between α" and α' is the dilution effect due to the long-term flows. Denote this effect B_2, $B_2 = \alpha'' - \alpha'$. It gives equation (6b).

When there are arbitrage flows responding to the expected short-term returns and correlated with fund returns—that is, $Cov(f_{t-1}, r_t^o)$ and $Cov(r_t^o r_{mt}, f_{t-1})$ are nonzero—the observed alpha now becomes α^o as in equation (5b). The difference between α^o and α'' is the dilution effect due to the arbitrage flows. Denote the dilution effect of arbitrage flows as B_3. $B_3 = \alpha^o - \alpha''$. It gives equation (6c). In algebra:

$$\alpha^o = (\alpha^o - \alpha'') + (\alpha'' - \alpha') + (\alpha' - \alpha) + \alpha = \alpha + B_1 + B_2 + B_3.$$

A2. The Aggregation of Daily Dilution to Monthly Dilution

Supposing that there are D days in each month and for each day d within the month, the following is derived:

(3) $$r_d^o = r_d^* / (1 + f_{d\text{-}1})$$

where r_d^o is the observed excess return of the fund, r_d^* is the would-be excess return of the fund with zero flows, and $f_{d\text{-}1}$ is the net flow as a percentage of the TNA. The return dilution on day d is

(A2.1) $$r_d^* - r_d^o = r_d^o f_{d\text{-}1}$$

Denoting the observed excess return for the month as r_p^o, the excess return without flows as r_p^*, and the flow of the month f_p, the monthly dilution is then

(A2.2) $$r_p^* - r_p^o = \sum r_d^* - \sum r_d^o$$

$$= \sum r_d^o f_{d\text{-}1}$$

$$= (1/D) \sum r_d^o \sum f_{d\text{-}1} + D\text{Cov}(r_d^o, f_{d\text{-}1})$$

(A2.3) $$\approx r_p^o f_p / D$$

From (A2.2) to (A2.3), there are two biases, both infeasible to address without observations of daily flows. First, the covariance between daily flows and subsequent returns is ignored. This omission biases the measured dilution downwards. Second, a difference between the flows on the last day of this month and that of last month is ignored. This bias may be positive or negative but of much smaller magnitude compared to the first one. Therefore, at the monthly frequency, the observed return is approximated by $r_p^o = r_p^* / (1+f_p/D)$. That is, when the proposed model is estimated with monthly flows, flows dilute contemporary returns. This approximation is quite intuitive. Overall, the sum of the daily dilutions, if documentable, should be stronger than those found here using monthly returns.

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Table 1

Summary Statistics for Monthly Returns and Flows by Fund Style

This table summarizes the fund returns and flows. All funds in each fund style are grouped month by month to form an equally weighted portfolio whose time series of returns and flows are summarized here. Flows are computed as in equation (7): $FLOW_{it} = (TNA_{it} - TNA_{it-1}(1 + R_{it})) / TNA_{it-1}$. Panel A presents the returns; panel B gives the flow summary. Returns are reported in percentage rate per month; fund flows are calculated as a percentage of the fund TNA. ρ_1 is the first order autocorrelation.

Fund Style	Begin	End	Mean	Min	Max	Std.	ρ_1
Panel A: Summary of fund returns							
Small Company Growth	1986	2007	1.15	-27.42	15.79	5.33	0.11
Other Aggressive Growth	1987	2007	1.07	-33.18	19.35	5.75	0.05
Growth	1973	2007	0.95	-23.56	15.61	4.40	0.07
Income	1973	2007	0.72	-5.68	8.50	1.89	0.16
Growth and Income	1973	2007	0.92	-16.82	12.62	3.58	0.05
Sector	1973	2007	1.01	-25.01	15.73	4.84	0.10
Maximum Capital Gains	1986	2007	0.94	-20.99	12.64	4.93	0.08
Timing	1987	2007	0.77	-8.84	16.62	2.70	-0.06
Panel B: Summary of fund flows							
Small Company Growth	1991	2007	0.84	-2.18	6.52	1.31	0.69
Other Aggressive Growth	1991	2007	-0.02	-26.98	18.99	3.30	0.48
Growth	1973	2007	0.42	-3.65	28.99	2.06	0.07
Income	1974	2007	1.20	-4.36	64.07	4.22	0.75
Growth and Income	1973	2007	0.11	-4.35	4.90	0.97	0.58
Sector	1991	2007	0.41	-2.77	3.31	0.88	0.60
Maximum Capital Gains	1990	2007	0.19	-6.18	8.25	1.60	0.46
Timing	1990	2007	0.71	-2.09	3.99	0.94	0.75

Table 2

Alpha and Bias Components at Style Group Level

This table presents the estimation results of equations (6d). The GMM system (based on moment conditions in equations 4a to 4h) at the style portfolio level is estimated for 1973-2007 sample period. The style portfolio is equally weighted month by month with funds within that style group. The estimated performance and biases are in annual percentage. α is the true alpha; α^o, the measured alpha; B_1, the statistical bias; B_2, the dilution of long-term flows; and B_3, the dilution of arbitrage flows. *, **, and *** represents significance level of 10%, 5%, and 1% respectively.

Style Groups	*A*	α^o	B_1	B_2	B_3
Small Company Growth	4.36	4.01	0.00	-0.03	-0.31***
	(0.03)	(0.03)	(0.00)	(-1.45)	(-18.18)
Other Aggressive Growth	4.27	4.04	0.00	-0.01	-0.22***
	(0.03)	(0.03)	(0.00)	(-0.79)	(-8.51)
Growth	0.86	0.73	0.00	0.00	-0.13***
	(0.01)	(0.01)	(0.00)	(-0.81)	(-12.30)
Income	2.23	2.20	0.00	-0.01***	-0.03***
	(0.04)	(0.04)	(0.00)	(-2.50)	(-18.28)
Growth and Income	1.26	1.20	0.00	-0.01***	-0.06***
	(0.01)	(0.01)	(0.00)	(-1.85)	(-6.62)
Sector	0.65	0.51	0.00	0.00	-0.14***
	(0.00)	(0.00)	(0.00)	(-0.39)	(-15.78)
Maximum Capital Gains	1.37	0.98	0.00	0.00	-0.38***
	(0.01)	(0.01)	(0.00)	(-0.23)	(-20.06)
Timing	1.21	1.17	0.00	-0.01***	-0.03***
	(0.01)	(0.01)	(0.00)	(-2.52)	(-5.53)

Table 3

Performance Evaluation Considering Stale Pricing and Endogenous flows—by Individual Fund

This table summarizes the estimated results of the GMM system (based on moment conditions in equations 4a to 4h) at the individual fund level for 1973-2007. The system is first estimated for each fund, then the estimated true alpha, observed alpha, and biases are summarized in annualized percentage. In the summary, the funds are sorted into five quintiles according to their stale pricing, the mean of each quintle and the statistical differences between the highest and lowest quintiles are presented. Estimates in panel A are based on after-expenses returns at the fund share class level. Estimates in panel B are based on before-expenses returns at the fund portfolio level. The before-expenses returns are obtained by first adding back expenses then averaging to the portfolio level with TNA as weights. *, **, and ** represents significance level of 10%, 5% and 1% respectively.

	α: True Alpha	α^o : Measured Alpha	B_1 : Statistical Bias	B_2 : Dilution of Long-Term Flows	B_3 : Dilution of Arbitrage Flows
Panel A: Sorted by stale pricing – Share class level after expenses					
Full sample	2.24	1.91	<0.001	-0.03	-0.31
Lowest: 1	2.33	2.13	< 0.001	-0.02	-0.17
2	2.59	2.36	< 0.001	-0.03	-0.20
3	2.42	2.12	< 0.001	-0.03	-0.27
4	2.22	1.86	< 0.001	-0.03	-0.34
Highest: 5	2.35	1.12	0.004	-0.02	-0.51
Highest – Lowest	0.02	-1.01***	0.004**	0.00	-0.34***
t-Stat of the difference	(0.13)	(-5.18)	(2.05)	(1.63)	(-5.32)
Panel B: Sorted by stale pricing –Portfolio level before expenses					
Full sample	3.60	3.19	0.001	-0.03	-0.38
Lowest: 1	3.76	3.56	< 0.001	-0.02	-0.18
2	3.94	3.59	< 0.001	-0.03	-0.32
3	3.10	2.61	< 0.001	-0.03	-0.45
4	3.09	2.82	< 0.001	-0.01	-0.26
Highest: 5	3.75	1.75	0.011	-0.01	-0.98
Highest – Lowest	-0.01	-1.81***	0.011**	0.01	-0.80***
t-Stat of the difference	(-0.04)	(-5.14)	(2.23)	(-0.36)	(-4.19)

Table 4

Summary of Estimated Stale Pricing of Individual Funds by Style Groups

This table summarizes the stale pricing of funds. For each fund, stale pricing is measured by estimating equations (9a)-(9d) with 36 window returns rolling by year. Panel A summarizes the estimated stale pricing, π, by fund styles. $\pi = -\text{Cov}(r_t^o, r_{t+1}^o) / \mu^2$; if $\text{Cov}(r_t^o, r_{t+1}^o) < 0$; otherwise 0; (9a). Only the mean of the uncensored observations are presented and the percentages of uncensored observations are in parentheses. Panel B summarizes the estimated stale pricing, ξ, by fund styles. $\xi = \Sigma\theta_j^2$; *where* $R_t^o = \Sigma\theta_j R_{t-j}$; *and* $\Sigma\theta_j = 1$; $\theta_j \epsilon [0,1]$; j=1, 2, - - k; (9b). Panel C and D summarize the estimated stale pricing BETA(r_t, r_{mt-1}) and BETA(r_t, r_{t-1}), respectively from equations (9c) and (9d).

Continue with table 4

	Mean	(π>0)	Std	Min	Max
Panel A: Stale pricing π (Lo and MacKinlay 1990)					
Growth Funds	0.46	(9.6%)	0.29	0.000	1.00
Maximum Capital Gain	0.48	(21.0%)	0.31	0.016	0.98
Other Aggressive Growth	0.50	(20.4%)	0.28	0.000	1.00
Income Funds	0.43	(14.5%)	0.29	0.002	1.00
Growth and Income	0.52	(22.0%)	0.29	0.003	1.00
Sector Funds	0.48	(15.7%)	0.29	0.005	0.99
Small Company Growth	0.44	(18.1%)	0.29	0.003	1.00
Timing	0.51	(21.3%)	0.28	0.002	1.00
Panel B: Stale pricing ξ (Getmansky, Lo, and Makorov 2004)					
Growth Funds		0.47	0.22	0.17	1
Maximum Capital Gain		0.44	0.23	0.17	1
Other Aggressive Growth		0.44	0.22	0.17	1
Income Funds		0.46	0.22	0.17	1
Growth and Income		0.44	0.22	0.17	1
Sector Funds		0.45	0.22	0.17	1
Small Company Growth		0.47	0.23	0.17	1
Timing		0.41	0.20	0.17	1
Panel C: Stale pricing BETA(r_t, r_{mt-1})					
Growth Funds		0.03	0.24	-0.84	1.11
Maximum Capital Gain		0.02	0.22	-0.44	0.69
Other Aggressive Growth		-0.01	0.16	-0.60	0.78
Income Funds		-0.03	0.10	-0.55	0.42
Growth and Income		-0.02	0.13	-0.60	0.66
Sector Funds		0.00	0.19	-1.89	0.83
Small Company Growth		-0.04	0.22	-0.95	0.71
Timing		-0.05	0.10	-0.46	0.30
Panel D: Stale pricing BETA(r_t, r_{t-1})					
Growth Funds		0.09	0.14	-0.44	1.66
Maximum Capital Gain		0.03	0.14	-0.46	0.43
Other Aggressive Growth		0.03	0.14	-0.65	0.52
Income Funds		0.10	0.19	-0.61	0.99
Growth and Income		0.02	0.15	-0.63	0.58
Sector Funds		0.05	0.13	-0.50	0.49
Small Company Growth		0.04	0.13	-0.46	0.50
Timing		0.01	0.15	-0.58	0.48

Table 5

Persistence in Stale Pricing

For each year, funds are classified into H or L according to their stale pricing. This table presents the joint probability of a fund falling into the high or low category in year t and $t + \tau$. Staleness, π, ξ, BETA(r_t, r_{mt-1}), and BETA(r_t, r_{t-1}) are from equations (9a), (9b), (9c), and (9d). For π, H means $\pi > 0$ and L means $\pi = 0$. For ξ, H means $\xi \geq 0.5$ and L means $\xi < 0.5$. For BETA(r_t, r_{mt-1}) and BETA(r_t, r_{t-1}), H means higher than the sample average and L means lower than the sample average.

t (τ = 0)	τ =1		τ =2		τ =3		τ =4		τ =5	
Panel A: Stale pricing π (Lo and MacKinlay 1990)										
	H	L	H	L	H	L	H	L	H	L
H	0.05	0.08	0.03	0.11	0.04	0.14	0.03	0.16	0.02	0.17
L	0.11	0.76	0.13	0.72	0.14	0.68	0.10	0.71	0.10	0.71
Panel B: Stale pricing ξ (Getmansky, Lo, and Makorov 2004)										
	H	L	H	L	H	L	H	L	H	L
H	0.11	0.21	0.10	0.20	0.11	0.22	0.11	0.24	0.11	0.24
L	0.20	0.47	0.21	0.50	0.20	0.47	0.20	0.45	0.20	0.46
Panel C: Stale pricing BETA(r_t, r_{mt-1})										
	H	L	H	L	H	L	H	L	H	L
H	0.46	0.00	0.48	0.00	0.50	0.00	0.51	0.00	0.50	0.00
L	0.00	0.54	0.00	0.52	0.00	0.50	0.00	0.49	0.00	0.50
Panel D: Stale pricing BETA(r_t, r_{t-1})										
	H	L	H	L	H	L	H	L	H	L
H	0.36	0.17	0.22	0.28	0.20	0.24	0.21	0.17	0.24	0.19
L	0.14	0.33	0.28	0.23	0.30	0.25	0.29	0.32	0.26	0.31

Table 6

Traditional Performance Measures and Stale Pricing—Fama and MacBeth Approach

This table displays the relation between fund stale pricing and traditionally evaluated performance. The dependent variables are alphas in annual percentages before expenses. The explanatory variables are stale pricing, lagged fund characteristics, and fund styles. The discretionary turnover is the turnover component that is orthogonal to fund flows. The explanatory variables are studentized. Both alphas and stale pricing are estimated with 36 months returns and rolled over by year. The Fama-MacBeth coefficients and *t*-statistics are presented. The standard errors of the coefficients on staleness are adjusted by an MA(2) process. *, **, and *** represents significance level of 10%, 5% and 1% respectively.

Continue with table 6

	Alpha from Unconditional CAPM	Alpha from Conditional CAPM	Unconditional and Style Benchmarks	Conditional and Style Benchmarks	Carhart's Four Factors	Market & Liquidity Premium
Panel A: Stale pricing π (Lo and MacKinlay 1990)						
Intercept	3.66	5.58	-0.70	-0.40	0.22	5.06
	(12.07)	(15.19)	(-3.14)	(-0.99)	(1.00)	(13.49)
Staleness	-0.12	-0.15	0.09	-0.09	-0.54***	0.07
	(-1.08)	(-1.12)	(0.87)	(-0.71)	(-2.94)	(0.76)
Flow	1.22***	1.27	1.10*	1.27***	1.11***	0.96***
	(3.50)	(1.59)	(1.82)	(6.97)	(5.75)	(6.60)
log(Age)	0.00	-0.09**	0.12***	-0.01	-0.05	0.04
	(-0.09)	(-2.11)	(4.49)	(-0.28)	(-1.51)	(1.21)
Log(TNA)	-0.04	0.04	-0.01	-0.09	-0.11	-0.01
	(-0.60)	(0.54)	(-0.25)	(-1.34)	(-1.56)	(-0.13)
Income	0.77***	0.86***	1.30***	1.66***	0.40***	0.57***
	(11.09)	(9.15)	(12.74)	(12.06)	(5.37)	(8.72)
CAP_GNS	0.28***	0.36***	-0.08	0.14	0.08**	0.29***
	(3.35)	(2.80)	(-1.16)	(1.14)	(2.12)	(3.30)
Discretionary Turnover	-0.18***	-0.15***	-0.31***	-0.33***	0.08	-0.36***
	(-5.95)	(-4.25)	(-8.69)	(-10.74)	(1.38)	(-12.47)
Total Load	0.29***	0.12*	0.13***	0.05	0.44***	0.35***
	(4.74)	(1.86)	(3.33)	(1.13)	(5.58)	(4.91)
Expense	0.07	0.44***	0.20***	0.44***	-0.18	0.39***
	(0.82)	(5.87)	(2.69)	(4.18)	(-1.37)	(5.85)
Styles	Controlled with dummy variables					
Panel B: Stale pricing ξ (Getmansky, Lo, and Makorov 2004)						
Intercept	1.40	2.22	-0.14	-0.38	0.62	1.70
	(2.52)	(4.67)	(-0.27)	(-0.71)	(2.12)	(2.76)
Staleness	-0.29***	-0.33***	-0.42***	-0.42***	-0.11***	-0.25***
	(-3.53)	(-3.83)	(-4.73)	(-4.45)	(-2.78)	(-3.19)
Flow	0.78***	1.16***	1.07***	1.71***	-0.24	0.61***
	(4.22)	(7.54)	(5.30)	(8.11)	(-1.07)	(3.12)
Log(Age)	0.25**	0.19*	0.28**	0.27*	-0.04	0.29***
	(2.07)	(1.68)	(2.04)	(1.78)	(-0.67)	(2.41)
Log(TNA)	-0.21	-0.17	-0.33	-0.55**	0.30***	-0.16
	(-1.21)	(-0.91)	(-1.58)	(-2.19)	(6.11)	(-0.88)
Income	0.78***	0.84***	0.99***	1.20***	0.18**	0.83***
	(5.09)	(4.95)	(5.15)	(5.28)	(2.13)	(5.38)
CAP_GNS	1.46***	1.25***	1.40***	1.38***	0.58***	1.49***
	(5.44)	(4.65)	(4.30)	(3.58)	(6.92)	(5.62)
Discretionary Turnover	-1.64***	-1.00**	-1.53***	-0.95*	-1.84***	-1.64***
	(-4.05)	(-2.22)	(-3.78)	(-1.73)	(-5.80)	(-3.57)
Total Load	0.26***	0.16***	0.22***	0.20***	0.37***	0.36***
	(10.37)	(4.23)	(9.70)	(5.65)	(8.29)	(9.71)
Expense	-0.60***	-0.40**	-0.57***	-0.60***	-0.14**	-0.47***
	(-3.34)	(-2.13)	(-3.07)	(-2.76)	(-2.18)	(-2.55)
Styles	Controlled with dummy variables					

Continue with table 6

	Alpha from Unconditional CAPM	Alpha from Conditional CAPM	Unconditional and Style Benchmarks	Conditional and Style Benchmarks	Carhart's Four Factors	Market & Liquidity Premium
Panel C: Stale pricing BETA(r_t, r_{mt-1})						
Intercept	2.08	3.45	-2.00	-1.28	-0.06	3.39
	(6.96)	(11.29)	(-8.52)	(-3.06)	(-0.19)	(8.47)
Staleness	-0.26**	-0.61***	-0.54***	-0.73***	-0.18**	-0.50***
	(-2.07)	(-5.12)	(-3.00)	(-3.56)	(-2.25)	(-2.87)
Flow	1.13***	1.21***	1.31***	1.49***	0.24	1.21***
	(7.71)	(5.15)	(6.81)	(4.36)	(1.48)	(7.73)
Log(Age)	-0.12***	-0.20***	-0.01	0.00	-0.01	-0.04
	(-3.24)	(-5.22)	(-0.11)	(0.07)	(-0.13)	(-1.01)
Log(TNA)	0.19***	0.46***	0.17***	0.20***	0.18***	0.25***
	(3.35)	(6.58)	(2.82)	(2.63)	(4.33)	(3.89)
Income	0.10	0.04	0.41***	0.62***	0.08	-0.14
	(1.23)	(0.50)	(3.69)	(5.49)	(0.92)	(-1.46)
CAP_GNS	0.46***	0.01	0.08	-0.19***	0.42***	0.41***
	(5.85)	(0.28)	(1.02)	(-2.69)	(7.26)	(4.81)
Discretionary	0.08	0.88***	-0.14	0.75**	0.73***	0.22
Turnover	(0.59)	(3.26)	(-1.34)	(2.26)	(2.59)	(1.13)
Total Load	0.10	-0.05	0.20***	0.12*	0.18**	0.17***
	(1.57)	(-0.72)	(3.31)	(1.82)	(2.24)	(2.63)
Expense	0.30***	0.44***	0.23***	0.39***	0.36***	0.40***
	(3.40)	(5.50)	(3.13)	(4.80)	(3.79)	(4.73)
Styles			Controlled with dummy variables			
Panel D: Stale pricing BETA(r_t, r_{t-1})						
Intercept	0.53	2.41	-0.38	0.87	-1.00	0.42
	(1.03)	(4.73)	(-1.13)	(1.61)	(-2.53)	(0.73)
Staleness	0.20**	0.01	-0.01	-0.14	0.46***	0.62***
	(2.00)	(0.08)	(-0.08)	(-0.72)	(5.74)	(9.68)
Flow	0.51***	0.92***	0.72***	1.32***	-0.18	0.33***
	(4.22)	(9.17)	(6.27)	(8.73)	(-0.86)	(2.59)
Log(Age)	0.06	-0.01	0.06	-0.01	-0.01	0.12
	(0.81)	(-0.10)	(0.75)	(-0.12)	(-0.23)	(1.43)
Log(TNA)	0.26***	0.26***	0.20***	0.03	0.29***	0.36***
	(4.16)	(2.88)	(3.49)	(0.32)	(6.02)	(4.77)
Income	0.41***	0.54***	0.60 ***	0.76***	0.12**	0.41***
	(5.40)	(5.45)	(5.56)	(5.92)	(2.25)	(4.66)
CAP_GNS	0.57***	0.36***	0.41***	0.27***	0.47***	0.53***
	(7.03)	(6.71)	(6.61)	(3.33)	(7.39)	(6.11)
Discretionary	-1.08***	-0.44*	-0.83***	-0.15	-2.06***	-1.05***
Turnover	(-4.69)	(-1.66)	(-4.53)	(-0.49)	(-5.72)	(-3.93)
Total Load	0.20	0.09***	0.21***	0.19***	0.24***	0.28***
	(4.15)	(4.27)	(4.10)	(7.98)	(9.74)	(5.32)
Expense	-0.22	-0.08	-0.15	-0.18	-0.10	-0.02
	(0.20)	(0.01)	(-0.01)	(-0.14)	(0.46)	(0.62)
Styles			Controlled with dummy variables			

Table 7

Performance Estimated with the Proposed Model and Stale Pricing Using a 2-Stage Approach

This table displays the relation between the proposed true performance and various measures of stale pricing of funds. The dependent variable is the true alpha estimated from the proposed model with after-expenses returns in annualized percentage. The explanatory variables are four different measures of stale pricing (equation 9a–9d), fund characteristics, and fund styles. The stale pricing measures and the fund characteristics are studentized. *, **, and *** represents significance level of 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)
Intercept	2.66	2.18	2.67	2.68
	(6.68)	(4.63)	(6.78)	(6.81)
Stale pricing π (Lo and MacKinlay 1990)	-0.31			
	(-0.47)			
Stale pricing ξ (Getmansky, Lo, and Makorov 2004)		0.47		
		(0.80)		
Stale pricing BETA(r_t, r_{mt-1})			-0.01	
			(-0.01)	
Stale pricing BETA(r_t, r_{t-1})				0.56
				(0.40)
Flow	0.62	0.66	0.63	0.62
	(1.25)	(1.27)	(1.25)	(1.24)
Log(Age)	-0.44***	-0.40***	-0.44***	-0.44***
	(-4.74)	(-4.21)	(-4.71)	(-4.74)
Log(TNA)	0.78***	0.82***	0.79***	0.79***
	(3.44)	(3.42)	(3.47)	(3.49)
Income	-0.12**	-0.13***	-0.12**	-0.12**
	(-2.21)	(-2.35)	(-2.26)	(-2.24)
CAP_GNS	0.23	0.19	0.23	0.23
	(1.15)	(0.95)	(1.14)	(1.14)
Discretionary Turnover	-0.11	-0.14	-0.13	-0.13
	(-0.51)	(-0.65)	(-0.62)	(-0.61)
Total Load	0.70**	0.69**	0.70**	0.70**
	(2.24)	(2.21)	(2.24)	(2.24)
Expense	-0.52***	-0.44**	-0.51***	-0.52***
	(-2.68)	(-2.19)	(-2.68)	(-2.69)
Styles	Controlled with dummy variables			
# of obs.	2541	2318	2541	2541
F-Test	27.99	24.39	27.8	27.88
R^2	0.15	0.15	0.15	0.15

Table 8

The Attenuation Bias and the Bias Caused by Correlated Errors

This table presents the estimated attenuation bias and the bias caused by correlated errors in the two-stage regressions. These biases are estimated using eight funds, each randomly drawn from a style group. Each row in the table presents a random drawn sample. Cov(ε_1, ε_2), Var(ε_2), A, Φ, and implied g are given in the table.

$$\hat{g} = \mathrm{Cov}(\hat{a}_1, \hat{a}_2) / \mathrm{Var}(\hat{a}_2) = g A + \Phi$$

where *g is the true slope,* $\hat{g}$ *is the estimated slope,*

$$A = \mathrm{Var}(a_2) / [\mathrm{Var}(a_2) + (x_2' x_2)^{-1}\mathrm{Var}(\varepsilon_2)],$$

and $$\Phi = (x_1' x_1)^{-1} (x_1' x_2)(x_2' x_2)^{-1} \mathrm{Cov}(\varepsilon_1, \varepsilon_2) / [\mathrm{Var}(a_2) + (x_2' x_2)^{-1}\mathrm{Var}(\varepsilon_2)]$$

x_1 *and* x_2 are explanatory variables in the first stage regressions, in which a_1 and a_2 are estimated. a_1 is dependent variable in the second stage and a_2 is the explanatory variable in the second stage regression. ε_1 and ε_2 are observation errors for a_1 and a_2 in the second stage regression.

Cov(e_1, e_2) is computed to proxy for Cov(ε_1, ε_2) and Var(e_2) for Var(ε_2). Var(a_2) equals Var($\hat{a}_2$) - $(x_2' x_2)^{-1}$Var(ε_2). The attenuation bias A, and the bias caused by correlated errors Φ, are also computed. This procedure is repeated ten times with funds redrawn randomly for each iteration.

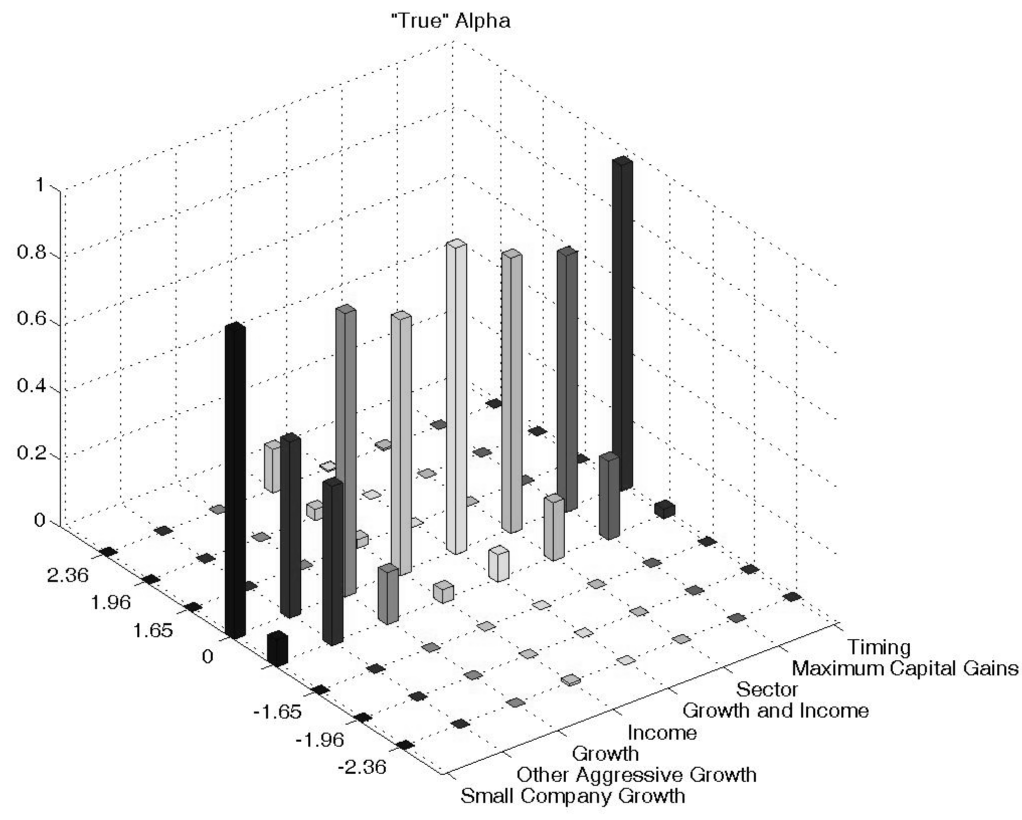
		Cov(ε_1, ε_2)	Var(ε_2)	A	Φ	Implied g If $\hat{g}$ = 40 Basis Points
Jan.1992–Dec. 2000	1	0.15	0.31	0.90	0.001	33
	2	0.21	0.38	0.91	< 0.001	40
	3	0.21	0.38	0.91	< 0.001	40
	4	0.20	0.38	0.89	< 0.001	43
	5	0.20	0.38	0.89	< 0.001	43
Jan. 1981–Dec.1989	6	0.26	0.28	0.93	0.005	-8
	7	0.19	0.21	1.00	< 0.001	37
	8	0.21	0.22	1.00	< 0.001	38
	9	0.25	0.27	1.00	< 0.001	38
	10	0.22	0.23	0.99	< 0.001	36

Figure 1

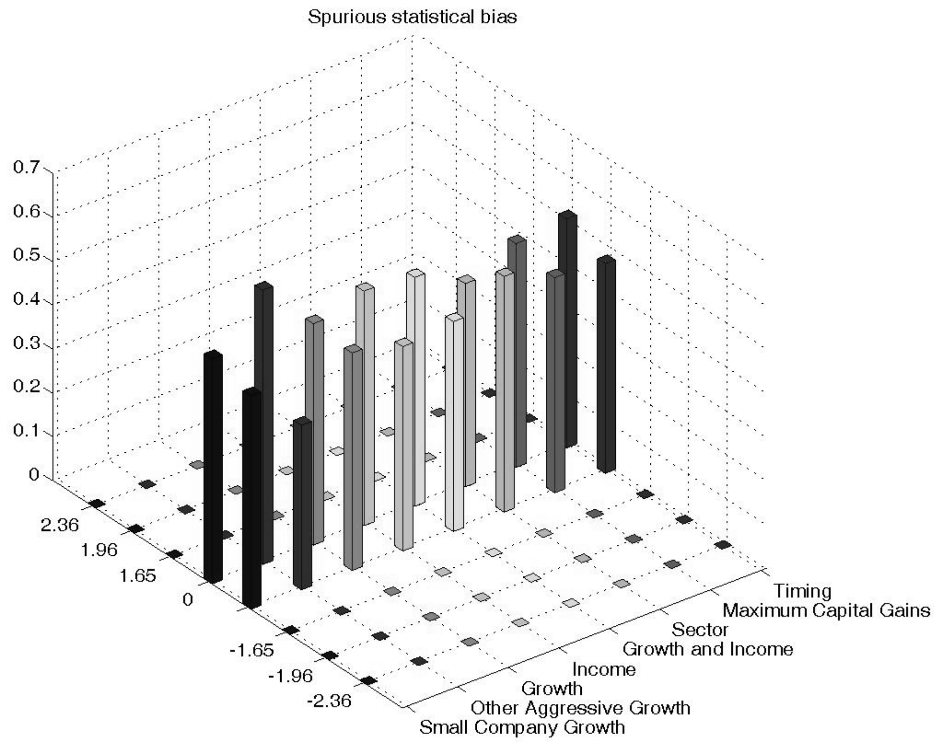
Distribution of *t*-statistics of True Alpha and Biases in the Observed Alpha

The empirical transformation of system (4) is estimated with GMM approach fund by fund (portfolio level) with before expenses returns, and their *t*-statistics are grouped and then plotted by style group. The four plots are for (A) True alpha; (B) Statistical bias; (C) Dilution of long-term flows; and (D) Dilution of arbitrage flows.

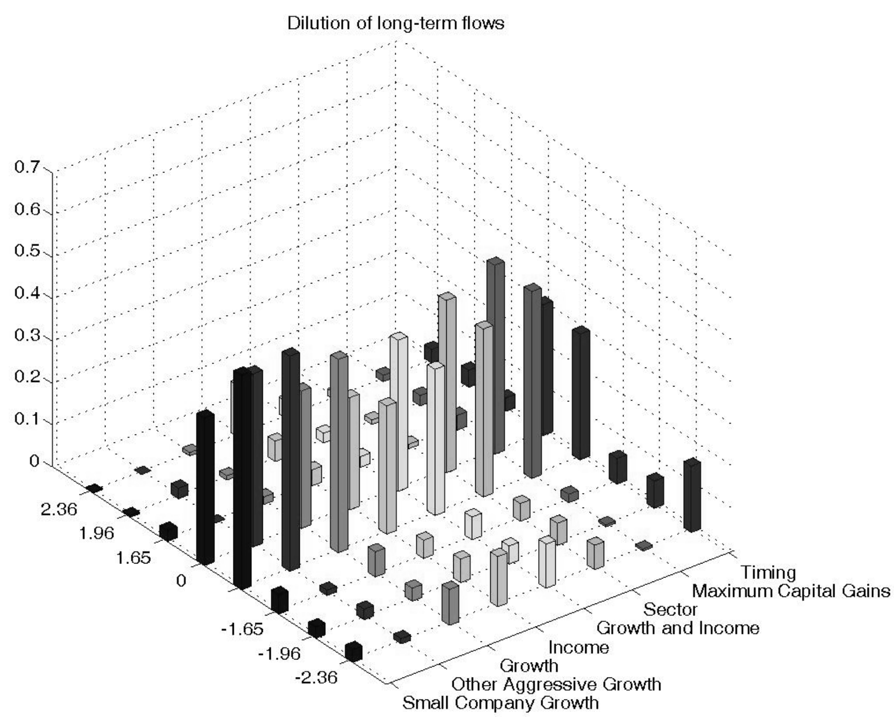
The X-axis presents the fund style group. The Y-axis presents the range of the *t*-values: $t > 2.36$, $1.96 < t < 2.36$, $0 < t < 1.96$, $0 < t < -1.96$, $-1.96 < t < -2.36$, $t < -2.36$. The Z-axis presents the percentage of funds that fall into the range of the *t*-values for each style group.



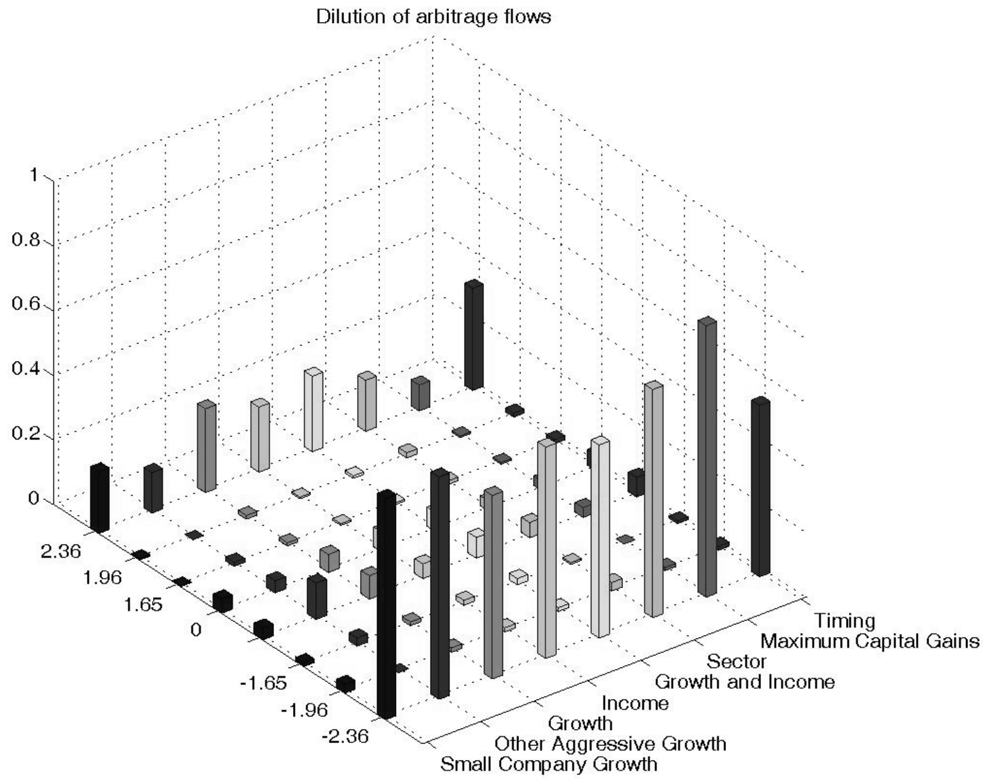
Graph A: Distribution of t-statistics for the true alpha



Graph B: Distribution of t-statistics for the statistical bias



Graph C: Distribution of t-statistics for the dilution of long-term flows



Graph D: Distribution of t-statistics for the dilution of arbitrage flows

Figure 2

Time Series Trend of Stale Pricing and Arbitrage Dilution

This figure plots the estimated stale pricing and arbitrage dilution with fund level observations by year. The X-axis denotes year. The left-hand Y-axis denotes the stale pricing level and the corresponding values are designated by the columns in the figure. The right-hand Y-axis denotes dilution in the annualized percentage and the corresponding values are designated by the line connected dots.