Do fund managers make informed asset allocation decisions?

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Abstract

We derive a model of dynamic asset allocation that allows us to infer whether, and the degree to which, a portfolio manager is optimally using available information to shift funds to and from equities. We test the model on a large dataset of mutual fund holdings and find that the asset allocation decision of the typical mutual fund manager, whether a professed market timer or not, is largely uninformed and fails to incorporate public information into their asset allocation decision. We estimate that this shortcoming can impose a cost on mutual fund investors of roughly 50-60 basis points per year.

Keywords: Market timing, asset allocation, portfolio management, mutual funds.

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1. Introduction

Every active fund manager has to make asset allocation decisions, and changes in the portfolio weights of major asset classes should be viewed as a function of the manager's information set and his or her ability to optimally use that information set. This paper develops a model that can be employed to infer how much of a portfolio manager's asset allocation decision is made based on information and how much is uninformed. Uninformed asset allocation decisions are those that *needlessly* incorporate noise, and our model enables us to quantify the presence of such noise. We show that uninformed weight changes impose a cost on the fund's investors because they add uncompensated volatility to the fund's returns. We then apply the model to the portfolio weights of US mutual funds holding primarily US common equity from 1979Q3 until 2006Q4. We find that, consistent with prior studies of timing over holding horizons of a month or more, the asset allocation decisions of the typical mutual fund manager exhibit an absence of both public and private information. Fund managers whose explicit objective is to time the market fare no better. We estimate that the certainty equivalent cost of making uninformed asset allocation decisions for an investor amounts to a few basis points of the invested wealth per year. The opportunity costs of not using publicly available information in asset allocation decisions is significantly greater at roughly 50 basis points.

1.1. Motivation and literature review

The literature on portfolio management generally views 'market timing' as the shifting of funds between broad asset categories (such as 'US equities', or 'US Government bonds') in an attempt to capture higher risk-adjusted returns. Skillful market timers are said to divine those times during which returns on one major asset class will exceed those of another. However, in contrast with successful stock-picking, some forms of market timing are theoretically possible even in an informationally efficient market. Research over the past 20 years clearly suggests that the equity premium and market Sharpe Ratio are predictable using well known and easy to acquire public information, and that the application of this knowledge can provide additional value to investors, measured in terms of risk-adjusted returns, of about 1-2% per year.[1] Thus, at least in principle, one might expect market timing to be widely practiced even if it is only based on public information.

1.1.1. Studies that do not support successful market timing

Most of the literature (e.g., Treynor and Mazuy, 1966; Henriksson and Merton, 1981; Pesaran and Timmermann, 1994) focuses on a manager's ability to shift resources between cash and the US equity market, although recent studies also test for market timing ability with respect to a broader range of asset classes. Despite the econometric issues that can arise in testing fund *returns* for evidence of market timing (see Jagannathan and Korajczyk, 1986; Ferson and Schadt, 1996; Edelen, 1999; Goetzmann, Ingersoll, and Ivković, 2000; Kothari and Warner, 2001), most studies searching for timing ability have only examined returns, largely concluding that active fund managers do not demonstrate better risk-return tradeoffs via market timing over monthly or longer horizons.[2] On the other hand, recent literature directly analyzing fund holdings appears to conclusively indicate that professional active fund managers exhibit significant skill in selecting individual securities (although their investors do not generally benefit because of the fees and expenses charged by skilled managers).[3] The disparity between active managers' ability to select individual securities and their inability to deliver value through 'market timing' is especially puzzling given the research cited earlier in support of the predictability of the market's Sharpe Ratio.

[1] The predictability of market returns has been documented in Keim and Stambaugh (1986); Campbell and Shiller (1988a,b); Breen, Glosten, and Jagannathan (1989); Lettau and Ludvigson (2001); Campbell (2002). The potential benefits from making use of this information in asset allocation decisions is documented in, among other papers, Kandel and Stambaugh (1996) and Whitelaw (1997).

[2] Studies finding no (or negative) evidence for timing include Treynor and Mazuy (1966); Henriksson and Merton (1981); Ferson and Schadt (1996); Graham and Harvey (1996); Wermers (2000); Kacperczyk, Sialm, and Zheng (2005); Kosowski, Timmermann, Wermers, and White (2006); Kacperczyk and Seru (2007). Daniel, Grinblatt, Titman, and Wermers (1997) search for ability in timing characteristics by looking at holdings. The papers that test market timing in multiple asset-allocation context include Daniel, Grinblatt, Titman, and Wermers (1997); Kacperczyk, Sialm, and Zheng (2005); Kosowski, Timmermann, Wermers, and White (2006); Kacperczyk and Seru (2007).

[3] See Daniel, Grinblatt, Titman, and Wermers (1997); Wermers (2000); Chen, Jegadeesh, and Wermers (2000); Cohen, Coval, and Pastor (2005); Kosowski, Timmermann, Wermers, and White (2006); Kacperczyk, Sialm, and Zheng (2005); Kacperczyk and Seru (2007).

1.1.2. Studies that do support successful market timing

There are several studies that find evidence of positive timing ability. In particular, the consensus of studies that test fund returns for evidence of timing ability over daily horizons appears favorable (Busse, 1999; Bollen and Busse, 2001; Chance and Hemler, 2001; Fleming, Kirby, and Ostdiek, 2001). Such ability, however, likely has little to do with slower-moving macroeconomic information shown to be useful for predicting returns at a much longer horizon. Moreover, possessing the ability to time the market at the daily horizon does not preclude the use of public information that forecasts the market at longer horizons. A more promising study is Jiang, Yao, and Yu (2007) who estimate aggregate portfolio betas from mutual fund holdings and find that funds tend to hold higher beta securities prior to when market returns are high. Because they investigate timing ability using portfolio holdings, their work is closest to ours.

1.1.3. Timing ability and funds' equity holdings

The fact that active fund-managers are not generally deemed successful at market timing does not appear to be for lack of trying. For instance, Figure 1 plots standardized values for the consumption-wealth ratio variable (cay) constructed in Lettau and Ludvigson (2001), the aggregate dividend ratio (dp), and the average domestic equity exposure (relative to their sample mean) for funds identified as market-timers in our sample (an average of 27 funds each quarter).[4] Both cay and dp are thought to have forecasting power for the equity premium (see Lettau and Ludvigson, 2001; Campbell, 2002), and over this period, the correlation of cay, lagged one quarter, with excess return on the CRSP value-weighted index has been 17%, which is significant at the 10% level. By contrast, equity exposures are far from significantly correlated ($\rho = -10\%$) with the market, and possess negative correlation with cay or dp (-56% and -30%, respectively).[5] Moreover, funds' average equity exposure in our data is significantly less persistent, indicating that the series is either considerably more noisy

[4] We describe in detail our method for classifying funds as market timers in Section 3 below.

[5] Other variables that are thought to forecast the equity premium include the term spread and default spread. The correlation of equity exposures with these variables is also weak.

than either cay or dp, or primarily contains high frequency information about changes in the equity premium. Finally, when one multiplies the lagged change in equity exposure for each fund by the market's excess returns, then averages this quantity across funds and quarters the result is a statistically and economically insignificant single basis point. Thus, if the changes in equity exposure reflect an attempt to time the market over this period, then at least at first blush, such efforts have not clearly translated into a valuable service.

On the other hand, cay and dp themselves are noisy predictors of the equity premium, and if one naively uses asset allocation weights whose changes are proportional to cay, then the average of 'lagged weight changes × market returns' is also statistically insignificant. Moreover, weight changes ought to account for conditional volatility as well as conditional means. Thus it is insufficient to consider Figure 1 in isolation as evidence against effective asset allocation ability.

This sets up the research questions we investigate: To what degree do fund managers' asset allocation decisions reflect information rather than noise, and to what extent can one assess the cost to investors induced by purposeless asset-allocation? The second issue arises for two reasons: Firstly, asset allocation that is largely noise can lead to utility loss to investors because the random changes in weight induce spurious, and therefore uncompensated, risk relative to an alternative policy.[6] Secondly, by ignoring public information, fund managers (and thus their investors) can miss an opportunity to enjoy higher Sharpe ratios. We pose this question in relation to the asset allocation decision of any fund, not only those that profess to be 'market timers'.

1.2. Our contribution

In an attempt to shed additional light on these issues, this paper examines 'market timing' from several new perspectives. Firstly, consistent with the literature on the predictability of aggregate returns, we assume that fund managers receive noisy signals about the market Sharpe Ratio and accordingly adjust their portfolio weights. Such a strategy is known

[6] We establish this formally in the paper. Cox and Leland (2000) derive similar results.

to deliver value (Fleming, Kirby, and Ostdiek, 2001; Kandel and Stambaugh, 1996) when the signal corresponds to public information. Our model augments this by considering some degree of private information as well, potentially reflecting heterogeneity in the way macroeconomic news is interpreted. Correspondingly, we characterize the Bayesian-optimal changes in weights of a market timer who invests in the market or in short-term bonds, and with a mean-variance myopic objective function, when he or she can condition on *all* past information, and *all* past market returns.

Secondly, our theoretical analysis leads to some surprising results that easily lend themselves to empirical testing. The model predicts that the equity exposure of every portfolio manager, whether they are market timers or not, ought to have an autocorrelation coefficient similar to that of the time-varying equity premium. In particular, this autocorrelation ought to be the same across funds regardless of their information structure. The intuition for this result is simple: Say that the market's conditional Sharpe Ratio is not directly observable but is known to have a persistence characterized by an autocorrelation coefficient of ϕ. Because all fund managers are using their information optimally to infer the market's conditional Sharpe Ratio, the time series of their best guess of it would also have an autocorrelation of ϕ (otherwise, the fund manager would know that he or she has been systematically over- or underestimating the conditional Sharpe Ratio). Given that portfolio market weights are essentially proportional to the market's Sharpe Ratio, the time series of market weights of any fund that is optimally timing the market ought to have an autocorrelation of ϕ independent of the fund's identity.[7]

The model also predicts that a regression of market returns on lagged fund weights, with appropriate controls, should result in a slope coefficient that is independent of the volatility of the fund weights (i.e., the more the portfolio weight varies, the higher the forecasting power). The intuition here is also simple. A large variation in portfolio weights reflects better precision in forecasting the equity premium. The slope coefficient from a regression

[7] This is exactly true in a mean-variance portfolio allocation model where return volatility is constant. Our empirical tests adjust for the presence of time-varying return volatility and attempt to control for the presence of non-myopic hedging demand.

of market returns on lagged fund weights is proportional to the correlation between weights and returns, and inversely proportional to the volatility in weights. These two effects balance each other, thereby leaving the slope coefficient constant.

A final prediction is that, because fund asset allocations reflect both public and private information, they ought to predict returns at least as well as any variable constructed only from public information.

These predictions should be robust because the economic rationale behind them transcends the particular model we use. Nevertheless, the model used to derive these results is rich in allowing a great deal of heterogeneity in fund managers and their private information. We test the model predictions on a large panel of US mutual fund holdings, and are able to, at least partially, assess the degree to which asset allocation decisions reflect information as well as obtain rough estimates of the cost to investors induced by suboptimal asset-allocation decisions. Our battery of empirical tests of the model's predictions suggest that, contrary to Jiang, Yao, and Yu (2007), little or no information is contained in funds' asset allocation decisions.[8] This appears to be robust to various econometric specifications and holds up in the cross section and in the aggregate. Our most conservative estimate is that 67% or more of the typical asset allocation decision is uninformed, and that there is compelling evidence that fund managers, whether they profess to have timing ability or not, appear to be neglecting valuable public information in their asset allocation decision. We estimate, through a parametric model, that the combined certainty equivalent costs, due to spurious asset allocation and neglect of public information, can amount to between 50 and 60 basis points of annual returns on invested wealth.

It is important, however, to temper our negative results by noting that the holdings data used in our empirical tests are generally limited to US equity weights only. We have no information on how funds invest outside of this asset class. Although our treatment of fund holdings is consistent with that of other studies, these funds could in principal make use of instruments such as index futures or high-yield bonds to change their effective equity

[8]Although we confirm the results of Jiang, Yao, and Yu (2007) for portfolio betas, we test and find that the equity portfolios generating these betas exhibit returns with no hint of timing ability.

exposure and our study would not pick this up.[9] Moreover, it is also possible that the reported poprtfolio holdings suffer from window dressing.

Section 2 develops the model. Section 3 describes our data set, the empirical methodology, and reports our tests of the model. This section also compares our findings with the, apparently contradictory, conclusions of Jiang, Yao, and Yu (2007). Section 4 estimates the certainty equivalent costs of suboptimal asset allocation based on the empirical results. Section 5 concludes.

2. A model of optimal market timing

We begin by considering a typical market-timing fund manager, identified by the index i, who receives a noisy signal each period about the market risk premium and adjusts his portfolio accordingly. Our assumptions represent a rich information environment, both across managers and across time. Doing so enables us to achieve a level of realism and generality beyond the typical static modeling of the asset allocation decision under asymmetric information.

The noisy signal received by manager i at date t is

$$s_{it} = n_{it} + m_t, \tag{1}$$

while the market's excess return is assumed to be:

$$\tilde{r}^e_{t+1} = \bar{\mu} + m_t + \tilde{\varepsilon}_{t+1}, \tag{2}$$

where $\bar{\mu}$ is the unconditional premium and m_t is its time-varying component. Thus n_{it} is the noise component of the manager's signal and the signal, s_{it}, incorporates public information (available to all fund managers) as well as private information.

The empirical literature notes that market return volatility is predictable. Consistent

[9]Almazan, Brown, Carlson, and Chapman (2004) document that few funds use derivatives.

with this, we assume that ε_{t+1} has an observable date-t conditional variance of $\sigma^2_{\varepsilon t}$.[10] We also assume that the conditional variances of u_t and v_{it} are constant and denoted as σ^2_u and σ^2_v, respectively. We further assume that

$$m_t = (1 - \phi_m)m_{t-1} + u_t,$$

$$n_{it} = (1 - \phi_{in})n_{it-1} + v_{it},$$

such that each shock in the collection, $\{\frac{\varepsilon_s}{\sigma_{\varepsilon s-1}}, \frac{u_s}{\sigma_u}, \frac{v_{is}}{\sigma_{iv}}\}_{s\leq t}$ is a standard normal iid random variable, independent of the process that generates $\sigma^2_{\varepsilon t}$. Under our assumptions, m_t and $\sigma^2_{\varepsilon t}$ are independent and universal to all managers while n_{it} may or may not be correlated across managers.[11] Moreover, the variance of noise in managers' signals is heterogeneous in precision as well as persistence.

Under our assumptions, $\text{Var}[m_t] = \frac{\sigma^2_u}{1-(1-\phi_m)^2}$ and $\text{Var}[n_{it}] = \frac{\sigma^2_{iv}}{1-(1-\phi_{in})^2}$; we'll refer to these unconditional variances as $\text{Var}[m]$ and $\text{Var}[n_i]$, respectively. Let I_{it} correspond to manager i's information set, consisting of observations of $s_{ix}, \sigma^2_{\varepsilon x}$ and r^e_{ix} for all dates $x \leq t$. Finally, we assume that the manager seeks to myopically maximize a mean-variance function of his portfolio returns, implying that the optimal allocation at date t is

$$w_{it} = A_i \frac{\bar{\mu} + E[m_t|I_{it}]}{\sigma^2_{\varepsilon t} + \text{Var}[m_t|I_{it}]}. \tag{3}$$

The proportionality factor, A, can be viewed as a measure of relative risk tolerance and is assumed constant through time. Thus, if $\sigma_m = m_0 = 0$ and $\sigma^2_{\varepsilon t}$ is constant (i.e., there

[10] It appears realistic to assume that investors observe the conditional volatility of market returns (using, for example, the S&P500 volatility index). In other words, $\text{Var}[r^e_{t+1}|\mathcal{P}_t]$ is observable, with $\mathcal{P}_t$ representing a common knowledge (public) information set. Under the assumption that m_t is independent of $\tilde{\varepsilon}_{t+1}$, assuming the observability of $\sigma^2_{\varepsilon t}$ presupposes that $\text{Var}[m_{t+1}|\mathcal{P}_t]$ is separately observable.

[11] Without loss of generality and without changing our main results, one can replace $\bar{\mu}$ with $\xi\sigma^2_{\varepsilon t}$ plus a constant, consistent with various asset pricing models. Various studies explore the relationship between the market's conditional variance and expected returns. Whitelaw (1994) demonstrates that the theoretical relationship may not be monotonic, French, Schwert, and Stambaugh (1987) find a positive relationship while Breen, Glosten, and Jagannathan (1989) and Breen, Glosten, and Jagannathan (1989) do not. In light of this, we elected not to explicitly model such a relationship, although we account for its potential presence in the empirical section

is no predictability in the market's Sharpe Ratio), then the manager follows a strategy of rebalancing to constant weights. When we test the model, we revisit this assumption and control for alternative specifications that are consistent with dynamic portfolio management for an optimizing agent (e.g., a buy and hold strategy, or a portfolio insurance strategy). Assuming a mean-variance objective function is consistent with the preferences of a log-investor who can rebalance continuously, but the assumption ignores the additional hedging demands of other types of investors. In neglecting a hedging demand component, we note that its sign and magnitude vary with investor preferences and horizon, while *all* investors place some (often considerable) weight on the myopic allocation given by Eq. (3).[12] Finally, we note that, to the extent that the equity premium affects the expected returns of all stocks, Eq. (3) ought to apply to all managers of equity portfolios (i.e., both 'stock pickers' and 'market timers').

The following proposition establishes properties of the manager's optimal forecast of the time-varying component of the equity premium.

Proposition 1.

$$\hat{m}_{it} \equiv E[m_t|I_{it}] = \left(\sum_{j=0}^{\infty} a_{itj} s_{it-j} + \sum_{j=0}^{\infty} b_{itj} (r^e_{t-j} - \bar{\mu}) \right), \tag{4}$$

where the coefficients $\{a_{itj}, b_{itj}\}_{j=0}^{\infty}$ *provide a solution to the following infinite set of linear*

[12]Kim and Omberg (1996) and Wachter (2002) demonstrate that when the Sharpe Ratio is an AR(1) process in continuous time, any investor who can rebalance continuously and has utility over terminal wealth with constant relative risk aversion will allocate her wealth to equities by modifying Eq. (3) to include calendar-time dependence in A and an additional calendar-time dependent constant. Detemple, Garcia, and Rindisbacher (2003) find that variations in the hedging demand are significantly less pronounced than those of the myopic solution. Overall, this suggests that Eq. (3) captures much of the information content in changes to equity allocations even in the presence of a hedging demand.

equations:

$$(1-\phi_m)^k\, Var[m] = \sum_{j=0}^{\infty} a_{ijt}\Big(Var[m](1-\phi_m)^{|k-j|} + Var[n_i](1-\phi_{in})^{|k-j|}\Big) + \sum_{j=0}^{\infty} b_{ijt}\, Var[m](1-\phi_m)^{|k-j-1|}, \;\; k \geq 0$$

$$(1-\phi_m)^{k+1}\, Var[m] = b_{ikt}\sigma^2_{\varepsilon t-k-1} + \sum_{j=0}^{\infty} a_{ijt}\, Var[m](1-\phi_m)^{|k+1-j|} + \sum_{j=0}^{\infty} b_{ijt}\, Var[m](1-\phi_m)^{|k-j|}, \;\; k \geq 0.$$

Moreover,

$$Var[m_t|I_{it}] = \sigma^2_{\varepsilon t-1}(1-\phi_{in})b_{i0t} + Var[n_i]a_{i0t}\phi_{in}(2-\phi_{in}). \tag{5}$$

Proofs to all results are found in Appendix A. Although being able to actually solve the infinite set of equations in Proposition 1 is not germane to our analysis in this paper, it is worth noting that the infinite set of coefficients in Proposition 1 can be approximated extremely well by truncating the higher order equations. In numerically experimenting with the equations, we've found that for realistic parameter settings it suffices to keep only those coefficients for which $k \leq 5$.

2.1. Testable predictions

The next result is central to the empirical tests we develop.

Proposition 2. *The unconditional autocorrelation of $\hat{m}_{it}$ is $1-\phi_m$, coinciding with the unconditional autocorrelation of m_t.*

Thus, controlling for the denominator in (3) (say, by multiplying w_{it} by $\sigma^2_{\varepsilon t}$ and assuming $\sigma^2_{\varepsilon t} \gg \mathrm{Var}[m_t|I_{it}]$), the autocorrelation of the optimal weight assigned to the market is the same across managers despite the rich heterogeneity in managers' information structure. One can understand the intuition for the result as follows: Every manager knows that the conditional equity premium has persistence of $(1-\phi_m)$. If her estimate of the equity premium,

$\hat{m}_{it}$, exhibits a different level of persistence, then the manager is either over-reacting or under-reacting to new information.

A second result that is key to our empirical tests relies on the observation that, controlling for the denominator in (3), the variation in weight is related to the quality of the manager's signal. If the quality of the signal is poor (i.e., $\frac{\text{Var}[m]}{\text{Var}[m]+\text{Var}[n_i]}$ is small), then the manager will optimally react by being careful not to make dramatic changes in the weights, which are proportional to changes in $E[m_t|I_{it}]$. Likewise, a high quality signal will be associated with larger shifts in weights in response to the signal. Thus, a higher variance of portfolio weights ought to reflect better forecasting power for the market returns. This is the subject of the next result.

Proposition 3. *The regression of $\tilde{r}^e_{t+1}$ on $\hat{m}_{it}$ yields a slope coefficient of $\beta = 1$, and the unconditional correlation of $\tilde{r}^e_{t+1}$ with $E[m_t|I_{it}]$ is $\rho_{r\hat{m}_i} = \frac{\sigma_{\hat{m}_i}}{\sigma_r}$, where σ_r is the unconditional standard deviation of equity returns and $\sigma_{\hat{m}_i}$ is the unconditional standard deviation of $\hat{m}_{it}$.*

In particular, controlling for the conditional volatility (again, by multiplying w_{it} by $\sigma^2_{\varepsilon t}$ and assuming $\sigma^2_{\varepsilon t} \gg \text{Var}[m_t|I_{it}]$), the slope coefficient in a regression of market returns on lagged weights ought to be proportional to $\frac{1}{A_i}$ — which in turn is related to the average unconditional portfolio weight. Given that the data allows one to estimate the latter quantity, this is essentially how we will test Proposition 3.

2.2. Suboptimal asset allocation

In this section we establish that it is inadvisable for a portfolio manager to make uninformed asset allocation decisions. By an 'uninformed asset allocation decision' we refer to changes in portfolio weights that are not contingent on past or present return-relevant variables (e.g., the tossing of a coin).

Because it is easier to make our point in a continuous-time setting, we consider a filtration generated by multi-dimensional Brownian motion, and corresponding to the information set of the manager. Suppose that the continuous-time random variables, $r_{ft}, \mu_{et}, \sigma_{et}, w^*_t, r_{et}$ and η_t are adapted to the filtration and that η_t is independent of the other variables and has an unconditional mean of zero. Interpret r_{ft} as the instantaneous risk-free rate, μ_{et} and σ_{et} are, respectively, the optimal estimates of the instantaneous market risk premium and the instantaneous market return volatility based on the manager's information, r_{et} is the realized market excess return, and w_t^* corresponds to a set of weights adapted to the filtration generated by $\{r_{ft}, \mu_{et}, \sigma_{et}, r_{et}\}$. Suppose that the manager chooses $w_t \equiv w_t^* + \eta_t$ to be the portfolio weight. An investor who invests with the manager over the horizon $[0, T]$ will see his wealth grow from W_0 at time 0 to W_T at time T and given by

$$W_T = W_0 \exp\Big(\int_0^T \big(r_{ft} + w_t \mu_{et} - \frac{1}{2}\sigma_{et}^2 w_t^2\big)\, dt \; + \; \int_0^T w_t \sigma_{et} dB_t \Big), \tag{6}$$

where dB_t is an infinitesimal Brownian increment that is adapted to the filtration generated by $\{r_{ft}, \mu_{et}, \sigma_{et}, r_{et}\}$. In what follows, we only consider investors with utility over date-T wealth, neglecting consumption or income considerations.[13]

Proposition 4. *Any investor with utility only over date-T wealth who is at least as risk-averse as a log-investor will strictly prefer that the manager use the investment policy w_t^* rather than w_t. Moreover, the certainty equivalent loss for such an investor, measured in terms of an annual fee on managed wealth, is at least*

$$f = \frac{1}{2T} E\Big[\int_0^T \eta_t^2 \sigma_{et}^2 dt \Big]. \tag{7}$$

It is worth emphasizing that the certainty equivalent cost in Eq. (7) is assessed relative to *any* policy w_t^*. In particular, the expression does not incorporate the lost opportunity cost of failing to take advantage of the predictability in expected returns. We assess the latter in Section 4.

[13]It is tedious, though not hard, to extend the results here to the case where the investor consumes from savings and/or makes periodic contributions from labor income.

3. Empirical investigation

Our empirical work is guided by the model results of Section 2.1 where it is assumed that the portfolio weight assigned to the market are given by Eq. (3). Before we can apply the results of the model to open-end mutual funds holding domestic equity, we have to address two issues. First, funds may not follow a strategy that rebalances to constant weights in the absence of information (i.e., time-varying Sharpe Ratios). One example of this is a buy-and-hold strategy, while another is portfolio insurance. In the case of iid returns, it is well known (e.g., Cox and Leland, 2000; Leland, 1980) that these three dynamic strategic do not dominate each other in the sense that certain investors (e.g., those exhibiting a particular version of decreasing relative risk aversion) might prefer portfolio insurance while others might prefer a rebalancing strategy. Moreover, in the presence of trading costs, it may be optimal to allow weights to wander within an 'inaction' region (see Davis and Norman, 1990) and the optimal allocation of new funds might therefore exhibit a lag. Because all of these alternative reasons for weight changes are contingent on past returns or fund flows, which are orthogonal to the error term in forecasting m_t, one can still test the model by controlling for past returns and fund flows.

Second, the Propositions pertain to the numerator of Eq. (3), whereas in practice portfolio weights incorporate the denominator as well. Thus, in testing whether asset allocation is informed, one must control for the conditional volatility. This can be done using a volatility index such as the vix, acknowledging that such a market forecast of volatility will differ, though likely not by much, from the manager's own volatility forecast.[14]

Recapping the insights from Section 2, controlling for the conditional market volatility,

1. The autocorrelation of weights allocated to equity should be the same across funds.

2. A regression of market returns against lagged portfolio weights allocated to equity ought to yield a positive slope coefficient inversely proportional to the average uncon-

[14]The difference between $\text{Var}[r^e_{t+1}|\mathcal{P}_t]$, where $\mathcal{P}_t$ represents a common knowledge (public) information set, and $\text{Var}[r^e_{t+1}|I_{it}]$ amounts to the difference between $\text{Var}[m_{t+1}|\mathcal{P}_t]$ and $\text{Var}[m_{t+1}|I_{it}]$, which ought to be small relative to $\sigma^2_{\varepsilon t}$.

ditional portfolio weight.

3. $\hat{m}_{it}$, and therefore a fund's equity weight, ought to forecast the equity premium at least as well as publicly available variable. Moreover, one would anticipate that it should be positively correlated with macroeconomic variables that predict the conditional market's Sharpe Ratio.

3.1. Data

We obtain quarterly holdings information for all mutual funds, from 1979Q3 until 2006Q4, in the Thompson Financial CDA/Spectrum s12 database accessed through the Wharton Research Data Services (WRDS). The data is then linked to CRSP through WRDS' MFLinks service and the CRSP survivorship bias-free Mutual Fund Database (MFDB). For each quarter and each fund we obtain, whenever available, the portfolio weight corresponding to the total domestic equity holdings of the fund, the value-weighted return on those holdings in the three months immediately following the report date, the S&P objective, style and specialty fund codes (from CRSP MFDB), and the CDA/Spectrum s12 investment objective fund code.[15] We also obtain the return to fund investors, net of distributions, for each calendar quarter and document the dollar value of total assets managed by the fund. We augment this with quarterly data constructed from the monthly series of CRSP value-weighted returns and the risk-free rate (from WRDS), and quarterly data for the aggregate dividend yield and earnings-to-price ratio on the S&P500 index (Global Financial Data). Finally, we compute three different predictors of market volatilities: the first predictor is a naive monthly volatility calculated using the past month's daily CRSP value-weighted return data, the second corresponds to a fit of monthly CRSP value-weighted return data over the period 1954-2006 to a GARCH(1,3) model, and the third consists of the S&P100 volatility index (vxo from

[15] Because funds report their holdings at different times, the holding returns are not contemporaneous across all funds. When a fund reports holdings more than once in a quarter, we consider only the earliest report for that quarter. Many funds only report twice a year, the minimum SEC requirement, resulting in substantial 'seasonality' in the number of funds that report each quarter.

WRDS).[16] In merging this data with our quarterly observations, we choose the volatility predictor for the last month of each quarter.[17]

We initially start with 5278 funds. We filter out funds that at any point reported an equity portfolio weight of more than 200% (76 funds), funds that report holdings in fewer than eight quarters (983 more funds), and funds with an average equity portfolio weight of less than 50% (774 additional funds). We generally wish to investigate funds that invest in a broad enough range of domestic equity so that information about the US equity premium ought to particularly matter to them. Table 2 tabulates how the remaining 3445 funds are then categorized as 'broad domestic equity funds' using their CDA/Spectrum s12 investment objective codes, ICDI (MFDB) objective codes, and S&P objective codes.[18] Funds not highlighted in the table are considered 'broad domestic equity funds'. We exclude the other funds from the sample and are left with 2766 funds. Even for these remaining funds, some fields are missing for some (or all) quarters.

For each fund, we calculate the time-series average weight of domestic equity in the fund's portfolio, the average total net assets under management, the number of observations, the contemporaneous correlation of returns on the fund's domestic equity portfolio with the CRSP value-weighted index returns, the contemporaneous correlation between a fund's domestic equity portfolio weight and the various predictors of market return variance. We also calculate the correlation between the domestic equity portfolio weights of every pair

[16]We found the GARCH(1,3) model to be the most parsimonious best fit nested within a GARCH(4,4) framework. Of the three, the GARCH measure is the only one that is incorporates information unavailable contemporaneously because the coefficient estimates use the full time series. This turns out to be inconsequential for our tests.

[17]For the GARCH measure of volatility, while we could have used an average of the forecast for all three months of the quarter based on the last quarter's information, this doesn't significantly impact our test results. Moreover, weights are typically reported towards the end of the quarter and would therefore reflect a volatility prediction for that month (given that turnover ratios for the average mutual fund tend to be larger than what might be suggested from reported quarterly weight changes).

[18]Some funds change objective codes throughout the sample period. We assign a fund its modal investment code, and when there is more than one mode, we assign the 'largest' one (numerically or alphabetically). In classifying a fund, we rely firstly on its CDA/Spectrum s12 objective code and consider it not to be a broad domestic equity fund if the investment code is 1 ('International'), 5 ('Municipal Bonds'), 6 ('Bond and Preferred'), or 8 ('Metals'). Only 2289 of the 3445 funds surviving the initial filter have a CDA/Spectrum s12 objective code. Surprisingly, 170 funds have an investment code of 1, 5, 6, or 8, meaning that, despite their objective, they mostly hold U.S. domestic equity (150 of these are classified as 'International'). None of the unclassified funds have an entry for their MFDB policy code or Wiesenberger objective.

of funds in our sample that have at least eight overlapping weight data (2,677,052 pairs). Finally, we compute the CAPM β and α for the fund's domestic equity returns, the t-statistic for the α, and the Sharpe Ratio of the non-CAPM returns (i.e., the α divided by the standard deviation of the CAPM regression residual, or the 'information ratio'). Table 3 provides a summary of these statistics across funds.

The summary statistics indicate that the funds in our sample maintain a high average portfolio weight in equities, and that it is not unusual for this weight to fluctuate by 10% or more each quarter. Moreover, the equity portfolio held by the typical fund is highly correlated with the market portfolio (this is also confirmed by CAPM β of the equity portfolio held by the typical fund). Thus, even those managers who do not confess to have special timing ability could benefit from timing based on public information. A surprising fact is that the average fund slightly increases its weight in equities when market volatility is predicted to be high. This would be inconsistent with Eq. (3) and the basic objective of maximizing a fund's Sharpe Ratio even if the equity premium is proportional to the market variance. Another striking statistic is the low typical correlation between the equity weights of any two funds. This suggests that much of the asset allocation taking place is largely due to noise. Overall, the typical fund in our sample is not particularly good at picking stocks either, although according to Kosowski, Timmermann, Wermers, and White (2006) it is likely that the highest ranked funds do exhibit ability.

Of the 2766 funds we examine, we classify as 'timers' those funds that (i) explicitly specify flexibility or dynamic asset allocation in their MFDB policy code, S&P objective code, S&P style code, or S&P specialist code; and (ii) have a time-series standard deviation greater than 0.067 for portfolio weight allocated to domestic equity.[19] We list the names of the 54 funds classified as 'timers' in Table 4, and provide summary statistics in Table 5. The 'timers' tend, on average, to commit less money to equities and their equity portfolio is more highly correlated with the market. While they have a lower correlation with market

[19]We select 0.067 because this is the median standard deviation of weights for funds in our sample. The reason we add this minimum standard deviation requirement is because managers who are skilled at asset allocation ought to exhibit greater changes in portfolio weights than their counterparts.

volatility predictors, the typical pair-wise correlation among them is comparable to that in the unconditional sample.

3.2. Testing Proposition 2

We begin by examining the degree to which the dynamics of the weight allocated to equities is similar across funds, consistent with Proposition 2. In order to control for strategy and for time-varying volatility, we posit that the fund's weight in equity can be written as

$$w_{it} = A_i \frac{\hat{m}_{it}}{\hat{\sigma}^2_{it}} + B_i + \gamma_{i1} r_{it-1} + \gamma_{i2} r^2_{it-1} + \delta_i f_{it}, \tag{8}$$

where r_{it-1} is the excess return on the fund's equity, f_{it} is fund's growth in net assets due to net inflows, and B_i is a constant.[20] By including r_{it-1} and r^2_{it-1} we are controlling for persistent changes in weights due to strategies such as buy-and-hold or portfolio insurance. These terms, along with f_{it}, also control for the presence of 'no trade' regions that arise in the presence of transaction costs or other forms of illiquidity. Assuming that $\sigma^2_{\varepsilon t} + \mathrm{Var}[m_t|I_{it}]$ can be approximated with a predictor of market variance, say $\sigma^2_{\mathrm{p}\,t}$ (e.g., $\sigma^2_{\mathrm{vox}\,t}$), one can use the result from Proposition 2 to rewrite Eq. (8) as the following regression equation:[21]

$$\begin{aligned} \sigma^2_{\mathrm{p}\,t+1} w_{it+1} =& (1-\phi_m)\sigma^2_{\mathrm{p}\,t} w_t + \gamma_{i1}\sigma^2_{\mathrm{p}\,t+1} r_{it} + L.\gamma_{i1}\sigma^2_{\mathrm{p}\,t} r_{it-1} + \gamma_{i2}\sigma^2_{\mathrm{p}\,t+1} r^2_{it} + L.\gamma_{i2}\sigma^2_{\mathrm{p}\,t} r^2_{it-1} \\ &+ \delta_i \sigma^2_{\mathrm{p}\,t+1} f_{it+1} + L.\delta_i \sigma^2_{\mathrm{p}\,t} f_{it} + \epsilon_{it+1} + \tau_i \sigma^2_{\mathrm{p}\,t+1} + L.\tau_i \sigma^2_{\mathrm{p}\,t} + \mathrm{const}_i, \end{aligned} \tag{9}$$

If $\frac{\sigma^2_{\mathrm{p}\,t}}{\sigma^2_{\varepsilon t} + \mathrm{Var}[m_t|I_{it}]}$ is constant, then the residual ϵ_{it+1} is uncorrelated with all other variables on the right side of Eq. 9 (this follows from Proposition 2 and the Law of Iterated Expectations). Thus $1-\phi_m$ can be estimated through ordinary least squares (OLS). Likewise, it is straight forward to demonstrate that ϵ_{it+1} is correlated with r_{it+1}. Thus, had we used contemporaneous returns to control for strategy, we would not be able to estimate $1-\phi_m$

[20] If, as discussed in footnote 11, the predictable part of the equity premium includes a term such as $\xi\sigma^2_{\mathrm{p}\,t}$, then by including the constant B_i we ensure that $\hat{m}_{it}$ accounts for other predictive variables.

[21] In Eq. (9), each coefficient named $L.x$ should, in principle, be proportional to the coefficient x. When testing the regression, however, we allow these identified coefficients to be free because no estimation bias is introduced by doing so.

via OLS. In practice, $\frac{\sigma^2_{\mathrm{p}\,t}}{\sigma^2_{\varepsilon t}+\mathrm{Var}[m_t|I_{it}]}$ is unlikely to be constant. If its variation is small, then the consequent error-in-variables problem will not be serious. If the variation is large, then the bias in the estimate of $1-\phi$ is likely to be large. We therefore use various methods to estimate Eq. (9).[22]

To test the hypothesis that $1-\phi_m$ estimated via OLS is the same across funds we first perform the mixed-effects regression indicated in Eq. (9), assuming that residuals are heteroskedastic but uncorrelated across funds.[23] While this assumption is questionable, we are reassured by the fact that, as indicated in Table 3, the average cross-sectional correlation among the dependent variables (the equity weights) is low. Table 6 reports cross-sectional averages for the mixed panel regression under different assumptions for $\sigma^2_{\mathrm{p}\,t}$, for the entire sample of funds as well as for the sample of timers. It is evident that including some of the control variables is important while others are unimportant. For the most part, one can conclude that funds follow a strategy of rebalancing to constant weight with a negative response to flow, suggesting the presence of some lag in moving new funds (which are most likely to be cash) to the optimum allocation. Using the GARCH predictor for market volatility yields the highest autocorrelation, at 0.436. Timers have a significantly higher autocorrelation. For comparison, in our sample, the autocorrelations of cay, ep, and dp are $0.89, 0.97$, and 0.98, respectively, and of the three, cay is the best predictor of returns. The last line of Table 6 gives the result of a likelihood ratio test relative to a model that fixes the autocorrelation coefficient across funds. Across the board, one can strongly reject the hypothesis that funds share the same autocorrelation coefficient. Thus, our test of Proposition 2 is rejected. Moreover, the measured autocorrelation is significantly lower than what might be expected from a predictor of expected returns.[24]

To test the robustness of the conclusions from the mixed-effects regression reported in

[22]We attempted to use r^e_{t+1} as an instrument because, theoretically, it is unconditionally correlated with $\hat{m}_{it}$ and empirically unrelated to the other variables. In practice, however, the poor signal to noise in realized returns resulted in meaningless results.

[23]Fund flows are calculated as the difference between the growth in net assets under management less the growth in NAV per share. We drop observations for which the flow is less than -100% and more than 200% (269 out of 61251 instances where flow data was available).

[24]An alternative hypothesis is that funds make use of higher frequency information about expected returns. This is unlikely, given the lack of forecasting power in the weights (on which we report later).

Table 6, we also separately estimate the coefficients in Eq. (9) and calculate the statistic

$$\mathcal{C} = \frac{1}{N}\sum_{i=1}^{N}\frac{(\phi_m - \hat{\phi}_i)^2}{\mathrm{se}^2_{\phi_i}}, \tag{10}$$

where N is the number of funds, $1-\hat{\phi}_i$ is the estimate of the autocorrelation coefficient from the i^{th} regression and se_{ϕ_i} is its standard error. ϕ_m is taken to be the GLS estimator of the mean of the $\hat{\phi}_i$'s (i.e., $\phi_m = \frac{\sum_i \hat{\phi}_i/\mathrm{se}^2_{\phi_i}}{\sum_i 1/\mathrm{se}^2_{\phi_i}}$). Given the large number of funds and the fact that the weights are not highly correlated, and as long as the GLS estimator has a standard error much less than 1, $\mathcal{C}$ should be approximately normal with mean and standard deviation of 1 under the null. Table 7 reports the value of $1-\phi_m$, the test statistic $\mathcal{C}$, and its p-value under the null for the full sample, for the timers only, and using various proxies for the conditional volatility.[25] We report the estimation result imposing various filters for the minimum number of observations in a fund to mitigate the potential adverse impact of small sample distributions on the estimator $\hat{\phi}_i$. It appears that, by and large, the results are consistent with those in Table 6 and robust to small samples issues. The fact that the allocation persistence of short-lived funds in the unconditional sample is different from that of long-lived funds comes as a surprise given that Carhart (1997) and Kosowski, Timmermann, Wermers, and White (2006) find no difference in their relative performance.

3.3. Testing Proposition 3

Consider the following regression

$$r^e_{t+1} = \hat{\zeta}_i\sigma^2_{pt}w_{it} + \hat{\gamma}_{i1}\sigma^2_{pt}r_{it-1} + \hat{\gamma}_{i2}\sigma^2_{pt}r^2_{it-1} + \hat{\delta}_i\sigma^2_{pt}f_{it} + \hat{\tau}_i\sigma^2_{pt} + \hat{\epsilon}_{it+1} + \mathrm{const}_i. \tag{11}$$

Under our assumption, Eq. (8), $\sigma^2_{\mathrm{p}\,t}w_{it}$ corresponds to σ^2_{pt} times the sum of the control variables, plus $A_i\hat{m}_{it}$. Moreover, under the null the forecast error in m_t is orthogonal to the control variables in the equation, thus averaged across funds ζ in the regression equation

[25] If the ϕ_i's are highly correlated, $\mathcal{C}$ would resemble a χ^2 distribution. Even in this unlikely situation, the hypothesis that ϕ_i is the same across funds is solidly rejected at the 10% level across the board.

(11) should be positive and, according to Proposition 3 and Eq. (3), roughly equal to $\frac{1}{A_i}$. Assuming $\bar{\mu} > 0.01$ (quarterly), that the unconditional quarterly market volatility is lower than 0.10, and that the typical equity weight of a fund in our sample is less than 1.0, one can deduce a lower bound on ζ of $\frac{1}{A_i} > \frac{0.01}{1.0 \times 0.1^2} = 1.0$. Using sample means for $\bar{\mu}$, the market volatility, and average weights, one deduces a value closer to $\frac{1}{A_i} \approx 3$. A distribution of ζ_i's with mass significantly below 1 implies that weight changes in our sample of funds are suboptimal and incorporate an uninformed component.[26]

For each fund, we estimate ζ_i in Eq. (11) via an OLS regression. The assumption that $\zeta_i > 1$ implies that $\frac{\zeta_i}{se(\zeta)} > \frac{1}{se(\zeta)}$. By summing across funds, and assuming that the estimate $\hat{\zeta}_i$ is normally distributed with variance $se^2(\zeta)$, we arrive at $\frac{1}{N}\sum_i \left(\frac{\hat{\zeta}_i}{se(\zeta)} - \frac{1}{se(\zeta)}\right) > \mathcal{E}$, where $\mathcal{E}$ is the average of N correlated standard normal distributions. The correlation arises because the same dependent variable is used in each regression, thus the cross-sectional correlation between the errors of the estimates is the cross-sectional correlation between the $\hat{m}_{it}$'s. If N is large, $\mathcal{E}$ is normally distributed with variance equal to the average correlation among the $\hat{m}_{it}$'s. We approximate this average correlation to equal 0.08, consistent with the average correlation between the weights as documented in Tables 3 and 5. Table 8 reports average values of the ζ_i's, the probability that $\frac{1}{N}\sum_i \left(\frac{\zeta_i}{se(\zeta)} - \frac{1}{se(\zeta)}\right) > \mathcal{E}$ under the null, and the probability that $\frac{1}{N}\sum_i \left(\frac{\zeta_i}{se(\zeta)} - \frac{2}{se(\zeta)}\right) > \mathcal{E}$ under the null. The results suggest that the typical fund exhibits weight variation that is uninformed. In particular, the average ζ_i is well below its expected value of about 3, and even below the conservative lower bound of 1. If ζ is a fraction, say x, of what it should be, then x is also the fraction of the informed (i.e., optimal) variance over total variance of the fund's weight changes. I.e., $x = \frac{\mathrm{Var}[m_t|I_{it}]}{\mathrm{Var}[m_t|I_{it}]+\pi^2}$, where π^2 is the variance component in weight changes that is uninformative in the sense that, given I_{it}, it contains no information about future returns.

Table 8 implies that the population value of ζ is likely to be a fraction of 1. Given that the expected value of ζ based on optimal use of information is around 3, it appears that

[26] Alternatively, one can attribute a lower coefficient to an error-in-variables problem. The error-in-variable problem ought to equally affect the results in Tables 6 and 7. The results there suggest that this is not the source of the problem.

67% or more of the changes in asset allocation made by the typical fund are uninformed and suboptimal from our model's perspective.

3.3.1. Robustness

To confirm this negative result, we test, using a bootstrapping methodology, whether the cross-sectional distribution of ζ_i's in the regression equation (11) is different than what would arise under the null of $\hat{\zeta}_i = 0$ for all i. The methodology proceeds as follows:

1. Using the data, the regression equation (11) is estimated for each fund, and the t-statistics for $\hat{\zeta}_i$, denoted as t_i, is saved along with the corresponding regression residual. Because the residuals in our model are heteroskedastic, White (1980) standard errors are used when computing t-statistics.

2. Next, the regression equation (11) with $\hat{\zeta}_i$ set to zero is estimated:

$$r^e_{t+1} = \check{\gamma}_{i1}\sigma^2_{pt}r_{it-1} + \check{\gamma}_{i2}\sigma^2_{pt}r^2_{it-1} + \check{\delta}_i\sigma^2_{pt}f_{it} + \check{\tau}_i\sigma^2_{pt} + \check{\epsilon}_{it+1} + \text{const}_i,$$

   and the predicted returns, $\check{r}^e_{it+1} \equiv r^e_{t+1} - \check{\epsilon}_{it+1}$ are saved.

3. The set of dates $\{1979Q3, \ldots 2006Q4\}$ is randomly sampled, with replacement, to create 2000 sets of data, each of which has the same time-series length as the original sample. Denote by $\mathcal{T}(k,t)$ the random element from $\{1979Q3, \ldots 2006Q4\}$ corresponding to the t^{th} item in the k^{th} sample.

4. For each fund, we construct 2000 sets of bootstrapped sample returns under the null that $\hat{\zeta}_i = 0$ by combining randomly drawn residuals from the unrestricted model in step 1 with the predicted returns from step 2. Specifically, the return at date t of the k^{th} bootstrapped sample is:

$${r^e_{ikt}}^* = \check{r}^e_{it} + \hat{\epsilon}_{i\mathcal{T}(k,t)}.$$

This approach preserves the cross-sectional properties of the residuals in each of the 2000 bootstrapped panels.

5. For each fund, denoted by i, and bootstrapped sample, denoted by k, the following time-series regression is estimated:

$$r^{e}_{ikt+1}{}^{*} = \zeta^{*}_{ik}\sigma^{2}_{pt}w_{it} + \gamma^{*}_{ik1}\sigma^{2}_{pt}r_{it-1} + \gamma^{*}_{ik2}\sigma^{2}_{pt}r^{2}_{it-1} + \delta^{*}_{ik}\sigma^{2}_{pt}f_{it} + \tau^{*}_{ik}\sigma^{2}_{pt} + \epsilon^{*}_{ikt+1} + \text{const}^{*}_{ik}.$$

   The estimate for the t-statistic associated with each ζ^{*}_{ik} is saved. This exercise essentially samples the joint distribution of the t^{*}_{i}'s, the t-statistics associated with the ζ_i's, *under the null of no timing ability.* For the k^{th} bootstrapped panel, let $\Gamma^{k}(\ell)$ denote the cross-sectional ℓ^{th} percentile of among the t^{*}_{i}'s.

6. The one-sided p-values for the cross-sectional percentiles, $\Gamma(\ell)$, of t_i's from step 1 are computed according to

$$p(\ell) = \frac{1}{2000}\sum_{k=1}^{2000}\mathbf{1}\{\Gamma^{k}(\ell) > \Gamma(\ell)\},$$

   For instance, $p(50)$ corresponds to the likelihood, under the null, that we would observe by chance alone a sample median t_i as high or higher than the median t_i in step 1. In particular, if $p(50)$ is small, then this could be interpreted as evidence that the asset allocation decisions made by the median manager contain more information than would be expected under the null.

Table 9 reports various cross-section percentiles of t_i's when the regression is performed using our three different measures of market volatility and when various restrictions are imposed on funds' age in the panel. The bootstrapped p-values are reported below each estimated percentile. Fpr virtually all values of ℓ, $\Gamma(\ell)$ is not significantly greater than what is obtained under the null that $\hat{\zeta}_i = 0$. There is no evidence that the cross sectional distribution of ζ_i's is shifted to the right of what would expected under a null of $\zeta_i = 0$. Thus, consistent with the previous test, fund managers, including those with significant values of

t_i, do not appear to move portfolio weights between equity and non-equity in a manner that predicts future market returns.[27]

3.3.2. Interpreting the negative results in light of Jiang, Yao, and Yu (2007)

Jiang, Yao, and Yu (2007) report that lagged equity portfolio betas of open-end mutual funds predict market returns. Specifically, fund managers appear to be holding equity portfolios with higher betas prior to positive market outcomes, and tend to be in possession of equity portfolios with lower betas prior to negative market outcomes. This is viewed as supportive of timing ability on the part of active fund managers. Appendix B qualitatively confirms that, in our sample, equity portfolio betas also predict market returns. Our results differ somewhat from those of Jiang, Yao, and Yu (2007) (see their Table 3) in that we find no evidence of predictability at the 1- and 3-month horizon, whereas Jiang, Yao, and Yu (2007) do find such evidence at the 3-month horizon.

There are several ways to rationalize this with the negative results of the previous subsection. It might be the case that the vast majority of market timing efforts exerted by managers could be directed towards reallocating equity into or out of higher beta stocks rather than shifting weight from non-equities into or out of equities.[28] Alternatively, it might be that the Jiang, Yao, and Yu (2007) finding is not actually reflective of market timing ability, perhaps because of mis-measurement in the portfolio betas, because the shift into higher (lower) beta portfolios is accompanied by a shift into lower (higher) non-market systematic risk, or because changes in funds' equity portfolios might be taking place at a frequency that is too high to benefit from the predictability at 6- to 12-months' horizon.

To help shed light on whether the holdings-based predictability is indicative of market timing ability, we perform Treynor-Matzuy (TM) and Henriksson-Merton (HM) regressions on the cross section of funds' *equity portfolio* returns and compare the standardized timing

[27] We reached the same conclusions when we repeated the bootstrapping exercise using the Kosowski, Timmermann, Wermers, and White (2006) approach. Moreover, the bootstrapping procedure yields significantly positive results in a simulated sample of weights that do have weak predictive power for the equity premium. Thus the lack of evidence is unlikely to be because of a lack of power.

[28] If a significant minority of funds timed the market via asset allocation and the remainder did not, then one would still expect to find weak, though supportive, evidence for market timing in our test.

coefficients from these regressions with those from bootstrapped samples for which, by construction, there is no timing ability. Jiang, Yao, and Yu (2007) examine TM and HM return regressions for *fund* returns, although these suffer from the fact that the fund-level returns do not reflect the equity portfolio returns because the former result from trading at a frequency greater than quarterly and trading in assets other than equities. By contrast, we look at the results of TM and HM bootstrapped tests for the same portfolios whose market betas are shown to exhibit predictive power. Because the rebalancing period for these portfolios coincides with the observation frequency by construction, the criticism of Goetzmann, Ingersoll, and Ivković (2000) and Jagannathan and Korajczyk (1986) do not apply to our tests.

We performed two bootstrapping procedures to assess the significance of the TM and HM timing regressions. The first procedure proceeds similar to Bollen and Busse (2001) and attempts to obtain correct standard errors for the TM and HM timing coefficients. Using quarterly data, the regression

$$r^e_{it} = \text{const}_i + \sum_{j \in \{\text{m,smb,hml,umd}\}} \beta_j r^e_{jt} + \gamma_i f(r^e_{mt}) + \varepsilon_{it}, \tag{12}$$

is run for each fund, where r^e_{it} is the excess return on the equity portion of the fund's portfolio, r^e_{kt} is the return for Fama-French-Carhart factor k, and $f(r^e_{mt}) = (r^e_{mt})^2$ for the TM model and $f(r^e_{mt}) = \mathbf{1}\{r^e_{mt} > 0\} r^e_{mt}$ for the HM model. The fitted values, $\hat{r}^e_{it} \equiv \text{const}_i + \sum_{j \in \{\text{m,smb,hml,umd}\}} \beta_j r^e_{jt} + \gamma_i f(r^e_{mt})$ and the residuals are saved. We next create 2000 bootstrapped panels as follows. To create a single bootstrapped panel the set of dates is randomly resampled, with replacement, and the residuals for each fund reordered accordingly. Then, the resampled residuals are merged back with the $\hat{r}_{it}$'s, producing a time-series panel of pseudo-return data for the funds' equity portfolios. The equity portfolio pseudo-returns for a given fund is considered missing if no residual is available for the resampled date. The regression in (12) is re-run for each replication of each fund. The bootstrapped standard error of each estimated γ_i parameter is computed using

$$\text{Std. Err.}(\gamma_i) = \frac{1}{2000-1} \sum_{k=1}^{2000} \left(\gamma_{ik} - \overline{\gamma_{ik}}\right)^2 .$$

t-statistics are computed using the formula

$$t = \frac{\gamma_i}{\text{Std. Err.}(\gamma_i)},$$

and are compared to ± 1.96 to assess significance. For consistency with the Jiang, Yao, and Yu (2007) replication results, we require a fund have a minimum of 8 quarters of data to qualify for inclusion in the sample. Panel A of Table 10 shows the results for this procedure and is analogous to Table III in Bollen and Busse (2001). The fact that the number and magnitude of negative and positive timing coefficients is roughly the same suggests that there is no serious negative bias of the sort suggested in Jagannathan and Korajczyk (1986) and Goetzmann, Ingersoll, and Ivković (2000), and found in the analysis of fund-level returns by Jiang, Yao, and Yu (2007). The fact that highly significant coefficients are no more frequent than might be expected is evidence against timing ability, as reflected in equity portfolio returns.

A potential shortcoming of the test just reported is that the t-statistics might not be t-distributed, and thus inference of significance through a critical score of 1.96 might not be appropriate. Our second bootstrapping procedure, similar to the procedure used to test the timing regression in Section 3.3.1, is aimed at addressing this. We proceed similarly to the method outlined above except that $\check{r}^e_{it}$ is now defined as $\check{r}^e_{it} \equiv \text{const}_i + \sum_{j \in \{\text{m,smb,hml,umd}\}} \beta_j r^e_{jt}$, and the pseudo returns are generated by combining $\hat{r}_{it}$ with reordered values of $\hat{\varepsilon}_{i\mathcal{T}(k,t)}$, where $\mathcal{T}(k,t)$ is defined as in Section 3.3.1. The timing regression is then re-run for each replication of each fund, and right-tail p-values are calculated for various percentiles, as in Section 3.3.1.

The results, reported in Panels B and C of Table 10, confirm those from Panel A suggesting that there is no evidence of timing ability in funds' equity portfolios.

To recap, although the equity portfolios of actively managed funds, as reconstructed from quarterly holdings, exhibit portfolio betas that predict market returns at a horizon of 6 months or greater, we find no evidence that this translates into successful timing as measured in terms of quarterly portfolio returns. This could be because the portfolios are not held long enough to benefit from the predictability. Alternatively, this could be because of mis-measurement in the portfolio betas or because the shift into higher (lower) beta portfolios is accompanied by a shift into lower (higher) non-market systematic risk.

3.4. Forecasting returns using aggregate weight changes

Sections 3.2 and 3.3 examined the cross section of timing ability. If, as suggested by the empirical tests in these sections, funds' weight changes are not optimal, then by aggregating weights we ought to be able to diversify some of the suboptimal noise that is incorporated into the asset allocation strategy of individual funds to arrive at a more informed predictor of expected returns.[29] In particular, one would expect that such a predictor would contain at least as much information about the conditional Sharpe Ratio as publicly available time series. Specifically, we have in mind those public variables that are known, both empirically and theoretically, to have predictive power for the Sharpe Ratio.

The remaining portion of our empirical investigation tests these ideas to see whether one can diversify the uninformative component of the weight changes to arrive at an aggregate predictor of the equity premium that is at least as informative about the conditional Sharpe Ratio as Lettau and Ludvigson (2001)'s cay, the aggregate dividend yield (dp), and the aggregate earnings-price ratio (ep).

We focus on the predictability of $\frac{r^e_{t+1}}{\sigma^2_{\mathrm{p}\,t}}$ using date t weights. We could use $w_{it}\sigma^2_{\mathrm{p}\,t}$ to predict the market returns, r^e_{t+1}, but our measures of conditional market variance are much more volatile than the weights and, after aggregating across funds, $\sum_i w_{it}\sigma^2_{\mathrm{p}\,t}$ has an extremely high correlation with $\sigma^2_{\mathrm{p}\,t}$. In our model $E[\frac{r^e_{t+1}}{\sigma^2_{\mathrm{p}\,t}}|I_{it}] = \frac{\bar{\mu}+\hat{m}_{it}}{\sigma^2_{\mathrm{p}\,t}}$ which is proportional to the weight in equities, suggesting that the correlation of $\frac{r^e_{t+1}}{\sigma^2_{\mathrm{p}\,t}}$ with fund weights ought to be at least as high as what can be attained with public information. To get a sense of the

[29]Aggregating weights in this fashion should also help reduce the degree of mis-specifications potentially present in our regressions because of omitted variables.

predictability that is attainable using public information, we document in Table 11 the correlation between quarterly market returns normalized by measures of market variance (i.e., $\frac{r^e_{t+1}}{\sigma^2_{\mathrm{p}\ t}}$) and the variables cay, ep, and dp. Between the three, by far, cay is the best predictor.

We next aggregate weight changes, $w_{it+1} - w_{it}$, across various category of funds in our sample. We use weight changes rather than level weights because the entry of aggressively managed equity funds, heavily invested in equities, in the late 90's creates a spurious trend in the aggregate weighting that doesn't appear if one aggregates changes in weights. Beyond the category of 'timers', we also aggregate funds that are in the top performance quartile based on the information ratio calculated from CAPM α's and residual standard error. We view such funds as 'good stock pickers'. We likewise aggregate funds in the lowest performance quartile ('poor stock pickers'). We also aggregate the weights for funds whose equity portfolio returns exhibit the highest (top quartile) contemporaneous correlations with the market returns. We view these as 'indexers'. Finally, we similarly aggregate the weight changes for funds in the lowest market correlation quartile ('market neutral' funds). Table 12 reports correlations between the aggregated weights and the various macroeconomic predictors of the equity premium (cay, ep, and dp). The relationship appears, generally, to be negative. Table 13 supplements this with a report on the forecasting power (correlations) of aggregated values of w_{it} for future normalized market returns. Across volatility proxies, fund subgroups, and lags, fund weights appear to have little predictive power. This confirms the results from Section 3.3 that asset allocation decisions, by and large, do not reflect information about the equity premium.

Our tests of forecasting power do not control for the potential impact of aggregate flows. Intuition suggests that such an impact, if it exists, ought to lead to a positive relationship between aggregate weight changes and future market returns (Kraus and Stoll, 1972). Thus the absence of a positive forecasting relationship is unlikely to be because we neglected to control for fund flows. Moreover, in our sample, lagged aggregate fund flows have a negative and insignificant relation to market excess returns, while lagged market excess returns significantly and positively forecast aggregate fund flows.[30]

4. The utility loss from asset (mis)allocation

The previous section provides a conservative estimate that 67% or more of the variance in asset allocation decisions is uninformed. The evidence, moreover, is fairly consistent with the proposition that *all* of the asset allocation decision is uninformed. In particular, there is little evidence that asset allocation decisions reflect publicly available information. In this section we estimate the direct costs to investors of uninformed asset allocation (using Eq. (7)), as well as the indirect or opportunity costs associated with failing to make use of public information when making asset allocation decisions.

4.1. Direct costs of uninformed asset allocation

In estimating the costs from Eq. (7), assume that σ_{et}^2 and η_t^2 are sufficiently well behaved so that one can take the expectation inside the integral sign. This implies that $f = E[\sigma_{et}^2]E[\eta_t^2]$. The average return variance of equity portfolios held in our sample is 0.04 per year. If all the variation in weights was uninformed, then from Tables 3 and 5 one could estimate the $E[\eta_t^2]$, in annual terms, to be between 0.029 and 0.068. This corresponds to a certainty equivalent cost in Eq. (7) of between 6 and 14 basis points. Under the conservative assumption that noise comprises only 67% of the asset allocation decision, the cost is likewise reduced by 1/3. This would shrink even more (though not to zero) if the investor is assumed to allocate her wealth among many funds.

Thus, despite the fact that asset allocation is largely uninformed, the negative externality imposed on investors ought to be small.

[30] A similar relationship has been documented in Edelen and Warner (2001) at a daily horizon.

4.2. Opportunity costs of failing to use public information

We estimate the opportunity cost of not using public information via a parametric model and for various CRRA investors. Begin by assuming that an investor can divide her wealth between the market and a risk-free asset, and use the notation in Section 2.2. Suppose that $\hat{m}_{it} \equiv \hat{m}_t$ is based on a publicly observed variable (such as cay) and that the manager selects weights $w_{\text{mgr},t} = A\frac{\bar{\mu}+\hat{m}_t}{\text{Var}[r^e_{t+1}|\mathcal{P}_t]}$, where $\mathcal{P}_t$ is the public information filtration. The investor can allocate a proportion x of her wealth to the manager's fund, in which case her market exposure through time would become $w^I_t = xA\frac{\bar{\mu}+\hat{m}_t}{\text{Var}[r^e_{t+1}|\mathcal{P}_t]}$. Alternatively, the investor can simply continuously rebalance to the constant market exposure $w^U_t = xA\frac{\bar{\mu}}{\text{Var}[r^e_{t+1}]}$, corresponding to a policy that does not use the conditioning information. Henceforth, let $\hat{A} \equiv xA$. We ask, "how much market premium would the investor be willing to forego were he or she to invest in an actively managed fund that employs the strategy w^I_t rather than one employing w^U_t?" This corresponds to the opportunity cost of failing to make use of public information. We will assume that there are no cash borrowing constraints, so that the investor can invest any positive proportion of his or her wealth. The investor is assumed to have constant relative risk aversion utility given by

$$U(W) = \begin{cases} \frac{W^{1-\gamma}}{1-\gamma} & \text{if } \gamma \neq 1 \\ \ln W & \text{if } \gamma = 1, \end{cases}$$

and maximizes expected utility of wealth at terminal date T.

Following the setup in Section 2.2, there are two assets, one risk-free and one risky, with dynamics

$$\frac{dP_{0t}}{P_{0t}} = r_{ft}dt$$
$$\frac{dP_t}{P_t} = (r_{ft} + \mu_{et})dt + \sigma_{et}dB_t,$$

where μ_{et} is the estimate of the instantaneous market risk premium based on public information.

As in Kim and Omberg (1996), define $X_t \equiv \frac{\mu_{et}}{\sigma_{et}}$. Let X_t follow an Ornstein-Uhlenbeck process

$$dX_t = -\lambda_X \left(X_t - \bar{X}\right) dt + \sigma_X dB_t^X,$$

where B_t and B_t^X have instantaneous correlation ρ, and where $\bar{X}$ denotes the unconditional mean of X_t. Define a normalized risky asset return process by

$$dR_t = \frac{1}{\sigma_{et}} \left(\frac{dP_t}{P_t} - r_{ft} dt \right) = X_t dt + dB_t.$$

Thus, the wealth of the investor follows the process

$$dW_t = r_{ft} W_t dt + w_t W_t \sigma_{et} dR_t,$$

where w_t is the weight in the risky asset.

Denote by $\tau = T - t$ the time remaining until the terminal date. To compare the expected utility from a strategy that uses public information ($w_t^I = \hat{A} \frac{X_t}{\sigma_{et}}$) and one that ignores public information ($w_t^U = \hat{A} \frac{\bar{X}}{\sigma_{et}}$), the constant $\hat{A}$ will be chosen to maximize the utility from the strategy that *ignores* public information.

The conditional expected utility from following a given strategy

$$J(W, X, \tau) \equiv E_t \left[\frac{W_T^{1-\gamma}}{1-\gamma} \right]$$

satisfies the differential equation

$$-J_\tau - J_X \lambda_X \left(X_t - \bar{X}\right) + \frac{1}{2} J_{XX} \sigma_X^2 + J_W W \left(r + w\sigma X\right) + \frac{1}{2} J_{WW} W^2 w^2 \sigma^2 + J_{WX} W w \rho \sigma \sigma_X = 0,$$

along with the boundary condition

$$J(W,X,0)=U(W).$$

Conjecture an indirect utility function of the form

$$J(W,X,\tau)=\exp\left\{a(\tau)+b(\tau)X+\frac{1}{2}c(\tau)X^2\right\}U\left(We^{r_f\tau}\right),$$

with $a(0)=b(0)=c(0)=0$. This leads to the set of ODEs for a,b, and c.

In the informed case where $w_t=w_t^I=\hat{A}\frac{X_t}{\sigma_{et}}$, the ODEs become:

$$\begin{aligned}\sigma_X^2(b(\tau)^2+c(\tau))+2\lambda_X\bar{X}b(\tau)-2a'(\tau)&=0\\ \left(\sigma_X^2c(\tau)-\lambda_X+\hat{A}(1-\gamma)\rho\sigma_X\right)b(\tau)+\lambda_X\bar{X}c(\tau)-b'(\tau)&=0\\ (2-\hat{A}\gamma)(1-\gamma)\hat{A}-2(\lambda_X-\hat{A}(1-\gamma)\rho\sigma_X)c(\tau)+\sigma_X^2c(\tau)^2-c'(\tau)&=0,\end{aligned}$$

and in the uninformed case where $w_t=w_t^U=\hat{A}\frac{\bar{X}}{\sigma_{et}}$, they are

$$\begin{aligned}\sigma_X^2(b(\tau)^2+c(\tau))-\hat{A}^2\bar{X}^2\gamma(1-\gamma)+2\bar{X}b(\tau)(\lambda_X+\hat{A}(1-\gamma)\rho\sigma_X)-2a'(\tau)&=0\\ b(\tau)(\sigma_X^2c(\tau)-\lambda_X)+\hat{A}\bar{X}(1-\gamma)+\bar{X}c(\tau)(\lambda_X+\hat{A}(1-\gamma)\rho\sigma_X)-b'(\tau)&=0\\ \sigma_X^2c(\tau)^2-2\lambda_Xc(\tau)-c'(\tau)&=0.\end{aligned}$$

The last equation implies that $c(\tau)=0$, as would be expected in the case where the investment strategy does not depend on X_t.

Having solved for these values, for a given value of $\hat{A}$, one can compute the annual fee that an investor is willing to pay to use public information instead of ignoring it. This fee is the value of β that solves

$$E\left[\exp\left\{a_I(\tau)+b_I(\tau)X+\frac{1}{2}c_I(\tau)X^2\right\}\right]U\left(We^{-\beta\tau}e^{r_f\tau}\right)=E\left[\exp\left\{a_U(\tau)+b_U(\tau)X\right\}\right]U\left(We^{r_f\tau}\right),\tag{13}$$

where the expectation is calculated with respect to the unconditional distribution of X, and the functions a, b, and c have subscripts I and U in the informed and uninformed cases, respectively.[31] As mentioned above, $\hat{A}$ maximizes the right hand side of Eq. 13, and generally depends on γ and the horizon. Finally, the market premium that the investor would be willing to forego to invest in the actively managed fund corresponds to β/w_t^U.

We assume $\bar{\mu} = 0.08$, and treat $\sigma_{et} = 0.16$ as a constant so that the unconditional Sharpe Ratio is $\bar{X} = 0.5$. In the discrete-time model, $X_t = \frac{\bar{\mu}+\hat{m}_t}{\sqrt{\text{Var}_t(r_{t+1}^e)}}$, and $\text{Var}(X_t) = \frac{\text{Var}(\hat{m}_t)}{\text{Var}(\hat{m}_t)+\sigma_e^2}$ is simply the R^2 in a regression of returns on the predictive (lagged) variable $\hat{m}_t$. Setting this R^2 to 0.17^2, the squared forecasting correlation of cay with the market, identifies $\text{Var}(X_t) = 0.17^2$. Given that $\text{Var}(X_t) = \frac{\sigma_X^2}{2\lambda_X}$, and assuming that the mean reversion parameter $\lambda_X \approx 0.15$, consistent with the sample autocorrelation coefficient of cay at 0.85, allows us to pin down $\sigma_X = 0.093$. We set the instantaneous correlation $\rho = 0$, to capture the fact that shocks to m_t and r_{t+1}^e in the discrete-time model are uncorrelated.

The table below reports results for β/w_t' for various choices of γ and T.

	T			
γ	5	10	15	20
1	0.0046	0.0046	0.0046	0.0046
2	0.0046	0.0046	0.0045	0.0045
4	0.0046	0.0044	0.0043	0.0042
6	0.0046	0.0044	0.0042	0.0041
8	0.0045	0.0043	0.0041	0.0040

The calculation robustly suggests that the opportunity cost to investors, measured in terms of a reduction in the unconditional expected returns of the market portfolio, is in the order of 0.5%. The calculation understates this premium because it does not account for the fact that the $\hat{A}$ that optimizes the strategy w_t^U is generally different from the one that optimizes the strategy w_t^I. When combined with the calculation from Section 4.1, one can

[31] To calculate the expectation, we integrate over X using the density $\frac{1}{\sqrt{2\pi(\sigma_X^2/2\lambda_X)}} \exp\{-\frac{(X-\bar{X})^2}{2(\sigma_X^2/2\lambda_X)}\}$.

assess the total cost of investing with a market timer as, roughly, in the order of 50-60 basis points.

5. Conclusions

We derive a model of asset allocation based on a dynamic noisy information model. The model predicts that the equity exposure of every portfolio manager, whether they are market timers or not, ought to have an autocorrelation coefficient similar to that of the time-varying equity premium. In particular, this autocorrelation ought to be the same across funds regardless of their information structure. The model also predicts that a regression of future market returns on fund weights, with appropriate controls, should result in a slope coefficient that is independent of the relative variance of the fund weights (i.e., the more the portfolio weight varies, the higher the forecasting power). Finally, fund asset allocation ought to predict returns at least as well as any variable constructed from public information.

Instead, we find that equity exposures in open-end US domestic equity mutual funds have autocorrelations that vary too much across funds and are lower than would be expected for predictors of business-cycle variables. Fund weights do not exhibit forecasting power that increases with their variance; even when aggregated to reduce noise, fund weights are poor predictors of the equity premium, and much more so than easily obtained macroeconomic variables.

Overall, we estimate that the utility loss to investors from incorporating noise into the asset allocation decision and the opportunity cost of failing to incorporate public information is between 50 and 60 basis points per year of wealth invested.

Appendices

A. Proofs

Proof of Proposition 1: Since m_t, s_{it-j}, and $\tilde{r}_{t-j}$ are jointly normal, the conditional expectation takes the form of a linear projection of m_t onto s_{it-j} and $\tilde{r}_{t-j}$.

The equations defining the coefficients in such a linear projection are of the form

$$E[s_{it-k}m_t] = \sum_{j=0}^{\infty} a_{itj}E[s_{t-k}s_{t-j}] + \sum_{j=0}^{\infty} b_{itj}E[s_{t-k}(\tilde{r}^e_{t-j} - \bar{\mu})], \quad k \geq 0$$
$$E[(\tilde{r}^e_{t-k} - \bar{\mu})m_t] = \sum_{j=0}^{\infty} a_{itj}E[(\tilde{r}^e_{t-k} - \bar{\mu})s_{t-j}] + \sum_{j=0}^{\infty} b_{itj}E[(\tilde{r}^e_{t-k} - \bar{\mu})(\tilde{r}^e_{t-j} - \bar{\mu})], \quad k \geq 0.$$

Calculating the expectations in these expressions allows one to rewrite the first equation as

$$(1-\phi_m)^k \text{Var}[m] = \sum_{j=0}^{\infty} \Big(a_{itj} \left(\text{Var}[m](1-\phi_m)^{|k-j|} + \text{Var}[n_i](1-\phi_{in})^{|k-j|} \right) + b_{itj}\text{Var}[m](1-\phi_m)^{|k-j-1|} \Big). \tag{A1}$$

and the second equation as

$$(1-\phi_m)^{k+1} \text{Var}[m] = b_{itk}\sigma^2_{\varepsilon t-k-1} + \sum_{j=0}^{\infty} \Big(a_{itj}\text{Var}[m](1-\phi_m)^{|k+1-j|} + b_{itj}\text{Var}[m](1-\phi_m)^{|k-j|} \Big) \tag{A2}$$

As long as $1-\phi_m, 1-\phi_{in} \in (0,1)$, Austin (1987) guarantees that a solution to this infinite set of equations exists. This establishes the first claim in the proposition.

Next, consider $\text{Var}[m_t|I_{it}]$. The coefficients $\{a_{itj}, b_{itj}\}_{j=0}^{\infty}$ are chosen such that $m_t -$

$E[m_t|I_{it}]$ is orthogonal to $E[m_t|I_{it}]$, so $\text{Var}[m_t|I_{it}] = \text{Var}[m_t - E[m_t|I_{it}]]$. Hence,

$$\text{Var}[m_t|I_{it}] = \text{Var}[m] - 2\sum_{j=0}^{\infty}\left(a_{itj}\text{Var}[m](1-\phi_m)^j + b_{itj}\text{Var}[m](1-\phi_m)^{j+1}\right) + \text{Var}\left[\sum_{j=0}^{\infty}\left(a_{itj}s_{it-j} + b_{itj}(\tilde{r}^e_{t-j} - \bar{\mu})\right)\right] \tag{A3}$$

To simplify this, obtain an expression for the middle summation term by multiplying (A1) by a_{itk} and summing over k and by multiplying (A2) by b_{itk} and summing over k. Obtain an expression for the third term by expanding and simplifying it to write it as

$$\sum_{j,k} a_{itj}a_{itk}\left(\text{Var}[m](1-\phi_m)^{|k-j|} + \text{Var}[n_i](1-\phi_{in})^{|k-j|}\right) + \sum_{j,k} a_{itj}b_{itk}\text{Var}[m](1-\phi_m)^{|k+1-j|} + \sum_{j,k} a_{itk}b_{itj}\text{Var}[m](1-\phi_m)^{|k-j-1|} + \sum_{j,k} b_{itj}b_{itk}\text{Var}[m](1-\phi_m)^{|k-j|} + \sum_k b^2_{itk}\sigma^2_{\varepsilon t-k-1}$$

Substituting the results from these manipulations back into (A3) gives

$$\text{Var}[m_t|I_{it}] = \text{Var}[m] - \sum_{j,k} a_{itj}a_{itk}\text{Var}[m](1-\phi_m)^{|k-j|} - \sum_{j,k} a_{itj}b_{itk}\text{Var}[m](1-\phi_m)^{|k+1-j|} - \sum_{j,k} a_{itk}b_{itj}\text{Var}[m](1-\phi_m)^{|k-j-1|} - \sum_{j,k} b_{itj}b_{itk}\text{Var}[m](1-\phi_m)^{|k-j|} - \sum_{j,k} a_{itj}a_{itk}\text{Var}[n_i](1-\phi_{in})^{|k-j|} - \sum_k b^2_{itk}\sigma^2_{\varepsilon t-k-1}. \tag{A4}$$

To simplify this expression to one that does not depend on $\text{Var}(m)$, first multiply (A1) by a_{itk} and sum over k, then multiply (A2) by b_{itk} and sum over k, and finally sum the results of these manipulations to obtain

$$
\begin{aligned}
&-\sum_{j,k} a_{itj}a_{itk}\mathrm{Var}[m](1-\phi_m)^{|k-j|} - \sum_{j,k} a_{itj}b_{itk}\mathrm{Var}[m](1-\phi_m)^{|k+1-j|} \\
&\quad - \sum_{j,k} a_{itk}b_{itj}\mathrm{Var}[m](1-\phi_m)^{|k-j-1|} - \sum_{j,k} b_{itj}b_{itk}\mathrm{Var}[m](1-\phi_m)^{|k-j|} \\
&= \sum_{j,k} a_{itj}a_{itk}\mathrm{Var}[n_i](1-\phi_{in})^{|k-j|} + \sum_{k} b_{itk}^2\sigma_{\varepsilon t-k-1}^2 - \sum_{k}\left(a_{itk}\mathrm{Var}[m](1-\phi_m)^k + b_{itk}\mathrm{Var}[m](1-\phi_m)^{k+1}\right)
\end{aligned}
\tag{A5}
$$

Take $k=0$ in (A1) to get an expression to substitute for $\sum_k \left(a_{itk}\mathrm{Var}[m](1-\phi_m)^k + b_{itk}\mathrm{Var}[m](1-\phi_m)^{k+1}\right)$ then plug the result back to (A4) to obtain

$$
\mathrm{Var}[m_t|I_{it}] = \sum_j a_{itj}\mathrm{Var}[n_i](1-\phi_{in})^j \tag{A6}
$$

Finally, we obtain the result in the proposition by stepping (A1) forward from k to $k+1$, subtracting (A2), and taking $k=0$ to produce

$$
b_{it0}\sigma_{\varepsilon t-1}^2 = \sum_{j=0}^{\infty} a_{itj}\mathrm{Var}[n_i](1-\phi_{in})^{|1-j|}
$$

After minor manipulation, substituting this expression back into (A6) gives the desired formula. □

Proof of Proposition 2: Begin by using the definition of autocorrelation to write

$$\frac{1}{\mathrm{Var}[\hat{m}_{it}]}\mathrm{Cov}\left(\sum_{j=0}^{\infty}\left(a_{itj}s_{it-j}+b_{itj}\left(\tilde{r}^{e}_{t-j}-\bar{\mu}\right)\right),\sum_{k=0}^{\infty}\left(a_{itk}s_{it-1-k}+b_{itk}\left(\tilde{r}^{e}_{t-1-k}-\bar{\mu}\right)\right)\right)$$

$$=\frac{1}{\mathrm{Var}[\hat{m}_{it}]}\left[\sum_{j,k}\left(a_{itj}a_{itk}\left(\mathrm{Var}[m](1-\phi_m)^{|k+1-j|}+\mathrm{Var}[n_i](1-\phi_{in})^{|k+1-j|}\right)+b_{itj}a_{itk}\mathrm{Var}[m](1-\phi_m)^{|k-j|}\right.\right.$$

$$\left.\left.+a_{itj}b_{itk}\mathrm{Var}[m](1-\phi_m)^{|k+2-j|}+b_{itj}b_{itk}\mathrm{Var}[m](1-\phi_m)^{|k+1-j|}\right)+\sum_{k}b_{itk}b_{it(k+1)}\sigma^2_{\varepsilon\, t-2-k}\right] \tag{A7}$$

To simplify this expression, take (A1), advance k to $k+1$, multiply by a_{itk}, and sum over k. Similarly, take (A2), advance k to $k+1$, multiply by b_{itk} and sum over k. Add the two results to conclude that the term in brackets in (A7) equals

$$\mathrm{Var}[m]\sum_{k}\left(a_{itk}(1-\phi_m)^{k+1}+b_{itk}(1-\phi_m)^{k+2}\right). \tag{A8}$$

To simplify (A8) further take $k=0$ in (A1), multiply the result by $1-\phi_m$, and rearrange the result to obtain

$$\mathrm{Var}[m]\sum_{k}\left(a_k(1-\phi_m)^{k+1}+b_k(1-\phi_m)^{k+2}\right)=(1-\phi_m)\left(\mathrm{Var}[m]-\mathrm{Var}[n_i]\sum_{j}a_{itj}(1-\phi_{in})^{j}\right)$$

$$=(1-\phi_m)\left(\mathrm{Var}[m]-\mathrm{Var}[m_t|I_{it}]\right), \tag{A9}$$

where the second equality follows from (A6).

Finally, substitute from (A9) back into (A7) and use the fact that $\mathrm{Var}[\hat{m}_{it}]=\mathrm{Var}[m]-\mathrm{Var}[m_t-E[m_t|I_{it}]]$ to obtain the stated result. □

Proof of Proposition 3: We have

$$\begin{aligned}\beta &= \frac{\operatorname{Cov}\left[m_t, \hat{m}_{it}\right]}{\operatorname{Var}[\hat{m}_{it}]} \\ &= \frac{\operatorname{Cov}\left[(m_t - \hat{m}_{it}) + \hat{m}_{it}, \hat{m}_{it}\right]}{\operatorname{Var}[\hat{m}_{it}]} \\ &= 1,\end{aligned}$$

where the last equality follows since $\hat{m}_{it}$ is by definition orthogonal to $m_t - \hat{m}_{it}$.

We can also express β as

$$\begin{aligned}\beta &= \frac{\operatorname{Cov}\left[\tilde{r}^e_{t+1}, \hat{m}_{it}\right]}{\operatorname{Var}\left[\hat{m}_{it}\right]} \\ &= \frac{\rho_{r\hat{m}_i}\sigma_{\hat{m}_i}\sigma_r}{\sigma^2_{\hat{m}_i}}\end{aligned}$$

Using $\beta = 1$ and rearranging, we obtain the result.

Proof of Proposition 4: For a log-investor, Eq. (7) follows directly from taking the expected value of the log of W_T and subtracting the same with η set to zero. This implies that a log-investor would strictly prefer the policy w^*_t. To establish that this is true for every investor that is at least as risk averse as a log-investor, define $Q \equiv W_T\big(\{\eta_t\}|\{r_{ft}, \mu_{et}, \sigma_{et}, r_{et}\}\big)$ as the final date's wealth conditional on the path generated by $\{r_{ft}, \mu_{et}, \sigma_{et}, r_{et}\}$. The log-investor prefers $P \equiv e^{-fT}W_T\big(0|\{r_{ft}, \mu_{et}, \sigma_{et}, r_{et}\}\big)$ to Q. Because the former is conditionally deterministic, every investor that is at least as risk averse as the log investor prefers P to Q. Because this is true state by state, taking expectations preserves the ordering, implying the desired result.

B. Reproducing the results from Jiang, Yao, and Yu (2007)

For each fund and reporting date in the sample, data on portfolio holdings are obtained from the TFN S12 dataset. Individual stocks from the holdings file are matched with CRSP using CUSIPs and, when CUSIPs are not present in the holdings file, ticker symbols.

To compute holdings-based fund betas, closing prices from CRSP are used to first calculate the portfolio weights of the individual holdings of each fund on each reporting date. Denote by ω_{ijt} the weight of stock j in fund i's portfolio at time t. Next, for each stock on each reporting date t, daily returns for the preceding one-year period are pulled from CRSP. As in Jiang, Yao, and Yu (2007), the beta of stock j at date t is computed using the Dimson (1979) method. The regression

$$r^e_{j\tau} = a_{jt} + \sum_{q=-5}^{5} b_{jqt} r^e_{m,\tau-q} + \epsilon_{j\tau}, \qquad \tau \in \{t-364, t\}$$

is run, and the stock beta is estimated as the sum of the coefficients

$$b_{jt} = \sum_{q=-5}^{5} b_{jqt}.$$

At least 60 daily return observations are required for this regression. Stocks not meeting this criteria are assigned betas of one. All non-stock securities are assigned betas of zero. Combining the portfolio weights and stock beta estimates, the beta of fund i at time t is given by[32]

$$\beta_{it} = \sum_{j} \omega_{ijt} b_{jt}.$$

With the fund beta estimates, the Treynor-Mazuy and Henriksson-Merton timing mea-

[32] Jiang, Yao, and Yu (2007) calculate characteristic-adjusted betas (see Daniel, Grinblatt, Titman, and Wermers, 1997). Because they mention that their results are not sensitive to this adjustment, we do not make it.

sures can be estimated directly from the regressions

$$\beta_{it} = \alpha_i + \gamma_i r^e_{m,t+1} + \eta_{i,t+1}$$
$$\beta_{it} = \alpha_i + \gamma_i \mathbf{1}_{\{r^e_{m,t+1}>0\}} + \eta_{i,t+1}.$$

To test the null hypothesis that funds have no timing ability, first the TM and HM regressions are estimated for each fund and the regression coefficients and t-statistics saved. Following Jiang, Yao, and Yu (2007), only funds with at least 8 valid report dates are included in the analysis. Furthermore, the t-statistics are computed using the Newey-West procedure with a two-quarter lag window to correct for serial correlation in the residuals brought about by overlapping market returns. In the results below, four different horizons (one-, three-, six-, and 12-month) for the market excess return $r^e_{m,t+1}$ are reported.

The cross-section of t-statistics, t_i, is analyzed with a bootstrap procedure. The procedure proceeds by randomly sampling with replacement the set of market excess returns to produce 2000 time series, each with the length of the original time series. The TM and HM regressions above are re-run on the bootstrapped excess market return series to produce 2000 distinct cross-sectional panels of regression slope coefficients and associated t-statistics, t_i^k.

Consider the ℓ^{th} percentile $\Gamma(\ell)$ of the cross-sectional distribution of "actual" γ_i t-statistics. To test whether the ℓ^{th} percentile is significantly greater than expected under the null, we compare it to the percentiles $\Gamma^k(\ell)$ of the bootstrapped t-statistics. The p-value for a one-sided test of $\Gamma(\ell)$ is computed as

$$p(\ell) = \frac{1}{2000} \sum_{k=1}^{2000} \mathbf{1}\{\Gamma^k(\ell) > \Gamma(\ell)\}.$$

In short, a cross-sectional percentile is considered significantly larger than expected under the null if only a small number of bootstrap samples produce cross-sectional percentiles that are larger.

Table 14 reports the results of this test and confirms the findings in Jiang, Yao, and Yu (2007) that the equity portfolio betas forecast future market excess returns.

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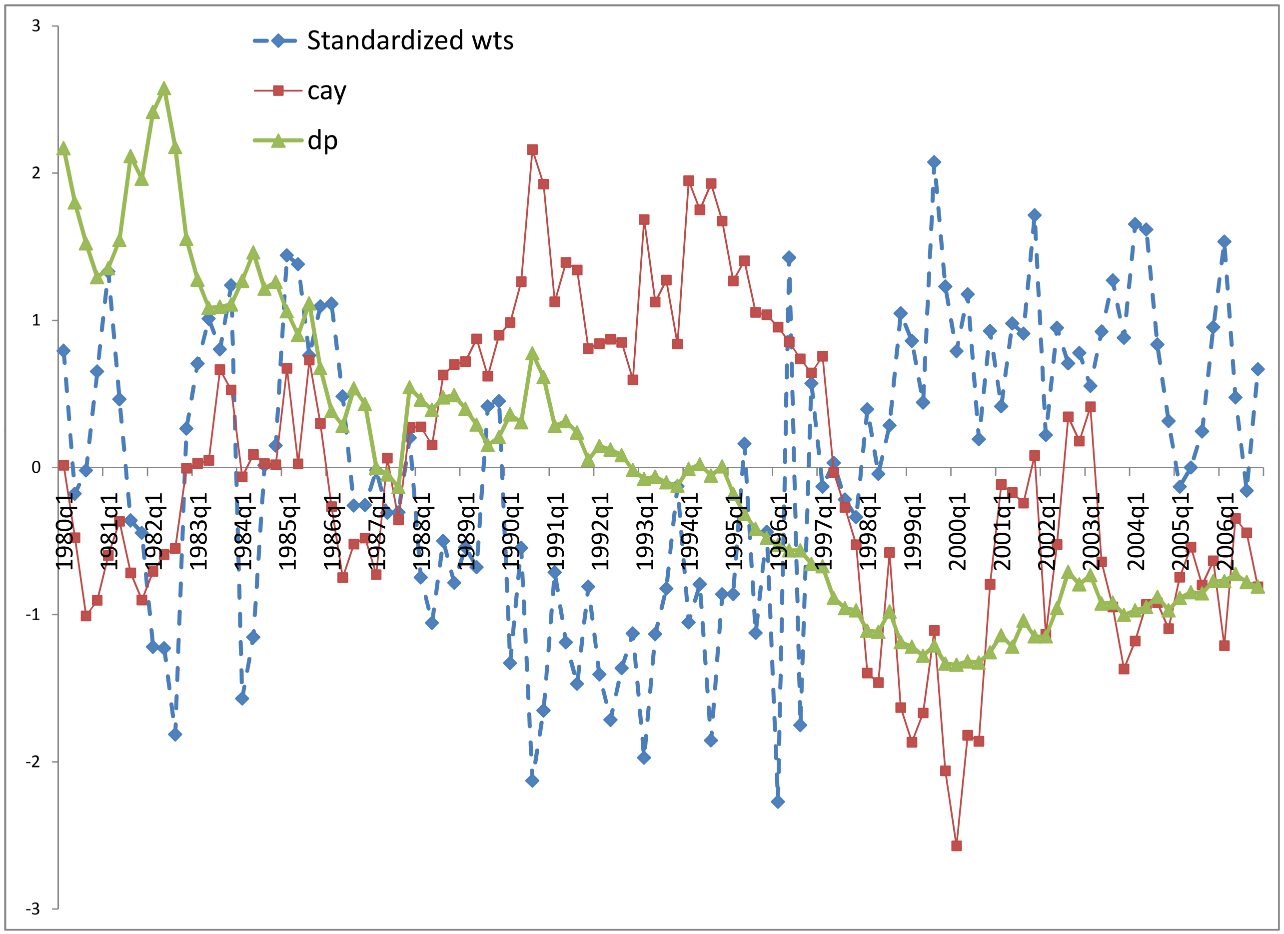

Table 1: A plot of standardized values for the consumption-wealth ratio variable (cay) constructed in Lettau and Ludvigson (2001), the aggregate dividend ratio (dp), and aggregated domestic equity exposure (relative to their sample mean) for funds identified as market-timers

modal ioc	CDA/Spectrum s12 objective	Number of funds
1	International	131
5	Municiple Bonds	1
6	Bond & Preferred	1
8	Metals	17
2	Aggressive Growth	209
3	Growth	1218
4	Growth & Income	390
7	Balanced	147
9 or NA	Unclassified or Unlisted	990
	Total dropped (shaded)	150

1964 (Aggressive Growth, Growth, Growth & Income, Balanced)

ICDI objective code	ICDI objective	Number of funds
GB	Global Bond	1
GE	Global Equity	8
IE	International Equity	4
MF	Monery Market Muni	2
SF	Sector Fund	116
UT	Utilities	3
AG	Aggressive Growth	189
BL	Balanced	8
GI	Growth and Income	98
IN	Income Fund	7
LG	Long-term Growth	244
TR	Total Return Fund	5
NA	Unclassified or unlisted	305
	Total dropped (shaded)	134

551 (AG through TR)

S&P objective code	S&P objective	Number of funds
NA	NA	9
EGG	Global Equity	5
EGX	Global Equity	6
EIG	International Equity	0
FIN	Financial Sector	1
HLT	Health Sector	9
NTR	Natural Resources	4
RLE	Real Estate	10
SEC	Sector Equity	3
TEC	Technology	4
UTI	Utilities	3
AGG	Aggressive growth	18
BAL	Balanced	5
FLX	Asset Allocation	7
GMC	Midcap equity	31
GRI	Growth and Income	38
GRO	Growth	82
ING	Growth and Income	7
SCG	Small-cap Equity	63
	Total dropped (shaded)	54

251 (AGG through SCG)

Table 2: This table depicts the objectives criteria we used for selecting funds for our sample. Funds were filtered sequentially depending on the availability of objectives from CDA/Spectrum s12, then ICDI, and then S&P. Funds with shaded objectives were dropped.

variable	mean	max	min	p5	p25	p50	p75	p95
$\bar{w}$	.88	1.1	.5	.59	.85	.92	.95	.99
σ_w	.085	.46	.0015	.017	.04	.067	.12	.21
Avg. tnam	597	28000	10	17	54	156	470	2313
# quarters	33	105	8	9	17	27	42	82
ρ_{mkt}	.86	1.0	-.22	.63	.81	.89	.94	.98
$\rho_{\sigma^2 \text{ naive}}$	.075	.89	-.96	-.45	-.084	.11	.26	.49
$\rho_{\sigma^2 \text{ GARCH}}$	.11	.9	-.91	-.46	-.091	.12	.32	.59
$\rho_{\sigma^2 \text{ vxo}}$	.069	1	-.97	-.52	-.11	.11	.28	.54
$\rho_{\text{bet wts}}$	.081	1	-1	-.46	-.14	.073	.31	.64
β	1.2	3.3	-.44	.81	1.0	1.1	1.4	1.8
α	-.0014	.12	-.084	-.025	-.0082	-.0012	.0056	.021
t_α	-.15	5.4	-7.4	-2.4	-1.1	-.17	.74	2.1
SR_α	-.088	2.8	-4.9	-1.1	-.4	-.063	.27	.85

Table 3: Summary statistics for the 2766 funds in our sample. $\bar{w}$ and σ_w correspond, respectively, to a fund's time-series average and standard deviation of weight allocated to domestic equity. Avg. tnam refers to a fund's time series average of total net assets under management. ρ_{mkt} denotes the contemporaneous correlation between the return on a fund's domestic equity portfolio and the CRSP value weighted index returns. Each of $\rho_{\sigma^2 \text{ naive}}$, $\rho_{\sigma^2 \text{ GARCH}}$, and $\rho_{\sigma^2 \text{ vxo}}$ is a contemporaneous correlation between the fund's domestic equity weight and a predictor of market variance (naive, GARCH(1,3), and the vox, respectively). $\rho_{\text{bet wts}}$ is the contemporaneous correlation between the domestic equity weights of two distinct funds. α and β are the CAPM regression statistics for each fund's domestic equity returns (t_α is the t-statistic for the fund's alpha, while SR_α is the fund's α divided by the residual standard deviation).

Fund wficn code	Fund name	Fund wficn code	Fund name
100036	ADV FUND	102342	NORTHEAST INVTS GROWTH
100150	AMANA MUTUAL FD-INCOME	102416	OPPENHEIMER DIRECTORS
100189	PROVIDENT FD. FOR INCOME	102573	PHOENIX TOTAL RETURN
100310	AVONDALE TOTAL RETURN FD	102734	PRUDENTIAL INST-ACT BAL
100344	BEACON GROWTH FUND	102793	QUEST FOR VALUE/ASSET AL
100358	ONE HUNDRED FUND	102979	SECURITY INVESTMENT FUND
100359	BERGER 101 FUND	103045	SHEARSON L.STRATEGIC INV
100473	CALVERT MANAGED GROWTH	103131	STAGECOACH LIFEPATH-2040
100546	LOOMIS-SAYLES MUTUAL	103166	STEADMAN ASSOCIATED
100743	DEAN WITTER STRATEGIST	103308	UNITED INCOME FUND
100753	DECATUR INCOME FUND	103399	UNIFIED MUTUAL SHARES
100879	ELFUN DIVERSIFIED	103415	UNITED CONTL. INCOME FD.
101075	FIDELITY ASSET MGR-GRWTH	103418	UNITED FIDUCIARY SHARES
101124	FIDUCIARY TOTAL RETURN	103491	VALUE LINE ASSET ALLOC
101141	FINANCIAL INDUST. INCOME	103495	VALUE LINE INCOME
101266	FOUNDERS EQUITY INCOME	103511	VANGUARD ASSET ALLOC FD
101353	GALAXY ASSET ALLOCATION	105569	IDEX II TACT ASSET ALLOC
101394	GENERAL SECURITIES	105629	SAND HILL PTF MGR FD
101483	HAMILTON INCOME FUND	105810	LEONETTI BALANCED FUND
101495	HANCOCK J SOVEREIGN BAL	105908	LEUTHOLD ASSET ALLOC FD
101876	LEXINGTON RESEARCH FUND	107655	VANTAGEPOINT ASSET ALLOC
101962	MAINSTAY TOTAL RETURN	109421	LORD ABBETT AMERICA'S VA
102076	MERRILL LYNCH CAP FUND	240418	LINDBERGH SIGNATURE FUND
102124	MUT.INV.FOUN.-MIF FUND	240436	MORGAN STANLEY ALLOCATOR
102131	MIMLIC ASSET ALLOCATION	240438	ALPINE DYNAMIC BALANCE F
102215	MUTUAL QUALIFIED INCOME	400220	AMERIPRIME IMS STRAT ALL
102234	NATIONAL DIVIDEND	410127	MERRILL LYNCH BASIC VAL

Table 4: Fund names and wficn codes for the 54 funds we consider as 'timers'.

variable	mean	max	min	p5	p25	p50	p75	p95
$\bar{w}$	.69	.97	.51	.52	.6	.66	.77	.91
σ_w	.13	.26	.071	.074	.1	.13	.16	.25
Avg. tnam	733	3991	11	13	64	242	886	3656
# quarters	54	99	12	14	32	51	76	96
ρ_{mkt}	.91	.98	.77	.82	.88	.93	.95	.97
$\rho_{\sigma^2 \text{ naive}}$	.036	.57	-.9	-.28	-.12	.077	.23	.37
$\rho_{\sigma^2 \text{ GARCH}}$	8.4e-04	.75	-.87	-.65	-.14	-.0077	.15	.53
$\rho_{\sigma^2 \text{ vxo}}$	.034	.65	-.96	-.38	-.11	.054	.24	.44
$\rho_{\text{bet wts}}$	.076	1	-.99	-.49	-.15	.072	.31	.64
β	1.1	1.6	.88	.89	1	1.1	1.2	1.3
α	-2.3e-04	.023	-.015	-.0087	-.0039	-4.9e-04	.0031	.0088
t_α	-.061	2.7	-3.1	-1.8	-.85	-.12	.49	2.3
SR_α	-.054	.79	-1.2	-.72	-.23	-.033	.17	.51

Table 5: Summary statistics for the 54 'timers' in our sample. $\bar{w}$ and σ_w correspond, respectively, to a fund's time-series average and standard deviation of weight allocated to domestic equity. Avg. tnam refers to a fund's time series average of total net assets under management. ρ_{mkt} denotes the contemporaneous correlation between the return on a fund's domestic equity portfolio and the CRSP value weighted index returns. Each of $\rho_{\sigma^2 \text{ naive}}$, $\rho_{\sigma^2 \text{ GARCH}}$, and $\rho_{\sigma^2 \text{ vxo}}$ is a contemporaneous correlation between the fund's domestic equity weight and a predictor of market variance (naive, GARCH(1,3), and the vox, respectively). $\rho_{\text{bet wts}}$ is the contemporaneous correlation between the domestic equity weights of two distinct funds. α and β are the CAPM regression statistics for each fund's domestic equity returns (t_α is the t-statistic for the fund's alpha, while SR_α is the fund's α divided by the residual standard deviation).

$\sigma^2_{\mathrm{p}\ t}$	$\sigma^2_{\mathrm{naive}}$		$\sigma^2_{\mathrm{GARCH}}$		σ^2_{vxo}	
	Unconditional	Timers	Unconditional	Timers	Unconditional	Timers
$1-\phi_i$	0.313	0.454	0.436	0.571	0.354	0.509
	0.005	0.029	0.005	0.035	0.005	0.034
γ_{i1}	-0.004	-0.021	-0.008	0.022	0.011	0.003
	0.006	0.052	0.005	0.038	0.005	0.045
γ_{i2}	0.13	0.36	0.03	-0.13	0.03	-0.14
	0.03	0.27	0.02	0.21	0.03	0.17
δ_i	-0.040	-0.111	-0.043	-0.062	-0.041	-0.017
	0.008	0.075	0.005	0.029	0.006	0.060
τ_i	0.886	0.683	0.877	0.671	0.884	0.680
	0.003	0.025	0.003	0.022	0.003	0.027
$L.\gamma_{i1}$	0.009	0.012	-0.001	0.014	-0.006	-0.044
	0.003	0.021	0.004	0.026	0.003	0.022
$L.\gamma_{i2}$	0.05	0.17	-0.06	-0.01	-0.03	-0.25
	0.02	0.16	0.02	0.11	0.01	0.14
$L.\delta_i$	-0.011	0.020	-0.004	0.049	-0.007	-0.010
	0.004	0.039	0.004	0.030	0.004	0.036
$L.\tau_i$	-0.269	-0.310	-0.366	-0.382	-0.300	-0.335
	0.004	0.021	0.004	0.024	0.005	0.026
const	-0.00012	-0.00007	-0.00019	-0.00001	-0.00027	-0.00021
	0.00002	0.00016	0.00002	0.00014	0.00004	0.00031
# Groups	2558	53	2558	53	2545	52
# Obs.	44466	1570	44466	1570	39967	1305
$p(\phi_i = \phi\ \forall i)$	0.0000		0.0000	0.0000	0.0000	0.0000

Table 6: This table reports the cross-sectional averages for the coefficients in various mixed-effects panel regressions based on Eq. (9). The columns correspond to estimations using the full sample or only the timers, and using various proxies for the conditional volatility. The last line reports the result of a likelihood ratio test relative to a model in which $1-\phi_m$ is constant across funds.

$\sigma^2_{\text{p}\,t}$	Unconditional min obs	$1-\phi_m$	$\mathcal{C}^2$	p-val	# funds	Timers min obs	$1-\phi_m$	$\mathcal{C}^2$	p-val	# funds
	8	0.50	20.66	0.000	1448	8	0.49	3.30	0.021	39
	16	0.35	4.13	0.002	979	16	0.49	3.22	0.027	32
σ^2_{naive}	24	0.39	4.52	0.000	604	24	0.51	3.33	0.020	28
	32	0.46	4.06	0.002	365	32	0.52	3.96	0.003	21
	40	0.49	4.12	0.002	242	40	0.52	4.56	0.000	18
	8	0.30	19.53	0.000	1448	8	0.70	3.59	0.010	39
	16	0.52	4.97	0.000	979	16	0.71	4.01	0.003	32
σ^2_{GARCH}	24	0.57	5.64	0.000	604	24	0.72	3.95	0.003	28
	32	0.62	5.51	0.000	365	32	0.72	4.23	0.001	21
	40	0.65	5.52	0.000	242	40	0.72	4.75	0.000	18
	8	0.29	18.42	0.000	1386	8	0.52	2.72	0.086	38
	16	0.42	3.77	0.006	909	16	0.53	2.43	0.153	31
σ^2_{vxo}	24	0.47	3.83	0.005	524	24	0.53	2.74	0.082	26
	32	0.51	3.97	0.003	310	32	0.53	2.84	0.066	18
	40	0.54	3.84	0.004	193	40	0.51	2.74	0.081	13

Table 7: This table reports estimates of $1-\phi_m$ by individually performing the regressions in Eq. (9) and calculating a GLS estimate of the resultant coefficients. The statistic $\mathcal{C}$ is assumed to be normally distributed with mean and variance 1. The associated p-value is reported.

		Unconditional				Timers			
$\sigma^2_{\mathrm{p}\,t}$	min obs	$\bar{\zeta}$	$p(\zeta > 1)$	$p(\zeta > 2)$	# funds	$\bar{\zeta}$	$p(\zeta > 1)$	$p(\zeta > 2)$	# funds
	8	-2.65	0.20	0.13	2026	0.35	0.09	0.03	48
	16	-4.19	0.13	0.06	1172	-0.09	0.04	0.01	38
${\sigma^2}_{\mathrm{naive}}$	24	-2.80	0.06	0.02	703	-3.22	0.00	0.00	28
	32	-2.42	0.03	0.01	446	-3.58	0.00	0.00	25
	40	-3.41	0.01	0.00	295	-3.50	0.00	0.00	19
	8	0.72	0.27	0.18	2026	1.85	0.14	0.05	48
	16	-3.70	0.20	0.11	1172	-0.22	0.03	0.01	38
${\sigma^2}_{\mathrm{GARCH}}$	24	-1.61	0.12	0.05	703	-2.48	0.00	0.00	28
	32	-1.33	0.08	0.02	446	-2.92	0.00	0.00	25
	40	-1.76	0.03	0.01	295	-2.65	0.00	0.00	19
	8	-0.57	0.19	0.07	1999	2.34	0.08	0.01	47
	16	-1.22	0.10	0.02	1123	0.58	0.02	0.00	37
${\sigma^2}_{\mathrm{vxo}}$	24	-1.01	0.04	0.00	653	-1.81	0.00	0.00	27
	32	-0.81	0.02	0.00	388	-1.82	0.00	0.00	23
	40	-1.28	0.00	0.00	242	-2.71	0.00	0.00	15

Table 8: This table reports the average regression coefficient of the cross-sectional regression in Eq. (11). The columns correspond to estimations using the full sample or only the timers, while the model refers to the use of various proxies for the conditional volatility. The p-value is an estimate of the probability that $\bar{\zeta} > 1$ or $\bar{\zeta} > 2$,respectively.

				t and p-values (σ_{naive})					
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-7.129	-3.579	-2.473	-1.372	-.2167	0.8799	2.1486	3.1654	7.2108
	0.4581	0.6796	0.7146	0.8777	0.8338	0.8074	0.6971	0.7081	0.5778
16	-5.528	-3.187	-2.312	-1.372	-.3146	0.6858	1.7336	2.4907	4.6792
	0.9711	0.9731	0.9466	0.9506	0.8812	0.7725	0.5190	0.3628	0.1712
24	-5.129	-2.873	-2.205	-1.318	-.3304	0.6538	1.4740	2.1574	4.0096
	0.9835	0.9451	0.9336	0.9281	0.8468	0.7021	0.6617	0.4731	0.1806
32	-4.224	-2.640	-2.205	-1.381	-.4173	0.4410	1.3368	1.7947	3.1109
	0.8897	0.8832	0.9281	0.9351	0.8743	0.8503	0.7166	0.7260	0.5559
40	-4.224	-2.574	-2.147	-1.381	-.4349	0.3026	1.1686	1.6744	3.1109
	0.9376	0.8598	0.9082	0.9271	0.8633	0.9037	0.8134	0.7575	0.4037
				t and p-values (σ_{GARCH})					
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.642	-3.195	-2.280	-1.219	-.1506	0.9182	2.1213	3.1076	6.3983
	0.3308	0.4212	0.5419	0.7455	0.7435	0.7315	0.6702	0.6916	0.7700
16	-5.067	-2.564	-2.033	-1.146	-.2072	0.7767	1.8129	2.6029	4.2747
	0.9681	0.8199	0.8683	0.8568	0.7759	0.6108	0.3074	0.1647	0.2011
24	-4.143	-2.397	-1.880	-1.001	-.1986	0.7418	1.5701	2.1756	3.2334
	0.9586	0.8348	0.8268	0.7390	0.7380	0.5579	0.4611	0.3433	0.3787
32	-3.027	-2.282	-1.784	-1.018	-.2301	0.6154	1.3747	1.7668	2.6208
	0.5564	0.8084	0.7819	0.7635	0.7430	0.6682	0.6143	0.6702	0.7355
40	-2.688	-2.160	-1.730	-.9920	-.2418	0.5292	1.2619	1.6795	2.7117
	0.4960	0.7370	0.7520	0.7435	0.7410	0.7171	0.6841	0.6747	0.4915
				t and p-values (σ_{vxo})					
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-5.899	-3.461	-2.497	-1.231	-.0984	1.0064	2.4041	3.6621	8.0372
	0.1118	0.5240	0.6891	0.6891	0.6467	0.6367	0.4346	0.3723	0.4651
16	-4.843	-2.888	-2.295	-1.221	-.1696	0.8603	1.9137	2.8649	5.7335
	0.8917	0.9007	0.9321	0.8513	0.6946	0.5055	0.3144	0.1257	0.0434
24	-3.820	-2.609	-2.051	-1.081	-.1997	0.7640	1.5849	2.2035	3.8087
	0.7834	0.8588	0.8488	0.7325	0.6851	0.5349	0.4990	0.4157	0.2889
32	-3.632	-2.317	-1.942	-1.165	-.2538	0.6174	1.3264	1.7404	2.8924
	0.7181	0.7236	0.8029	0.8079	0.7151	0.6557	0.6851	0.7435	0.6477
40	-3.530	-2.292	-1.903	-1.076	-.2279	0.6359	1.2644	1.6968	2.4974
	0.8318	0.7320	0.7919	0.7420	0.6846	0.6073	0.7046	0.7056	0.6931

Table 9: This table reports ℓ^{th} percentiles, $\Gamma(\ell)$ for ℓ = 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, and 99%, of the cross-sectional distribution of t-statistics of $\hat{\zeta}_i$ in the regressions $r^e_{t+1} = \hat{\zeta}_i \sigma^2_{pt} w_{it} + \hat{\gamma}_{i1} \sigma^2_{pt} r_{it-1} + \hat{\gamma}_{i2} \sigma^2_{pt} r^2_{it-1} + \hat{\delta}_i \sigma^2_{pt} f_{it} + \hat{\tau}_i \sigma^2_{pt} + \hat{\epsilon}_{it+1} + \text{const}_i$. Bootstrapped p-values for a test of the null hypothesis $\hat{\zeta}_i = 0$ for all i are below each estimate. Here, p denotes the probability, under the null, that we would observe an ℓ^{th} percentile as high or higher than the sample ℓ^{th} percentile. Each bootstrap sample is composed of 2000 replications.

Panel A	+	-	++	- -
Fraction				
TM	0.5242	0.4758	0.0061	0.0042
HM	0.5326	0.4674	0.0076	0.0061
Mean timing coefficient				
TM	1.2298	-1.0387	1.2766	-2.1912
HM	0.5819	-0.3903	0.4035	-0.6677

Panel B	t-stats with associated p-values for TM regression								
	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-4.662	-2.661	-1.995	-.8863	0.1243	1.1031	2.2092	2.9289	5.6924
	0.0324	0.1118	0.2420	0.2141	0.2759	0.4162	0.4711	0.6846	0.7360
16	-3.669	-2.355	-1.781	-.8286	0.1109	0.9875	1.9261	2.5471	3.7780
	0.6003	0.5519	0.5544	0.3797	0.2959	0.3169	0.2580	0.2410	0.3698
24	-3.239	-2.108	-1.576	-.6920	0.1905	0.9920	1.8440	2.3498	3.3549
	0.5978	0.5005	0.4536	0.2849	0.2086	0.2335	0.1861	0.1966	0.3288
32	-2.912	-1.952	-1.439	-.5842	0.2693	0.9982	1.7817	2.2331	3.0041
	0.4651	0.4167	0.3358	0.1946	0.1432	0.2101	0.1976	0.2330	0.4491
40	-2.921	-1.770	-1.375	-.5950	0.2321	0.9015	1.6524	2.0989	2.9876
	0.5434	0.2735	0.3273	0.2430	0.1886	0.3069	0.2954	0.3164	0.3987

Panel C	t-stats with associated p-values for HM regression								
8	-4.323	-2.525	-1.763	-.8962	0.1376	1.1014	2.1294	2.7054	5.1685
	0.0165	0.1043	0.1183	0.3154	0.2690	0.3733	0.5070	0.7994	0.8907
16	-3.279	-2.145	-1.644	-.8219	0.1413	1.0261	1.8897	2.4428	3.5407
	0.4566	0.4511	0.4905	0.4541	0.2520	0.2166	0.1971	0.2096	0.3548
24	-2.936	-1.895	-1.397	-.6770	0.2793	1.0513	1.8455	2.3107	3.0889
	0.5259	0.3762	0.3194	0.3278	0.1158	0.1352	0.1103	0.1362	0.3463
32	-2.824	-1.721	-1.297	-.5194	0.3305	1.0778	1.7706	2.2185	2.9021
	0.5993	0.2759	0.2720	0.1577	0.0913	0.1048	0.1317	0.1412	0.3378
40	-2.858	-1.657	-1.247	-.5110	0.3055	0.9981	1.5799	1.9427	2.8669
	0.6811	0.2839	0.2590	0.1826	0.1173	0.1732	0.2899	0.3558	0.3244

Table 10: The first two rows of Panel A report the fraction of estimated γ_i's (timing coefficients as in Bollen and Busse, 2001) that are positive or negative (+,-) and significantly positive or negative (++/- -). The second two rows report the conditional means of the γ_i's, given that they are positive, negative, significantly positive, or significantly negative. Panels B and C reports percentiles, $\Gamma(\ell)$, of the cross-sectional distribution of t for the timing coefficient in the TM and HM regressions. Bootstrapped one-sided p-values for a test of the null hypothesis of $\gamma = 0$ are included below each percentile. Each bootstrap consists of 2000 replications.

Normalization of returns	Lag	cay ρ	cay p	ep ρ	ep p	dp ρ	dp p
	1	0.21	0.03	0.03	0.77	0.03	0.79
	4	0.22	0.02	0.04	0.70	0.05	0.63
${\sigma^2}_{\text{naive}}$	8	0.20	0.05	-0.11	0.27	-0.03	0.77
	12	0.14	0.16	0.05	0.64	0.12	0.22
	16	0.03	0.76	-0.02	0.88	0.06	0.56
	20	-0.02	0.82	0.11	0.29	0.13	0.23
	1	0.20	0.04	0.06	0.51	0.04	0.72
	4	0.18	0.06	0.05	0.62	0.03	0.74
${\sigma^2}_{\text{GARCH}}$	8	0.19	0.05	-0.09	0.36	-0.05	0.64
	12	0.16	0.11	0.05	0.62	0.10	0.32
	16	0.05	0.60	-0.06	0.57	0.01	0.90
	20	-0.06	0.59	0.02	0.85	0.05	0.65
	1	0.19	0.08	0.24	0.03	0.11	0.33
	4	0.20	0.07	0.08	0.45	0.08	0.49
${\sigma^2}_{\text{vxo}}$	8	0.19	0.08	-0.04	0.71	0.01	0.90
	12	0.13	0.24	-0.04	0.71	0.04	0.71
	16	0.04	0.75	-0.12	0.28	-0.03	0.77
	20	-0.07	0.51	-0.08	0.49	-0.03	0.78

Table 11: This table reports the correlations between normalized quarterly market returns, cay, ep and dp over our sample period (1980-2006). The p-values indicate the two-tailed probability that the correlation is different from zero.

		agg. Weight changes		ep		dp	
Type	Indicator	ρ	p	ρ	p	ρ	p
Unconditional	cay	0.06	0.52	0.07	0.45	0.26	0.01
	ep	-0.22	0.02				
	dp	-0.15	0.13	0.91	0.00		
Timers	cay	0.01	0.90				
	ep	-0.11	0.25				
	dp	-0.08	0.41				
Good	cay	0.15	0.12				
Stock	ep	-0.14	0.16				
pickers	dp	-0.07	0.50				
Poor	cay	0.11	0.26				
Stock	ep	-0.15	0.13				
pickers	dp	-0.10	0.33				
Indexers	cay	0.02	0.84				
	ep	-0.13	0.19				
	dp	-0.11	0.25				
Market	cay	0.05	0.61				
Neutral	ep	-0.05	0.61				
	dp	-0.01	0.92				

Table 12: This table reports contemporaneous correlations between aggregated weights changes and the macroeconomic predictors of expected returns, cay, ep, and dp. The aggregation is done unconditionally as well as by various subgroups discussed in the text.

Type	Lag	σ^2_{naive} ρ	σ^2_{naive} p	σ^2_{GARCH} ρ	σ^2_{GARCH} p	σ^2_{vxo} ρ	σ^2_{vxo} p
Unconditional	1	0.09	0.34	0.02	0.82	0.09	0.42
	4	-0.04	0.70	0.00	1.00	0.08	0.49
	8	0.06	0.58	0.01	0.95	-0.16	0.15
	12	-0.10	0.34	-0.18	0.08	-0.14	0.20
	16	0.06	0.55	0.05	0.66	0.02	0.86
	20	-0.17	0.12	-0.16	0.14	-0.26	0.02
Timers	1	0.03	0.75	0.01	0.93	-0.08	0.49
	4	-0.05	0.59	-0.05	0.60	-0.06	0.61
	8	0.03	0.74	0.05	0.62	0.00	0.98
	12	-0.15	0.16	-0.24	0.02	-0.31	0.00
	16	0.09	0.40	0.05	0.66	0.07	0.54
	20	-0.18	0.09	-0.19	0.08	-0.27	0.01
Good Stock pickers	1	0.08	0.44	0.07	0.45	0.13	0.23
	4	0.08	0.40	0.11	0.27	0.22	0.05
	8	-0.01	0.93	-0.02	0.88	-0.07	0.51
	12	0.14	0.18	0.08	0.44	-0.03	0.81
	16	0.06	0.60	0.03	0.76	0.12	0.28
	20	0.01	0.95	-0.05	0.62	-0.15	0.19
Poor Stock pickers	1	0.14	0.14	0.11	0.26	0.13	0.23
	4	-0.07	0.48	-0.05	0.65	0.06	0.59
	8	0.13	0.19	0.05	0.60	-0.05	0.66
	12	0.14	0.17	0.06	0.57	0.15	0.17
	16	-0.12	0.24	-0.09	0.41	-0.08	0.48
	20	-0.19	0.08	-0.10	0.35	-0.25	0.02
Indexers	1	0.00	0.99	-0.05	0.61	-0.03	0.76
	4	-0.06	0.54	-0.02	0.88	0.04	0.74
	8	0.14	0.16	0.16	0.12	-0.02	0.88
	12	-0.09	0.36	-0.17	0.09	-0.11	0.32
	16	0.08	0.44	0.06	0.55	0.07	0.53
	20	-0.10	0.35	-0.11	0.30	-0.21	0.05
Market Neutral	1	0.19	0.04	0.14	0.16	0.20	0.07
	4	-0.06	0.54	-0.06	0.58	0.04	0.74
	8	-0.01	0.91	-0.13	0.19	-0.17	0.13
	12	0.03	0.77	-0.05	0.66	0.04	0.74
	16	0.04	0.71	-0.01	0.95	-0.03	0.82
	20	-0.03	0.77	-0.03	0.79	-0.09	0.43

Table 13: This table reports lagged correlations between aggregated weight changes and normalized market returns. The normalization is indicated by the top column heading. The aggregation is done unconditionally as well as by various subgroups discussed in the text.

	Percentiles									
	Mean	1%	5%	10%	25%	50%	75%	90%	95%	99%
1-month horizon										
γ	-.21	-4.3	-2.4	-1.7	-.76	-.11	0.44	1.12	1.71	3.21
p	0.83	0.91	0.92	0.90	0.83	0.72	0.63	0.56	0.51	0.54
t	-.19	-3.8	-2.3	-1.7	-.94	-.14	0.59	1.33	1.83	3.10
p	0.73	0.83	0.74	0.64	0.67	0.67	0.76	0.74	0.72	0.58
3-month horizon										
γ	0.08	-2.3	-1.1	-.70	-.24	0.12	0.45	0.79	1.09	2.00
p	0.24	0.87	0.73	0.62	0.33	0.12	0.10	0.20	0.25	0.27
t	0.27	-3.7	-2.1	-1.5	-.57	0.33	1.21	1.93	2.37	3.66
p	0.16	0.80	0.63	0.47	0.21	0.12	0.07	0.09	0.14	0.20
6-month horizon										
γ	0.10	-2.3	-1.1	-.69	-.20	0.15	0.45	0.81	1.07	2.04
p	0.13	1.00	0.99	0.96	0.51	0.02	0.00	0.01	0.01	0.00
t	0.40	-4.6	-2.5	-1.7	-.57	0.47	1.51	2.38	3.04	4.69
p	0.08	0.99	0.94	0.76	0.24	0.05	0.00	0.00	0.00	0.00
12-month horizon										
γ	0.06	-1.8	-.89	-.57	-.18	0.10	0.34	0.59	0.82	1.53
p	0.18	1.00	1.00	0.99	0.76	0.02	0.00	0.00	0.00	0.00
t	0.39	-5.3	-3.1	-2.0	-.72	0.46	1.58	2.77	3.71	5.68
p	0.08	1.00	1.00	0.96	0.44	0.06	0.00	0.00	0.00	0.00

Table 14: To generate this table we replicated the procedure used in Jiang, Yao, and Yu (2007) (see their Table 3). The table reports percentiles (and the mean) of the cross-sectional distribution of γ and t for the holdings-based Trenor-Mazuy regression along with the associated one-sided p-values for a test of the null hypothesis that each percentile equals zero. The bootstrap consists of 2000 replications.