Do fund managers make informed asset allocation decisions?

Bradyn Breon-Drish and Jacob S. Sagi

January, 2009*

Abstract

We derive a fully dynamic model of asset allocation based on private and public information. Roughly, the model predicts that the portfolio market weight of better informed managers will mean revert faster and be more variable. Conversely, portfolio weights that mean revert faster and are more variable should have better forecasting power for expected returns. We test the model on a large dataset of mutual fund domestic equity holdings and find mixed evidence for timing ability at the monthly horizon. At a longer horizon, our tests are more supportive of an alternative hypothesis: Shifts between equities and non-equities are not based on information about future market returns. In particular, such shifts do not seem to incorporate public conditioning information about the aggregate equity premium.

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

Journal of Economic Literature **Classification number:** G14.

*We thank Nick Bollen, David Chapman, Espen Eckbo, Wayne Ferson, Craig Lewis, Ron Masulis, Hans Stoll, and Avi Wohl for valuable discussions and comments. Research support from the Financial Markets Research Center at Vanderbilt University is gratefully acknowledged. Bradyn Breon-Drish is at the Haas School of Business, UC Berkeley, 545 Student Services Bldg., Berkeley CA 94720, Tel: 510-643-1423, email: `breon@haas.berkeley.edu`. Jacob S. Sagi is at the Owen Graduate School of Management, Vanderbilt University, 401 21st Avenue South, Nashville, TN 37203, Tel: 615.343.9387, email: `Jacob.Sagi@Owen.Vanderbilt.edu`.

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 fully dynamic model of the asset allocation decision, where each portfolio manager accounts for a historical time series of public *and* private information available to him or her. Such information, if used optimally, will be reflected in the dynamics of portfolio weights. The model leads to several testable and, to our knowledge, novel predictions. The two main predictions, after suitably controlling for the conditional volatility of market returns, are that (i) aggregate equity weights that mean revert faster reflect better information and should better forecast future market returns; and (ii) aggregate equity weights that are more volatile reflect better information and should better forecast future market 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 mixed evidence for the model predictions at short forecasting horizons (monthly), but very little or even contrary evidence at longer forecasting horizons. The timing ability we find at short horizons is consistent with a small number of recent studies, and we interpret it as indicative of better information about short-run future market returns. If one believes our model assumptions and empirical methodology are sound, one can attribute the general absence of timing ability at a longer horizons as evidence against the existence of much private information about long-run expected returns. Overall, even in the case of short-run predictability, the dynamic variation in aggregate equity weights does not convincingly reflect mostly information. This could be because of measurement error or because much of the weight variation exhibited by professional managers is noise rather than information-based.

Given that one could interpret our results, at least in part, as supportive of uninformed asset allocation, we theoretically investigate whether the presence of noise could hurt fund investors. The answer is that the direct negative impact would be fairly small.

Finally, our negative results for long-run asset allocation ability stand in contrast with the apparent predictability of the equity premium at long horizons using public information. While attempting to make use of such information might not benefit mutual fund investors in a general equilibrium setting, fund managers might themselves benefit from using public information to predict the equity premium (to the extent that they are compensated based on achieved Sharpe Ratios relative to a benchmark portfolio with constant weights). We find no evidence that fund managers incorporate public information that predicts the equity premium into their asset allocation decision, and calculate that by neglecting public information, fund managers (or their investors who cannot efficiently use public information themselves) annually forego about 40-50 basis points in performance on a risk adjusted basis.

1.1. Literature review and motivation

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.

Early tests of market timing ability were largely based on the regression methodologies of Treynor and Mazuy (1966) and Henriksson and Merton (1981), and looked for a convex relationship between fund-level returns and contemporaneous market returns. Results from these early experiments have largely shaped researchers' perception that professional portfolio managers do not exhibit timing ability.[1] This is despite the fact that such tests are susceptible to numerous criticisms (see Jagannathan and Korajczyk, 1986; Ferson and Schadt, 1996; Goetzmann, Ingersoll, and Ivković, 2000; Kothari and Warner, 2001). For instance, bias can result if a portfolio is rebalanced more frequently than the observation intervals used in the test. In addition, the standard errors may be highly non-normal and correlated across funds, leading one to potentially question the use of pooled statistics employed by all the early studies (this is similar to the criticism offered by Kosowski, Timmermann, Wermers, and White, 2006). Finally, even if managers possessed timing ability, one might

[1]Among the early tests are Treynor and Mazuy (1966); Henriksson and Merton (1981); Chang and Lewellen (1984); Henriksson (1984); Kon (1983).

not detect it using fund-level returns because the latter incorporate fees which, in a competitive market, could offset the value added by market timing (e.g., Berk and Green, 2004). Ferson and Schadt (1996) also point out that market timing tests should condition on public information relevant to predicting the market. When making the appropriate modifications, the negative results of earlier tests disappear and they even find weak support for timing ability, although their inference from pooled statistics does not account for cross-sectional correlations and highly non-normal standard errors. Edelen (1999) confirms these findings, pointing out that fund flows account for the negative results obtained in earlier studies.[2]

A number of subsequent studies have focused on holdings, often testing market timing in a multiple-asset allocation context. Those finding no evidence for timing include Daniel, Grinblatt, Titman, and Wermers (1997); Wermers (2000); Kacperczyk, Sialm, and Zheng (2005); Kosowski, Timmermann, Wermers, and White (2006); Kacperczyk and Seru (2007). Save for Kosowski, Timmermann, Wermers, and White (2006), these holding-based studies employ pooled statistics and, to our knowledge, do not fully adjust for the cross-sectional correlation in funds' weights when reporting significance. Such correlation may be particularly important when testing for timing because funds presumably attempt to time the same macroeconomic variables.[3] Standing in contrast with the other holdings-based mutual fund studies of timing 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.

All of the studies mentioned thus far examine monthly and/or quarterly holdings. Several recent studies that examine timing ability at a higher frequency have tended to yield positive evidence. Busse (1999) and Fleming, Kirby, and Ostdiek (2001) study volatility timing, while Chance and Hemler (2001) examine timing strategies based on the recommendations

[2]Eckbo and Smith (1998) apply the conditional performance test approach of Ferson and Schadt (1996) to assess the performance of insiders on the Oslo Stock Exchange. They find no evidence of timing ability among these insiders.

[3]While Kosowski, Timmermann, Wermers, and White (2006) use a bootstrap methodology, they only mention their results for timing in a footnote without reporting their test methodology. It is therefore not clear how they controlled for cross-sectional correlations in market weights when conducting their bootstrap tests for timing ability.

of 30 Registered Financial Advisers that, when pooled, yield significant evidence for market timing ability. The latter authors document that the use of daily data is key to their findings, confirming the negative results of Graham and Harvey (1996) who look at newsletter recommendations on a monthly basis. Bollen and Busse (2001) also find significant evidence for ability in their Treynor and Mazuy (1966) and Henriksson and Merton (1981) regression tests using daily data and bootstrapped standard errors, although they do not control for cross-sectional correlations in their tests.

Overall, the picture that emerges from reviewing the literature is that early studies, though flawed, found no or negative evidence for timing ability, while a survey of recent literature provides a substantially more mixed view of the topic. Of 14 mentioned papers written since the 1990's on the subject of timing, seven find supportive evidence. By and large, there does not appear to be a definitive answer to whether the average portfolio manager can create value through asset allocation. When one further considers that many of the papers can potentially be criticized on econometric grounds, the picture becomes hazier yet.

We attempt to shed additional light on this question by offering a new set of tests for timing ability, and design our empirical methodology keeping in mind the various econometric pitfall we've identified above. In addition, our tests address at least one additional issue ignored in this literature: If market returns are forecasted to be higher than average but the Sharpe Ratio is forecasted to be lower than average, it is not clear that a rational market timer would elect to increase her exposure to equities. As far as we know, all of the studies looking for market timing ability ignore the potential importance of conditional volatility on market timing, whereas this consideration plays a key role in our methodology.

1.2. Our contribution

We examine 'market timing' from several new perspectives. Consistent with the literature on the predictability of aggregate returns, we assume that fund managers receive noisy signals about future market returns.[4] This information comes in two forms: information about the slow-moving expected equity premium, some of which is known to be present in macroeconomic variables such as Lettau and Ludvigson (2001)'s cay; and information about the shock to market returns. The first type of information provides the manager with a refined sense of the premium of the market over bonds, while the second type of information can provide the manager with more dramatic insight such as whether bonds may fare better than stocks. We also consider two types of managers: 'type 1' who only have access to private and public information about the slow moving equity premium; and 'type 2', or highly informed managers, who in addition have access to information about the shock to market returns. Correspondingly, we characterize the Bayesian-optimal changes in weights of the two types of managers assuming they can invest in the market and/or in short-term bonds; the managers are assumed to optimize a mean-variance myopic objective function and can condition on their current as well as *all* past information, and *all* past market returns.

The model implies that, controlling for conditional volatility, the portfolio equity weights of *every* manager of the first type ought to have an autocorrelation coefficient that is equal to that of the time-varying expected equity premium. Roughly, the intuition for this result is that all 'type 1' managers are attempting to forecast the time-varying expected equity premium, which in our model has a persistence that is common knowledge. Their Bayesian-optimal forecasts should, therefore, exhibit this very same persistence. Because a manager's equity weight is proportional to the forecasted equity premium divided by conditional market volatility, the persistence of any manager's weights should (controlling for conditional volatility) reflect the persistence of the expected equity premium.

A second implication of the model is that the portfolio equity weights of a 'type 2' manager will have a lower autocorrelation than a 'type 1' manager, and the higher the signal-to-noise ratio of a 'type 2' manager, the lower her weight autocorrelation. The intuition for this

[4] 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); Whitelaw (1997); Andrade, Babenko, and Tserlukevich (2006).

result comes from considering that information about the shock to the market returns is, by definition, high frequency and iid. The more informed the manager, the more his portfolio weights will respond to the high-frequency portion of his information. Putting these two implications together leads to a testable prediction: the smaller the autocorrelation of a manager's equity exposure, the more information she ought to have about future market returns, and this should be reflected in the equity exposure of the fund.

The model also predicts that a manager whose portfolio equity weights change with a greater variance must possess better information. This too is intuitive: a manager who has more information will be able to take more extreme positions without increasing the portfolio risk. In summary, the forecasting power in a fund's portfolio equity weights should increase with its variance and decrease with its autocorrelation. Finally, to the extent that managers are incentivized to incorporate public information in their asset allocation decisions, their find's portfolio weights ought to predict returns at least as well as any variable constructed only from public information.

These predictions are made under the assumption that one can control for non-informational changes in portfolio weights (e.g., fund flows, or portfolio insurance strategies), and we attempt to do this in our empirical tests. With that caveat in mind, our model predictions ought to be robust because the economic rationale behind them is more general than the particular model we investigate. Nevertheless, the model used to derive these results is rich in allowing a great deal of heterogeneity in fund manager characteristics 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. Our battery of empirical tests of the model's predictions provides mixed results. We find evidence that at short horizons (monthly), the market forecasting power of funds' weights does decrease with the weights' persistence. At longer horizons the relationship disappears. Surprisingly, the model prediction does not hold, even at short horizons, when the universe of funds is restricted to market-timing funds. On the other hand, neither timers nor other funds appear to have weights whose market forecasting power increase with their variance. If anything, we find that the opposite is true at all horizons, lending some support to the alternative hypothesis that much of the variation in funds' weights is uninformative (i.e., noise).

We perform various other empirical tests that, by and large, confirm that there is little evidence of timing abilities at horizons longer than one month, while there is mixed evidence for timing ability at the one-month horizon. Either way, it appears that much of the variation in portfolio weights is noise. Our findings appear to contradict that of Jiang, Yao, and Yu (2007), who find evidence of timing ability at horizons of three months and longer, but not at the one-month horizon. We confirm their findings with respect to portfolio betas and run further tests to conclude that the forecasting power implied by portfolio betas in Jiang, Yao, and Yu (2007) does not translate into higher portfolio returns.

Another of our empirical conclusions is that fund weights do not seem to be correlated with public available macroeconomic variables that are known to contain information about the equity premium. 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 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 exposure and our study would not pick this up.[5] Moreover, it is also possible that the reported portfolio holdings suffer from window dressing and do not truly reflect funds' portfolio strategies.

Section 2 develops the model. Section 3 describes our data set, the empirical methodology, and reports our tests of the model. This section also reports the various robustness exercises and compares our findings with the 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.

[5]Koski and Pontiff (1999) and Almazan, Brown, Carlson, and Chapman (2004) document that few funds use derivatives.

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 market's excess return at date $t+1$ is assumed to be:

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

where $\bar{\mu}$ is the unconditional premium and m_t is its publicly unobserved time-varying component. The empirical literature notes that market return volatility is predictable. Consistent with this, we assume that ε_{t+1} has an observable date-t conditional variance of $\sigma^2_{\varepsilon t}$.[6]

There are two broad classes of portfolio managers. *Both* types receive a noisy signal about m_t of the form:

$$s_{it} = n_{it} + m_t, \tag{2}$$

where i indexes the identity of the manager and n_{it} is the noise component of the manager's signal. The signal s_{it}, incorporates public information (available to all fund managers) as well as private information about m_t. Whereas managers in both classes receive a private signal of the form s_{it}, only managers belonging to the second class receive an additional signal of the form,

$$q^H_{it} = e_{it} + \varepsilon_{t+1}, \tag{3}$$

[6]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, $\mathrm{Var}[r^e_{t+1}|\mathcal{P}_t]$ 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 $\mathrm{Var}[m_{t+1}|\mathcal{P}_t]$ is separately observable.

that provides information about the shock variable ε_{t+1}. We will refer to this second type of manager as being *highly informed* (the first class of managers will be referred to as non-highly informed).[7] For every highly informed manager the conditional variances of e_{it} and ε_{t+1} at date t have a ratio, denoted R_{qi}, that does not vary with time. That is to say, for the highly-informed manager, the signal-to-noise ratio of q_{it} is constant.

We further assume that

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

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

and that the conditional variances of u_t and v_{it} are constants, denoted as σ_u^2 and σ_v^2, respectively. Finally, each shock in the collection, $\{\frac{\varepsilon_s}{\sigma_{\varepsilon s-1}}, \frac{e_{is}}{\text{Var}[e_{is}]}, \frac{u_s}{\sigma_u}, \frac{v_{is}}{\sigma_{iv}}\}_{s\le t}$ is a standard normal iid random variable, independent of the process that generates $\sigma_{\varepsilon t}^2$. Under our assumptions, m_t and $\sigma_{\varepsilon t}^2$ are independent and universal to all managers while n_{it} (and e_{it} for highly informed managers) may or may not be correlated across managers.[8] Moreover, the variance of noise in managers' signals is heterogeneous in precision as well as persistence.

Given our assumptions, $\text{Var}[m_t] = \frac{\sigma_u^2}{1-(1-\phi_m)^2}$ and $\text{Var}[n_{it}] = \frac{\sigma_{iv}^2}{1-(1-\phi_{in})^2}$; 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 $s_{ix}, \sigma_{\varepsilon x}^2$ and r_{ix}^e (as well as q_{ix} for highly informed managers) for all dates $x \le t$. 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

$$w_{it} = A_i \frac{E[\tilde{r}_{t+1}^e | I_{it}]}{\text{Var}[\tilde{r}_{t+1}^e | I_{it}]}. \tag{4}$$

[7]There is no loss of generality in thinking of the non-highly informed managers as receiving a signal of the form q_{it}^H where $\text{Var}[e_{it}]$ is arbitrarily large.

[8]Without loss of generality and without changing our main results, one can replace $\bar{\mu}$ with $\xi\sigma_{\varepsilon t}^2$ 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

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 is no predictability in the market's Sharpe Ratio), then a non-highly informed 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. (4).[9] Finally, we note that, to the extent that the equity premium affects the expected returns of all stocks, Eq. (4) 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.

$$\hat{m}_{it} \equiv E[m_t|I_{it}] = \left(\sum_{j=0}^{\infty} a_{itj} s_{it-j} + \sum_{j=0}^{\infty} b_{itj} (r^e_{t-j} - \bar{\mu}) \right), \tag{5}$$

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

[9]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. (4) 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. (4) 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,

$$Var[m_t|I_{it}] = \sigma^2_{\varepsilon t-1}(1-\phi_{in})b_{i0t} + Var[n_i]a_{i0t}\phi_{in}(2-\phi_{in}). \tag{6}$$

Finally, for highly informed managers,

$$E[\varepsilon_{t+1}|I_{it}] = q_{it}\frac{1}{1+R_{qi}}, \tag{7}$$
$$Var[\varepsilon_{t+1}|I_{it}] = \frac{R_{qi}}{1+R_{qi}}\sigma^2_{\varepsilon t}. \tag{8}$$

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 set of results are central to the empirical tests we develop.

Proposition 2. *The unconditional autocorrelation of* $Var[r^e_{t+1}|I_{it}] \times w_{it} \propto E[r^e_{t+1}|I_{it}]$ *for a non-highly informed manager is* $1-\phi_m$*, coinciding with the unconditional autocorrelation of* m_t*.*

Thus, controlling for the denominator in (4) (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 *non-highly informed* managers despite the rich heterogeneity in their information structure. One can understand the intuition for the result as follows: Every non-highly informed 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.

Corollary to Proposition 2. *The unconditional autocorrelation of* $Var[r^e_{t+1}|I_{it}] \times w_{it} \propto E[r^e_{t+1}|I_{it}]$ *for a* <u>*highly*</u> *informed manager is strictly smaller than* $1 - \phi_m$,*and monotonically decreases with* $\frac{1}{1+R_{qi}}$.

Recall that R_{qi} is the ratio of the conditional variances of e_{it} to the conditional variance of ε_{t+1}. A high value of $\frac{1}{1+R_{qi}}$ is therefore a measure of the signal-to-noise ratio of the corresponding highly informed manager. The corollary states that a higher signal-to-noise ratio is associated with less persistence in $E[r^e_{t+1}|I_{it}]$. Controlling for the denominator in (4), this implies that more informed managers ought to exhibit *less* persistent equity portfolio weights. Putting together Propositions 2 and its corollary, one concludes that the R^2 in a regression of $\tilde{r}^e_{t+1}$ against $\mathrm{Var}[r^e_{t+1}|I_{it}] \times w_{it}$ should monotonically decrease with the persistence of the portfolio equity weights.

A second result that is key to our empirical tests relies on the observation that, controlling for the denominator in (4), the time-series variation in weights is related to the quality of the manager's signal. If the quality of the signal is poor (e.g., consider a non-highly informed manager with $\frac{\mathrm{Var}[m]}{\mathrm{Var}[m]+\mathrm{Var}[n_i]}$ small), then the manager will optimally react by being careful not to make dramatic changes in the weights, which are proportional to changes in $E[\tilde{r}^e_{t+1}|I_{it}]$. 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* $E[\tilde{r}^e_{t+1}|I_{it}]$ *yields a slope coefficient of* $\beta = 1$*, and the unconditional correlation of* $\tilde{r}^e_{t+1}$ *with* $E[\tilde{r}^e_{t+1}|I_{it}]$ *is*

$$\rho_{r\hat{m}_i} = \sqrt{\frac{Var\Big[E[\tilde{r}^e_{t+1}|I_{it}]\Big]}{\sigma_r^2}} = \begin{cases} \frac{\sigma_{\hat{m}_i}}{\sigma_r} & \text{if } i \text{ is non-highly informed} \\ \sqrt{\frac{\sigma^2_{\hat{m}_i}}{\sigma^2_r} + \frac{Var[q_{it}]}{(1+R_{qi})^2\sigma_r^2}} & \text{if } i \text{ is highly informed,} \end{cases} \tag{9}$$

where σ_r *is the unconditional standard deviation of equity returns and* $\sigma_{\hat{m}_i}$ *is the unconditional standard deviation of* $\hat{m}_{it}$*.*

An implication of Eq. 9 is that, controlling for the conditional volatility in Eq. (4), the R^2 in a regression of the market against lagged realizations of $\text{Var}[r^e_{t+1}|I_{it}] \times w_{it}$ (i.e., $\rho^2_{r\hat{m}_i}$) should be linearly related to the variance of $\text{Var}\Big[\text{Var}[r^e_{t+1}|I_{it}] \times w_{it}\Big] = \text{Var}\Big[E[\tilde{r}^e_{t+1}|I_{it}]\Big]$.

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. (4). 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 $\tilde{r}^e_t$, one can still test the model by controlling for past returns and fund flows.

Second, the Propositions pertain to the numerator of Eq. (4), whereas in practice portfolio weights incorporate the denominator as well:

$$w_{it} = \begin{cases} A_i \frac{\bar{\mu}+\hat{m}_{it}}{\sigma^2_{\varepsilon t}+\text{Var}[m_t|I_{it}]} & \text{if manager } i \text{ is non-highly informed} \\ \\ A_i \frac{\bar{\mu}+\hat{m}_{it}+\frac{q_{it}}{1+R_{qi}}}{\frac{R_{qi}}{1+R_{qi}}\sigma^2_{\varepsilon t}+\text{Var}[m_t|I_{it}]} & \text{if manager } i \text{ is highly informed.} \end{cases} \tag{10}$$

Thus, in testing whether asset allocation is informed, one must control for the conditional volatility in the denominator of Eq. (10). To do so, we begin by assuming that $\frac{R_{qi}}{1+R_{qi}}\sigma^2_{\varepsilon t} \gg \text{Var}[m_t|I_{it}]$, which appears reasonable given that the 'shock' component of market returns is harder to forecast than the equity premium and ought to vary substantially more.[10] Based on that assumption, one can approximate

$$\sigma^2_{\varepsilon t} w_{it} \approx \begin{cases} A_i\Big(\bar{\mu}+\hat{m}_{it}\Big) & \text{if manager } i \text{ is non-highly informed} \\ \\ A_i \frac{1+R_{qi}}{R_{qi}}\Big(\bar{\mu}+\hat{m}_{it}+\frac{q_{it}}{1+R_{qi}}\Big) & \text{if manager } i \text{ is highly informed.} \end{cases} \tag{11}$$

One can proxy for $\sigma^2_{\varepsilon t}$ using a volatility index such as the vix, acknowledging that a market forecast of volatility will differ, though likely not by much, from $\sigma^2_{\varepsilon t}$.[11] Eq. 11 provides a proxy for $\text{Var}[r^e_{t+1}|I_{it}] \times w_{it}$, and it is to this proxy that we will apply the insights from Section 2.1.

[10]For example, even if the equity premium has a m_t has a standard deviation of 4% per year, assuming that $R_{qi} = 1$, and that ε_t has an unconditional standard deviation of 16% per year, yields a ratio of $\frac{R_{qi}}{1+R_{qi}}\sigma^2_{\varepsilon t}$ to $\text{Var}[m_t|I_{it}]$ greater than 8.

[11]$\text{Var}[r^e_{t+1}|\mathcal{P}_t]$, where $\mathcal{P}_t$ represents a common knowledge (public) information set, should be approximately a constant proportion of $\text{Var}[r^e_{t+1}|I_{it}]$. The deviation from a constant proportionality should amount 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 $\sigma^2_{\varepsilon t}$.

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.[12] 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, our tests require a measure of conditional volatility, i.e., a proxy for $\sigma^2_{\varepsilon t}$. We compute four different such proxies 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 (vox from WRDS).[13] In merging this data with our quarterly observations, we choose the volatility predictor for the last month of each quarter.[14] The fourth proxy for $\sigma^2_{\varepsilon t}$ is a constant, corre-

[12]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.

[13]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.

[14]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).

sponding to a situation in which fund managers ignore changes in volatility when selecting the optimal equity position (the actual magnitude of this constant is immaterial as it can be absorbed into A_i in the definition of w_{it}).

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.[15] 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 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

[15]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.

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. (4) 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.[16] 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 volatility predictors, the typical pair-wise correlation among them is comparable to that in the unconditional sample.

[16]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.

3.2. *The autocorrelations of fund weights*

We begin by examining the degree to which the dynamics of the weight allocated to equities is similar across funds. Proposition 2 states that managers who are not highly informed should exhibit similar persistence in portfolio weights. As mentioned earlier, the observed portfolio weight may deviate from the expression in Eq. (4). In order to control for strategy and for time-varying volatility, we posit that the fund's *observed* weight in equity can be written as

$$w_{it}^{O} = w_{it} + B_i + \gamma_{i1} r_{it-1} + \gamma_{i2} r_{it-1}^2 + \delta_i f_{it}, \tag{12}$$

where w_{it} is the expression from Eq. (4), 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.[17] By including r_{it-1} and r_{it-1}^2 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.[18] Using the approximation in Eq. (11), we proxy for $\sigma_{\varepsilon t}$ using one of the four predictors of market variance described earlier, and denoted as $\sigma^2_{\mathrm{p}\,t}$ (e.g., $\sigma^2_{\mathrm{vox}\,t}$). One can now use the result from Proposition 2 to rewrite Eq. (12) as the following regression equation:[19]

$$\begin{aligned} \sigma^2_{\mathrm{p}\,t+1} w_{it+1}^{O} = &(1-\phi_i)\sigma^2_{\mathrm{p}\,t} w_t^{O} + \gamma_{i1}\sigma^2_{\mathrm{p}\,t+1} r_{it} + L.\gamma_{i1}\sigma^2_{\mathrm{p}\,t} r_{it-1} + \gamma_{i2}\sigma^2_{\mathrm{p}\,t+1} r_{it}^2 + L.\gamma_{i2}\sigma^2_{\mathrm{p}\,t} r_{it-1}^2 \\ &+ \delta_i \sigma^2_{\mathrm{p}\,t+1} f_{it+1} + L.\delta_i \sigma^2_{\mathrm{p}\,t} f_{it} + \epsilon_{it+1} + \tau_i \sigma^2_{\mathrm{p}\,t+1} + L.\tau_i \sigma^2_{\mathrm{p}\,t} + \mathrm{const}_i, \end{aligned} \tag{13}$$

where, according to Proposition (2) and its Corollary, $1-\phi_i = 1-\phi_m$ for all non-highly informed investors, and is strictly smaller than $1-\phi_m$ for highly informed investors. If

[17]If, as discussed in footnote 8, 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 w_{it} accounts for the remaining predictive variables.

[18]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).

[19]In Eq. (13), 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.

$\frac{\sigma^2_{\mathrm{p}\ t}}{\mathrm{Var}[\tilde{r}^e_{t+1}|I_{it}]}$ is constant, then the residual ϵ_{it+1} is uncorrelated with all other variables on the right side of Eq. 13 (this follows from Proposition 2 and the Law of Iterated Expectations).[20] In practice, $\frac{\sigma^2_{\mathrm{p}\ t}}{\mathrm{Var}[\tilde{r}^e_{t+1}|I_{it}]}$ is unlikely to be constant. If its variation is small, as assumed in Eq. (11), then the consequent error-in-variables problem will not be serious.[21]

We separately estimate the coefficients in Eq. (13) using a maximum-likelihood procedure that accounts for missing data, and calculate the statistic

$$\mathcal{C} = \frac{1}{N}\sum_{i=1}^{N}\frac{(\phi_m - \hat{\phi}_i)^2}{\mathrm{se}^2_{\phi_i}}, \tag{14}$$

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., $\phi_m = \frac{\sum_i \hat{\phi}_i/\mathrm{se}^2_{\phi_i}}{\sum_i 1/\mathrm{se}^2_{\phi_i}}$). Under a null that there are no highly-informed managers, given the large number of funds and the fact that the weights are not highly correlated, $\mathcal{C}$ should be approximately normal with mean 1 and variance equal to the average correlation among the summands. A far more conservative test would be to treat $\mathcal{C}$ as a $\chi^2(1)$ variable.[22] Table 6 reports the value of $1-\phi_m$, the test statistic $\mathcal{C}$, and its conservative (i.e., $\chi^2(1)$) p-value under the null for the full sample, for the timers only, and using various proxies for $\sigma^2_{\mathrm{p}\ t+1}$. 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 $\hat{\phi}_i$. Several patterns emerge from the table. The portfolio equity weights of Timers appear to be a bit more persistent than those of non-Timers; the null that all managers are both non-highly informed *and* using their information optimally (i.e., the result from Proposition 2) is solidly rejected; and the GLS estimate of $1-\phi_m$ is roughly in line with, though somewhat shy of, autocorrelation estimates of variables known

[20]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 $1-\phi_i$ via a procedure that assume the residual is uncorrelated with the regressors.

[21]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.

[22]It can be demonstrated that rejection of the conservative test at the 10% level or below implies rejection under the true distribution.

to predict the equity premium (e.g., cay has a quarterly autocorrelation of 0.85 over the sample period).

3.3. The market forecasting power inherent in weight dynamics

The results from the previous subsection suggest that, if fund managers use information optimally, then some are better informed than others. In particular, Proposition 2 and its corollary imply that managers with lower values of estimated $1-\phi_i$ should better forecast market returns. Likewise, an implication of Proposition 3 is that a larger estimated weight variance implies better forecasting power. By testing these predictions, we test whether the cross-sectional differences in portfolio weights (with respect to their persistence and variance) are related to ability or noise.

Consider the following forecasting regression

$$r^e_{t+1} = \hat{\zeta}_i \sigma^2_{pt} w^O_{it} + \hat{\gamma}_{i1}\sigma^2_{pt} r_{it-1} + \hat{\gamma}_{i2}\sigma^2_{pt} r^2_{it-1} + \hat{\delta}_i \sigma^2_{pt} f_{it} + \hat{\tau}_i \sigma^2_{pt} + \hat{\epsilon}_{it+1} + \text{const}_i. \tag{15}$$

Under our assumption, Eq. (12), $\sigma^2_{\mathrm{p}\,t} w^O_{it}$ corresponds to σ^2_{pt} times the sum of the control variables, plus $A_i E[\tilde{r}^e_{t+1}|I_{it}]$ from Proposition 3. Moreover, under the model assumptions, the forecast error in $E[\tilde{r}^e_{t+1}|I_{it}]$ is orthogonal to the control variables in the equation so that ζ_i and the residual variance can be estimated via OLS.

Table 7 reports the correlations between the adjusted R^2 (i.e., R^2_a) from the forecasting regression in Eq. (15) and the autocorrelation coefficient estimated for the corresponding fund in Eq. (13). Whereas the corollary to Proposition 2 predicts a negative relationship, this is only reliably found at the one-month forecasting horizon, and only for the unconditional sample of funds. This is robust across our various proxies for conditional market volatility. This is consistent with the model in the following way: All managers receive information about long-run market returns (i.e., about m_t), and if they use this information optimally, there should not be a significant *long-horizon* forecasting difference between those managers who only observe information about m_t and those who in addition receive short run information (i.e., about ε_{t+1}). In other words, cross-sectional differences in $1-\phi_i$ will not imply cross-sectional differences in *long* horizon forecasting power. However, because only some managers receive short-horizon information, cross-sectional differences in $1 - \phi_i$ correspond to a significant *short-horizon* forecasting difference between the managers.

Surprisingly, however, the timers often exhibit a significant positive relationship. One possible reason for this is that managers who profess to be timers tend to shift their portfolio weights in reaction to noise. This both reduces the forecasting power of weight and simultaneously reduces their persistence. If 'noise trading' is viewed as an alternative hypothesis to the Bayesian optimal use of information, then the data supports the alternative hypothesis.

To test the implication of Proposition 3, one needs to estimate the variance of $\text{Var}[r^e_{t+1}|I_{it}] \times w_{it}$. Because we do not observe this directly, we instead estimate the residual variance from the following equation, based on Eq. (12):

$$\sigma^2_{pt} w^O_{it} = \text{constant} + B_i \sigma^2_{pt} + \sigma^2_{pt} \gamma_{i1} r_{it-1} + \gamma_{i2} \sigma^2_{pt} r^2_{it-1} + \delta_i \sigma^2_{pt} f_{it} + \text{noise}. \tag{16}$$

Under our assumptions, the residual variance from Eq. (16) is the variance of $A_i E[\tilde{r}^e_{t+1}|I_{it}]$. If there is no relation between the long-run target of the fund's equity exposure, corresponding to A_i, and the quality of information available to the manager, then Proposition 3 implies an overall positive relationship between the residual variance in Eq. (16) and the adjusted R^2 from Eq. (15). Table 8 reports on this relationship at the one-month and three-month forecasting horizons, using each of our four proxies for market volatility. If anything, the data suggests that the relationship between the variance of the portfolio exposure and forecasting ability is negative. In almost every instance in which there is a significant relationship between weight variance and forecasting ability, the sign is negative, supporting the alternative hypothesis that the larger weight variance corresponds to noise. In order to check that this rejection of the model is not a result of an unanticipated cross-sectional relationship between the A_i's and the variance of $E[\tilde{r}^e_{t+1}|I_{it}]$, we re-did the test by normalizing the residual variance of Eq. (16) by the squared sample mean of $\sigma^2_{pt} w^O_{it}$, taking care to adjust the denominator for bias.[23] There was no substantial difference in the conclusions, indicating that no systematic

[23] The normalization will, theoretically, remove any dependence on the A_i's. The bias mentioned in the

bias is introduced in Table 8 by ignoring the variation in A_i's.

Overall, the tests provide mixed results. There is weak evidence for timing ability over short horizons (i.e., 1-mo), and evidence that some of this ability is compromised by noisy asset allocation. The remainder of this section seeks to examine the robustness of these conclusions.

3.3.1. Robustness

The results reported in Tables 8 and 7, bring us to question whether one can reject the hypothesis that there is no information in managers' equity weight exposures. To address this, we test, using a bootstrapping methodology, whether the cross-sectional distribution of ζ_i's in the regression equation (15) 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 (15) 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 (15) 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.

text arises from dividing through by something with an estimation error. We correct for this using the 'delta'-method.

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.

Tables 9 and 10 report various cross-section percentiles of t_i's when the regression is performed using our four different measures of market volatility, when various restrictions are imposed on funds' age in the panel, and for a 1-month versus 3-months forecast. The bootstrapped p-values are reported below each estimated percentile. For 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 $\zeta_i = 0$. Similar conclusions are reached when the bootstrapping exercise is repeated using the Kosowski, Timmermann, Wermers, and White (2006) approach. Thus the lack of evidence is unlikely to be because of a lack of power. In summary, consistent with our previous tests, either fund managers do not appear to move portfolio weights between equity and non-equity in a manner that predicts future market returns, or their timing ability is swamped by noisy allocation.

3.3.2. Comparison with 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 3-month horizon, whereas Jiang, Yao, and Yu (2007) do find such evidence. Both Jiang, Yao, and Yu (2007) and we fail to find evidence that portfolio betas forecast market returns at the one-month horizon. This stands in contrast with the results of this Section, in that evidence of timing ability, as reflected in portfolio weights, was weakly present at the one-month horizon, and otherwise absent (or even contrary).

There are several ways to rationalize the conflicting results. 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.[24] Alternatively, it might be that the Jiang, Yao, and Yu (2007) finding is not actually reflective of market timing ability, perhaps because of mismeasurement 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 findings of Jiang, Yao, and Yu (2007) are 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 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, which suffers from the various criticisms mentioned in the Introduction (fund-level returns do not reflect the equity portfolio returns because the former results from trading at a frequency greater than quarterly as well as from 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 forecast future market returns. 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

$$r^e_{it} = \text{const}_i + \sum_{j \in \{\text{m,smb,hml,umd}\}} \beta_j r^e_{jt} + \gamma_i f(r^e_{mt}) + \varepsilon_{it}, \tag{17}$$

[24]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 tests.

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 (17) 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 11 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 11, confirm those from Panel A suggesting that there is no evidence of timing ability in funds' equity portfolios. We also re-ran the procedure using a monthly, rather than quarterly, forecasting horizon.[25] At the monthly horizon, we did find evidence of timing in the HM regression test, though not clearly for the TM test. This serves to confirm the mixed results we obtained at the monthly horizon for our weight-based holdings tests.

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. We do find, however, additional support for timing ability at the 1-mo horizon, consistent with our original findings.

3.4. Forecasting returns using aggregate weight changes

Sections 3.2 and 3.3 examined the cross section of timing ability. The empirical tests in these sections suggest that funds' weight changes do not contain information about the market at a horizon of 3-mo or more. This could be because ability at such a forecasting

[25] The table is available upon request.

horizon is swamped by noise, or because there is no significant ability at such horizons. In the former case, by aggregating weights we ought to be able to diversify some of the noise that is incorporated into the asset allocation strategy of individual funds to arrive at a more informed predictor of expected returns.[26] 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 $E[\frac{r^e_{t+1}}{\sigma^2_{\mathrm{p}\ t}}|I_{it}]$ 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 predictability that is attainable using public information, we document in Table 12 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

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

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 13 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 14 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.[27]

Should fund managers' portfolio weights reflect public information? The answer would be 'yes' if the marginal investor in mutual funds could not use such information themselves to shift between funds. Thus, one can argue that mutual fund managers need not feel obligated to make use of publicly available information in their asset allocation decision. This view, however, neglects the fact that asset allocation may not be costless for the typical investor (just as diversification is not costless). Moreover, to the extent that managers are concerned about their Sharpe Ratios as a performance metric, they would have an incentive to take advantage of public information to achieve higher expected Sharpe Ratios (see, for instance, Andrade, Babenko, and Tserlukevich, 2006).

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

4. The utility loss from asset (mis)allocation

The empirical work suggests that much of the variance in asset allocation decisions is noise. 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, as well as the indirect or opportunity costs associated with failing to make use of public information when making asset allocation decisions. The latter is only relevant to investors who cannot make use of public information themselves.

4.1. Direct costs of uninformed 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

$$W_T = W_0 \exp\Big(\int_0^T \big(r_{ft} + w_t \mu_{et} - \frac{1}{2} \sigma_{et}^2 w_t^2 \big)\, dt \ + \ \int_0^T w_t \sigma_{et} dB_t \Big), \tag{18}$$

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.[28]

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*

$$f = \frac{1}{2T} E\Big[\int_0^T \eta_t^2 \sigma_{et}^2 dt\Big]. \tag{19}$$

It is worth emphasizing that the certainty equivalent cost in Eq. (19) 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 shortly.

In estimating the costs from Eq. (19), 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. (19) of between 6 and 14 basis points. 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.

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

[28] 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.

between the market and a risk-free asset, and use the notation in Section 4.1. Because we are interested in public information, we assume that the manager is non-highly informed. 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 $w_{\mathrm{mgr},t} = A\frac{\bar{\mu}+\hat{m}_t}{\mathrm{Var}[r^e_{t+1}|\mathcal{P}_t]}$, 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 $w^I_t = xA\frac{\bar{\mu}+\hat{m}_t}{\mathrm{Var}[r^e_{t+1}|\mathcal{P}_t]}$. Alternatively, the investor can simply continuously rebalance to the constant market exposure $w^U_t = xA\frac{\bar{\mu}}{\mathrm{Var}[r^e_{t+1}]}$, 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 4.1, 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:

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

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

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

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

$$E\left[\exp\left\{a_I(\tau) + b_I(\tau)X + \frac{1}{2}c_I(\tau)X^2\right\}\right] U\left(We^{-\beta\tau}e^{r_f\tau}\right) = E\left[\exp\left\{a_U(\tau) + b_U(\tau)X\right\}\right] U\left(We^{r_f\tau}\right), \tag{20}$$

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.[29] As mentioned above, $\hat{A}$ maximizes the right hand side of Eq. 20, 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, $X_t = \frac{\bar{\mu}+\hat{m}_t}{\sqrt{\mathrm{Var}_t(r_{t+1}^e)}}$, and $\mathrm{Var}(X_t) = \frac{\mathrm{Var}(\hat{m}_t)}{\mathrm{Var}(\hat{m}_t)+\sigma_e^2}$ 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 $\mathrm{Var}(X_t) = 0.17^2$. Given that $\mathrm{Var}(X_t) = \frac{\sigma_X^2}{2\lambda_X}$, 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 assess the total cost of investing with a market timer as, roughly, in the order of 50-60 basis points.

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

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 that decreases with the quality of information that the manager has. The model also predicts that a more volatile equity exposure should be linked to higher quality of information about the equity premium. Finally, to the extent that fund managers seek to maximize their Sharpe Ratios, fund asset allocation ought to predict returns at least as well as any variable constructed from public information.

Although we find weak evidence for the first prediction, overall it appears that changes in equity exposures of open-end US domestic equity mutual funds are largely noise. 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 could be as high as 50 to 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 $\tilde{r}_{t-j}$ (recall that q_{it} is orthogonal to m_t).

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

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

and the second equation as

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

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 $\mathrm{Var}[m_t|I_{it}]$. 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,

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

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

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

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

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

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

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

Take $k=0$ in (A1) to get an expression to substitute for $\sum_k \big(a_{itk}\mathrm{Var}[m](1-\phi_m)^k + b_{itk}\mathrm{Var}[m](1-\phi_m)^{k+1}\big)$ 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

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

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

The result for the highly-informed manager is standard and relies on the fact that the shocks are not serially correlated and the assumption that the conditional variances of e_{it} and ε_{t+1} at date t have a ratio, denoted R_{qi}, that is time-invariant. □

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 Corollary to Proposition 2: One can write $E[r^e_{t+1}|I_{it}]=\hat{m}_{it}+E[\varepsilon|I_{it}]=\hat{m}_{it}+\frac{q_{it}}{1+R_{qi}}$. Because q_{it} is serially iid, Proposition 2 can be used to write the autocorrelation of $E[r^e_{t+1}|I_{it}]$ as

$$\frac{1-\phi}{\sqrt{\left(1+\frac{\sigma^2_{\varepsilon t}}{(1+R_{qi})\mathrm{Var}(\hat{m})}\right)\left(1+\frac{\sigma^2_{\varepsilon t-1}}{(1+R_{qi})\mathrm{Var}(\hat{m})}\right)}}.$$

This establishes the corollary. $\square$.

Proof of Proposition 3: Let $\hat{r}^e_{it+1} \equiv E[\tilde{r}^e_{t+1}|I_{it}]$. We have

$$\begin{aligned}
\beta &= \frac{\mathrm{Cov}\left[\tilde{r}^e_{t+1}, \hat{r}^e_{it+1}\right]}{\mathrm{Var}[\hat{r}^e_{it+1}]} \\
&= \frac{\mathrm{Cov}\left[(\tilde{r}^e_{t+1} - \hat{r}^e_{it+1}) + \hat{r}^e_{it+1}, \hat{r}^e_{it+1}\right]}{\mathrm{Var}[\hat{r}^e_{it+1}]} \\
&= 1,
\end{aligned}$$

where the last equality follows since $\hat{r}^e_{it+1}$ is by definition orthogonal to $\tilde{r}^e_{t+1} - \hat{r}^e_{it+1}$.

We can also express β as

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

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

Proof of Proposition 4: For a log-investor, Eq. (19) 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[30]

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

With the fund beta estimates, the Treynor-Mazuy and Henriksson-Merton timing measures 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^k_i.

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-

[30]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.

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 15 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.

References

Almazan, A., K. C. Brown, M. Carlson, and D. A. Chapman, 2004, "Why Constrain your Mutual Fund Manager?," *Journal of Financial Economics*, 73(2), 289–321.

Andrade, S., I. Babenko, and Y. Tserlukevich, 2006, "Market timing with CAY," *Journal of Portfolio Management*, pp. 70–80.

Austin, K., 1987, "Finite and Infinite Systems," *The Mathematical Gazette*, 71(456), 107–109.

Berk, J. B., and R. C. Green, 2004, "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy*, 112(6), 1269–1295.

Bollen, N. P. B., and J. A. Busse, 2001, "On the Timing Ability of Mutual Fund Managers," *Journal of Finance*, 56(3), 1075–1094.

Breen, W., L. R. Glosten, and R. Jagannathan, 1989, "Economic Significance of Predictable Variations in Stock Index Returns," *Journal of Finance*, 44(5), 1177–89.

Busse, J. A., 1999, "Volatility Timing in Mutual Funds: Evidence from Daily Returns," *Review of Financial Studies*, 12(5), 1009–41.

Campbell, J. Y., and R. J. Shiller, 1988a, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, 1(3), 195–228.

Campbell, J. Y., and R. J. Shiller, 1988b, "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, 43(3), 661–76.

Campbell, J. Y., 2002, "Consumption-Based Asset Pricing," Harvard Institute of Economic Research Working Papers 1974, Harvard - Institute of Economic Research.

Chance, D. M., and M. L. Hemler, 2001, "The performance of professional market timers: daily evidence from executed strategies," *Journal of Financial Economics*, 62(2), 377–411.

Chang, E. C., and W. G. Lewellen, 1984, "Market Timing and Mutual Fund Investment Performance," *Journal of Business*, 57(1), 57–72.

Cox, J. C., and H. E. Leland, 2000, "On dynamic investment strategies," *Journal of Economic Dynamics and Control*, 24(11-12), 1859–1880.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance*, 52(3), 1035–58.

Davis, M.H.A., ., and A. R. Norman, 1990, "Portfolio selection with transaction costs," *Mathematics of Operations Research*, 15(4), 676–713.

Detemple, J. B., R. Garcia, and M. Rindisbacher, 2003, "A Monte Carlo Method for Optimal Portfolios," *Journal of Finance*, 58(1), 401–446.

Dimson, E., 1979, "Risk measurement when shares are subject to infrequent trading," *Journal of Financial Economics*, 7(2), 197–226.

Eckbo, B. E., and D. C. Smith, 1998, "The Conditional Performance of Insider Trades," *Journal of Finance*, 53(2), 467–498.

Edelen, R. M., and J. B. Warner, 2001, "Aggregate price effects of institutional trading: a study of mutual fund flow and market returns," *Journal of Financial Economics*, 59(2), 195–220.

Edelen, R. M., 1999, "Investor flows and the assessed performance of open-end mutual funds," *Journal of Financial Economics*, 53(3), 439–466.

Ferson, W. E., and R. W. Schadt, 1996, "Measuring Fund Strategy and Performance in Changing Economic Conditions," *Journal of Finance*, 51(2), 425–61.

Fleming, J., C. Kirby, and B. Ostdiek, 2001, "The economic value of volatility timing," *Journal of Finance*, 56(1), 329–352.

French, K. R., G. W. Schwert, and R. F. Stambaugh, 1987, "Expected stock returns and volatility," *Journal of Financial Economics*, 19(1), 3–29.

Goetzmann, W. N., J. Ingersoll, and Z. Ivković, 2000, "Monthly Measurement of Daily Timers," *The Journal of Financial and Quantitative Analysis*, 35(3), 257–290.

Graham, J. R., and C. R. Harvey, 1996, "Market timing ability and volatility implied in investment newsletters' asset allocation recommendations," *Journal of Financial Economics*, 42(3), 397–421.

Henriksson, R. D., and R. C. Merton, 1981, "On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills," *Journal of Business*, 54(4), 513–33.

Henriksson, R. D., 1984, "Market Timing and Mutual Fund Performance: An Empirical Investigation," *Journal of Business*, 57(1), 73–96.

Jagannathan, R., and R. A. Korajczyk, 1986, "Assessing the Market Timing Performance of Managed Portfolios," *Journal of Business*, 59(2), 217–35.

Jiang, G. J., T. Yao, and T. Yu, 2007, "Do mutual funds time the market? Evidence from portfolio holdings," *Journal of Financial Economics*, 86, 724–758.

Kacperczyk, M., and A. Seru, 2007, "Fund Manager Use of Public Information: New Evidence on Managerial Skills," *Journal of Finance*, 62(2), 485–528.

Kacperczyk, M., C. Sialm, and L. Zheng, 2005, "On the Industry Concentration of Actively Managed Equity Mutual Funds," *Journal of Finance*, 60(4), 1983–2011.

Kandel, S., and R. F. Stambaugh, 1996, "On the Predictability of Stock Returns: An Asset-Allocation Perspective," *Journal of Finance*, 51(2), 385–424.

Keim, D. B., and R. F. Stambaugh, 1986, "Predicting returns in the stock and bond markets," *Journal of Financial Economics*, 17(2), 357–390.

Kim, T. S., and E. Omberg, 1996, "Dynamic Nonmyopic Portfolio Behavior," *Review of Financial Studies*, 9(1), 141–61.

Kon, S. J., 1983, "The Market-Timing Performance of Mutual Fund Managers," *Journal of Business*, 56(3), 323–47.

Koski, J. L., and J. Pontiff, 1999, "How Are Derivatives Used? Evidence from the Mutual Fund Industry," *Journal of Finance*, 54(2), 791–816.

Kosowski, R., A. Timmermann, R. Wermers, and H. White, 2006, "Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis," *Journal of Finance*, 61(6), 2551–2595.

Kothari, S., and J. Warner, 2001, "Evaluating Mutual Fund Performance," *Journal of Finance*, 56(5), 1985–2010.

Kraus, A., and H. R. Stoll, 1972, "Parallel Trading by Institutional Investors," *The Journal of Financial and Quantitative Analysis*, 7(5), 2107–2138.

Leland, H. E., 1980, "Who Should Buy Portfolio Insurance?," *Journal of Finance*, 35(2), 581–94.

Lettau, M., and S. Ludvigson, 2001, "Consumption, aggregate wealth and expected stock returns," *Journal of Finance*, 56, 815–849.

Treynor, J. L., and K. Mazuy, 1966, "Can mutual finds outguess the market?," *Harvard Business Review*, 44, 131–136.

Wachter, J. A., 2002, "Portfolio and Consumption Decisions under Mean-Reverting Returns: An Exact Solution for Complete Markets," *Journal of Financial and Quantitative Analysis*, 37(1), 63–91.

Wermers, R., 2000, "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses," *Journal of Finance*, 55(4), 1655–1703.

Whitelaw, R. F., 1994, “Time Variations and Covariations in the Expectation and Volatility of Stock Market Returns,” *Journal of Finance*, 49(2), 515–41.

Whitelaw, R. F., 1997, “Time-Varying Sharpe Ratios and Market Timing,” New York University, Leonard N. Stern School Finance Department Working Paper Seires 98-074, New York University, Leonard N. Stern School of Business-.

White, H., 1980, “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity,” *Econometrica*, 48(4), 817–38.

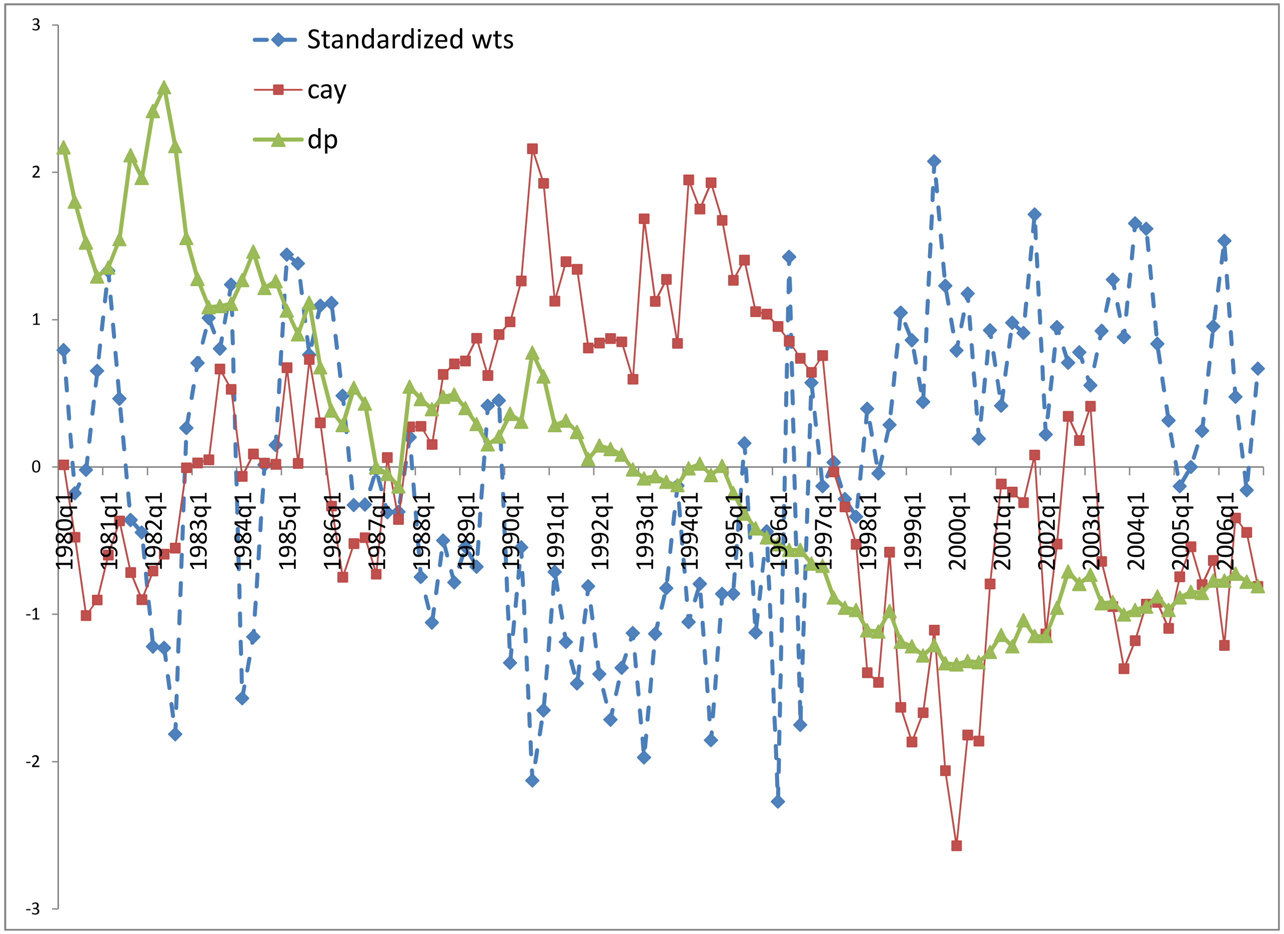

Table 1: A plot of standardized values for the consumption-wealth ratio variable (cay) constructed in Lettau and Ludvigson (2001), the aggregate dividend ratio (dp), and aggregated domestic equity exposure (relative to their sample mean) for funds identified as market-timers

CDA/Spectrum s12 objective modal ioc	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	1964
4	Growth & Income	390	
7	Balanced	147	
9 or NA	Unclassified or Unlisted	990	
	Total dropped (shaded)	150	

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	551
IN	Income Fund	7	
LG	Long-term Growth	244	
TR	Total Return Fund	5	
NA	Unclassified or unlisted	305	
	Total dropped (shaded)	134	

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	251
GRI	Growth and Income	38	
GRO	Growth	82	
ING	Growth and Income	7	
SCG	Small-cap Equity	63	
	Total dropped (shaded)	54	

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
$\rho_{\sigma^2 \text{ vox}}$	.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 $\rho_{\sigma^2 \text{ vox}}$ 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
$\rho_{\sigma^2 \text{ vox}}$	.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 $\rho_{\sigma^2 \text{ vox}}$ 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).

	Unconditional					Timers				
$\sigma^2_{\mathrm{p}\ t}$	min obs	$1-\phi_m$	$\mathcal{C}$	p-val	# funds	min obs	$1-\phi_m$	$\mathcal{C}$	p-val	# funds
	16	0.55	17.44	0.000	1709	16	0.76	5.43	0.020	43
${\sigma^2}_{\mathrm{naive}}$	24	0.63	9.74	0.002	1175	24	0.74	5.18	0.023	38
	32	0.64	9.31	0.002	785	32	0.73	4.43	0.035	30
	40	0.67	7.20	0.007	512	40	0.73	4.81	0.028	26
	16	0.72	13.60	0.000	1700	16	0.87	7.46	0.006	47
${\sigma^2}_{\mathrm{GARCH}}$	24	0.75	11.80	0.001	1168	24	0.87	8.45	0.004	40
	32	0.76	10.44	0.001	783	32	0.84	7.33	0.007	32
	40	0.79	8.08	0.004	513	40	0.85	7.82	0.005	27
	16	0.66	15.74	0.000	1684	16	0.79	5.08	0.024	44
${\sigma^2}_{\mathrm{vox}}$	24	0.69	11.88	0.001	1135	24	0.77	5.63	0.018	36
	32	0.69	10.59	0.001	745	32	0.74	5.92	0.015	30
	40	0.71	6.56	0.010	445	40	0.74	6.61	0.010	26
	16	0.75	18.04	0.000	1767	16	0.90	6.84	0.009	47
${\sigma^2}_{\mathrm{const}}$	24	0.76	21.46	0.000	1193	24	0.90	6.81	0.009	40
	32	0.81	10.13	0.001	790	32	0.89	7.51	0.006	32
	40	0.82	8.22	0.004	514	40	0.90	7.77	0.005	27

Table 6: This table reports estimates of $1-\phi_m$ by individually performing maximum likelihood estimations of $1-\phi_i$ and calculating a GLS estimate of the resultant coefficients. The statistic $\mathcal{C}$ tests whether all the $1-\phi_i$'s are equal (see Proposition 2). The associated p-value are conservative, and calculated from a $\chi^2(1)$ distribution.

$\sigma^2_{\mathrm{p}\ t}$	Horizon	Unconditional min obs	Corr$(R^2_a, 1-\hat{\phi}_i)$	p-val	# funds	Timers min obs	Corr$(R^2_a, 1-\hat{\phi}_i)$	p-val	# funds
σ^2_{naive}	1	16	-0.08	0.001	1720	16	0.19	0.209	44
		24	-0.08	0.008	1175	24	0.20	0.219	38
		32	-0.09	0.013	785	32	-0.07	0.729	30
		40	-0.12	0.006	512	40	-0.07	0.724	26
	3	16	-0.01	0.632	1720	16	0.10	0.518	44
		24	-0.00	0.942	1175	24	0.19	0.243	38
		32	0.03	0.421	785	32	0.06	0.743	30
		40	-0.00	0.966	512	40	0.12	0.559	26
	6	16	0.03	0.274	1720	16	0.15	0.327	44
		24	0.05	0.100	1175	24	0.20	0.238	38
		32	0.05	0.170	785	32	0.34	0.070	30
		40	0.02	0.711	512	40	0.16	0.428	26
	12	16	-0.03	0.269	1686	16	-0.11	0.491	44
		24	-0.03	0.278	1158	24	-0.09	0.579	38
		32	-0.03	0.433	762	32	0.09	0.647	29
		40	-0.03	0.555	483	40	0.06	0.779	26
σ^2_{GARCH}	1	16	-0.04	0.089	1707	16	0.23	0.116	48
		24	-0.06	0.041	1168	24	0.26	0.099	40
		32	-0.05	0.184	783	32	0.09	0.607	32
		40	-0.06	0.186	513	40	0.18	0.369	27
	3	16	-0.05	0.051	1707	16	0.16	0.268	48
		24	-0.02	0.503	1168	24	0.13	0.433	40
		32	0.00	0.980	783	32	0.13	0.484	32
		40	-0.01	0.749	513	40	0.12	0.540	27
	6	16	-0.03	0.269	1707	16	0.16	0.287	48
		24	0.00	0.967	1168	24	0.10	0.552	40
		32	-0.01	0.750	783	32	0.09	0.608	32
		40	-0.07	0.127	513	40	-0.03	0.887	27
	12	16	-0.01	0.593	1675	16	-0.10	0.503	48
		24	0.01	0.847	1149	24	-0.20	0.228	40
		32	0.01	0.833	760	32	-0.15	0.411	31
		40	0.01	0.744	484	40	-0.15	0.455	27

Table 7: This table reports the Spearman rank correlations between the ML estimates of $1-\phi_i$ from Eq. (13) and the adjusted-R^2 from the forecasting Eq. (15) for various forecasting horizons, conditional volatility proxies, and timers. The associated p-value is reported.

Table 7, continued.

		Unconditional				Timers			
$\sigma^2_{\mathrm{p}\ t}$	Horizon	min obs	Corr$(R_a^2, 1-\hat{\phi}_i)$	p-val	# funds	min obs	Corr$(R_a^2, 1-\hat{\phi}_i)$	p-val	# funds
$\sigma^2{}_{\mathrm{vox}}$	1	16	-0.08	0.001	1690	16	0.00	0.989	45
		24	-0.07	0.014	1135	24	-0.01	0.941	36
		32	-0.10	0.006	745	32	-0.09	0.643	30
		40	-0.10	0.039	445	40	-0.19	0.346	26
	3	16	-0.01	0.565	1690	16	0.24	0.112	45
		24	0.01	0.634	1135	24	0.27	0.117	36
		32	0.00	0.973	745	32	0.17	0.369	30
		40	-0.02	0.617	445	40	0.18	0.386	26
	6	16	0.01	0.705	1690	16	-0.04	0.813	45
		24	0.02	0.574	1135	24	-0.01	0.975	36
		32	-0.01	0.753	745	32	0.04	0.829	30
		40	-0.04	0.387	445	40	0.22	0.274	26
	12	16	0.03	0.271	1651	16	-0.24	0.115	44
		24	0.05	0.105	1118	24	-0.33	0.049	36
		32	0.04	0.323	718	32	-0.28	0.139	29
		40	0.03	0.599	429	40	-0.18	0.368	26
$\sigma^2{}_{\mathrm{const}}$	1	16	0.01	0.535	1769	16	0.09	0.553	48
		24	-0.03	0.280	1193	24	0.05	0.768	40
		32	-0.03	0.431	790	32	0.01	0.971	32
		40	-0.10	0.030	514	40	0.06	0.765	27
	3	16	0.02	0.464	1769	16	0.04	0.762	48
		24	-0.04	0.132	1193	24	-0.13	0.412	40
		32	0.00	0.998	790	32	-0.11	0.560	32
		40	-0.03	0.552	514	40	-0.10	0.621	27
	6	16	0.03	0.264	1769	16	0.18	0.231	48
		24	-0.02	0.595	1193	24	0.00	0.990	40
		32	-0.02	0.671	790	32	0.15	0.423	32
		40	-0.08	0.077	514	40	0.00	0.981	27
	12	16	0.03	0.235	1735	16	0.00	0.996	48
		24	0.05	0.092	1172	24	-0.15	0.366	40
		32	0.09	0.016	767	32	0.04	0.829	31
		40	0.04	0.341	485	40	0.02	0.904	27

one-month horizon	Unconditional				Timers			
$\sigma^2_{\mathrm{p}\ t}$	min obs	Corr(R^2_a, Var[$\hat{m}_i$])	p-val	# funds	min obs	Corr(R^2_a, Var[$\hat{m}_i$])	p-val	# funds
	16	-0.08	0.001	1790	16	-0.02	0.878	48
$\sigma^2{}_{\mathrm{naive}}$	24	-0.04	0.177	1199	24	-0.09	0.596	40
	32	-0.06	0.069	792	32	-0.20	0.281	32
	40	-0.05	0.275	515	40	-0.23	0.259	27
	16	-0.09	0.000	1790	16	0.04	0.776	48
$\sigma^2{}_{\mathrm{GARCH}}$	24	-0.08	0.003	1199	24	-0.16	0.336	40
	32	-0.07	0.043	792	32	-0.28	0.115	32
	40	-0.03	0.495	515	40	-0.21	0.303	27
	16	-0.11	0.000	1745	16	-0.03	0.849	47
$\sigma^2{}_{\mathrm{vox}}$	24	-0.03	0.253	1152	24	-0.07	0.678	36
	32	-0.09	0.018	754	32	-0.23	0.229	30
	40	-0.05	0.282	446	40	-0.23	0.261	26
	16	0.07	0.002	1790	16	0.18	0.229	48
$\sigma^2{}_{\mathrm{const}}$	24	0.05	0.074	1199	24	0.11	0.496	40
	32	0.06	0.110	792	32	0.16	0.367	32
	40	0.04	0.356	515	40	0.10	0.634	27
three-month horizon								
	16	-0.15	0.000	1790	16	-0.01	0.947	48
$\sigma^2{}_{\mathrm{naive}}$	24	-0.10	0.000	1199	24	0.05	0.745	40
	32	-0.06	0.074	792	32	0.13	0.489	32
	40	-0.02	0.699	515	40	-0.01	0.952	27
	16	-0.15	0.000	1790	16	0.09	0.528	48
$\sigma^2{}_{\mathrm{GARCH}}$	24	-0.11	0.000	1199	24	0.09	0.588	40
	32	-0.08	0.033	792	32	-0.03	0.875	32
	40	-0.05	0.236	515	40	-0.15	0.453	27
	16	-0.16	0.000	1745	16	0.07	0.650	47
$\sigma^2{}_{\mathrm{vox}}$	24	-0.02	0.553	1152	24	0.19	0.276	36
	32	-0.00	0.936	754	32	0.12	0.517	30
	40	0.04	0.422	446	40	0.06	0.761	26
	16	-0.03	0.250	1790	16	0.08	0.606	48
$\sigma^2{}_{\mathrm{const}}$	24	-0.07	0.022	1199	24	0.02	0.885	40
	32	-0.06	0.112	792	32	0.15	0.412	32
	40	-0.07	0.132	515	40	-0.03	0.866	27

Table 8: This table reports Spearman rank correlations between the residual variance of Eq. (16) and the adjusted-R^2 from the forecasting equation (15) for a one-month and three-month forecasting horizons. The associated p-values are reported.

t and p-values (σ_{naive})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.294	-3.469	-2.466	-1.267	-.2136	0.8297	2.2312	3.3132	6.9868
	0.1941	0.5078	0.6268	0.7399	0.8219	0.8694	0.6548	0.6433	0.6278
16	-5.758	-3.021	-2.293	-1.238	-.2935	0.6834	1.8321	2.6359	4.9891
	0.9775	0.9190	0.9200	0.8674	0.8644	0.7984	0.4292	0.2936	0.1191
24	-4.483	-2.880	-2.113	-1.174	-.2721	0.6505	1.6762	2.3107	4.1919
	0.9205	0.9465	0.8959	0.8249	0.7959	0.7304	0.4407	0.3547	0.1396
32	-4.166	-2.476	-1.970	-1.131	-.1999	0.6478	1.5165	1.9983	3.7947
	0.9190	0.8099	0.8394	0.7944	0.7029	0.6728	0.5288	0.5398	0.1481
40	-3.042	-2.313	-1.834	-1.078	-.1765	0.6334	1.4176	1.9317	3.0230
	0.4872	0.7239	0.7479	0.7584	0.6583	0.6443	0.5828	0.5278	0.4967

t and p-values (σ_{GARCH})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.397	-3.415	-2.425	-1.278	-.2071	0.8558	2.0276	3.0306	5.7485
	0.2611	0.5313	0.6483	0.7879	0.8054	0.8239	0.8134	0.8044	0.9135
16	-5.050	-3.127	-2.275	-1.247	-.2582	0.6773	1.7487	2.3171	3.9416
	0.9625	0.9775	0.9545	0.9080	0.8169	0.7509	0.4507	0.4922	0.4167
24	-4.419	-2.773	-2.143	-1.160	-.2390	0.6249	1.5657	2.0845	3.2151
	0.9575	0.9640	0.9515	0.8579	0.7749	0.7179	0.4722	0.4672	0.4887
32	-4.013	-2.532	-1.926	-1.062	-.1655	0.6507	1.4392	1.8780	2.7638
	0.9640	0.9170	0.8789	0.7919	0.6698	0.6233	0.5393	0.5673	0.5748
40	-3.311	-2.074	-1.646	-.8838	-.0962	0.7232	1.3774	1.8653	2.5425
	0.7829	0.6593	0.6963	0.6198	0.5898	0.5078	0.5593	0.4997	0.6878

t and p-values (σ_{vox})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.003	-3.214	-2.288	-1.143	-.0454	1.0122	2.3148	3.5732	7.1897
	0.1231	0.2756	0.3842	0.5343	0.5488	0.6178	0.5478	0.4187	0.5853
16	-5.286	-2.843	-2.077	-1.120	-.1525	0.8519	1.8825	2.7057	4.9834
	0.9280	0.7889	0.7439	0.7309	0.6843	0.5713	0.4222	0.2941	0.1551
24	-4.632	-2.603	-1.972	-1.092	-.1618	0.7857	1.6694	2.2972	4.2289
	0.9395	0.8184	0.7954	0.7524	0.6688	0.5448	0.4597	0.3922	0.1546
32	-3.769	-2.219	-1.831	-.9791	-.0711	0.7709	1.4444	1.9874	3.3708
	0.8394	0.6273	0.7249	0.6603	0.5548	0.5083	0.5918	0.5318	0.3322
40	-3.080	-1.994	-1.525	-.7513	0.1140	0.8463	1.4720	2.1161	3.1254
	0.5288	0.4872	0.4892	0.4412	0.3652	0.4102	0.5243	0.3727	0.4532

t and p-values (σ_{const})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-4.209	-2.819	-2.079	-1.052	-.0336	0.9442	2.1010	3.0875	5.8758
	0.0325	0.3982	0.5323	0.6018	0.5348	0.5443	0.4102	0.3392	0.3932
16	-4.164	-2.536	-1.961	-1.024	-.0887	0.8419	1.7602	2.4124	4.0355
	0.8534	0.8549	0.8744	0.7634	0.6123	0.4642	0.3027	0.2266	0.2181
24	-3.804	-2.416	-1.858	-1.034	-.1241	0.7892	1.7059	2.2858	3.7734
	0.9100	0.8999	0.8674	0.8019	0.6383	0.4872	0.2266	0.1626	0.1021
32	-3.471	-2.319	-1.749	-.9272	-.0918	0.7530	1.5567	2.1092	3.5347
	0.8799	0.8759	0.8094	0.6903	0.5943	0.4882	0.3442	0.2411	0.0900
40	-2.778	-2.071	-1.517	-.8461	-.0756	0.6883	1.4763	1.9011	2.8524
	0.4862	0.6953	0.5828	0.6023	0.5718	0.5448	0.4052	0.4422	0.4247

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 $r^e_{t+1} = \hat{\zeta}_i \sigma^2_{pt} w_{it} + \hat{\gamma}_{i1} \sigma^2_{pt} r_{it-1} + \hat{\gamma}_{i2} \sigma^2_{pt} r^2_{it-1} + \hat{\delta}_i \sigma^2_{pt} f_{it} + \hat{\tau}_i \sigma^2_{pt} + \hat{\epsilon}_{it+1} + \text{const}_i$, with a 1-month forecasting horizon. 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.

t and p-values (σ_{naive})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-7.028	-3.676	-2.736	-1.533	-.3961	0.8447	2.0489	3.1729	7.2126
	0.4312	0.7354	0.8874	0.9605	0.9650	0.8534	0.8114	0.7009	0.5788
16	-5.702	-3.487	-2.676	-1.551	-.4677	0.7029	1.8119	2.5687	4.2517
	0.9745	0.9940	0.9945	0.9870	0.9605	0.7664	0.4442	0.3137	0.3637
24	-5.337	-3.287	-2.563	-1.478	-.4686	0.6125	1.6535	2.2911	4.0474
	0.9870	0.9970	0.9945	0.9705	0.9290	0.7689	0.4662	0.3647	0.2056
32	-4.639	-3.078	-2.467	-1.455	-.5134	0.5687	1.4945	2.0730	4.0262
	0.9730	0.9830	0.9850	0.9580	0.9245	0.7599	0.5623	0.4807	0.1246
40	-4.200	-2.792	-2.267	-1.414	-.5694	0.5120	1.4012	1.9365	3.0115
	0.9085	0.9280	0.9450	0.9355	0.9260	0.7629	0.6123	0.5428	0.5068
t and p-values (σ_{GARCH})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.508	-3.421	-2.412	-1.305	-.2531	0.8902	1.9809	2.9990	5.9723
	0.2886	0.6008	0.6778	0.8224	0.8649	0.7574	0.8409	0.7899	0.8889
16	-5.336	-3.055	-2.256	-1.311	-.3062	0.7641	1.7370	2.3386	4.7899
	0.9755	0.9720	0.9520	0.9345	0.8744	0.6308	0.4272	0.4057	0.0780
24	-4.470	-2.790	-2.122	-1.245	-.3195	0.6974	1.5899	2.0420	4.1959
	0.9745	0.9690	0.9515	0.9110	0.8449	0.6203	0.4447	0.4882	0.0555
32	-3.935	-2.602	-2.042	-1.147	-.3205	0.6479	1.4671	1.9809	3.2661
	0.9570	0.9460	0.9320	0.8504	0.8199	0.6188	0.5088	0.4327	0.2346
40	-3.503	-2.263	-1.832	-1.082	-.3311	0.5643	1.4078	1.8800	2.6549
	0.8334	0.7909	0.8224	0.7954	0.8089	0.6793	0.5153	0.4722	0.6078
t and p-values (σ_{vox})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-6.757	-3.482	-2.512	-1.346	-.2271	0.9725	2.1779	3.4100	8.0936
	0.3657	0.6038	0.7324	0.8149	0.8224	0.6788	0.6588	0.5113	0.3482
16	-5.148	-3.249	-2.407	-1.350	-.2702	0.8038	1.8917	2.5932	5.1580
	0.9210	0.9640	0.9535	0.9225	0.8179	0.6298	0.3637	0.3252	0.1186
24	-4.387	-2.902	-2.170	-1.326	-.3210	0.6860	1.7284	2.3275	4.7171
	0.9085	0.9450	0.9050	0.9075	0.8229	0.6658	0.3582	0.3302	0.0690
32	-4.151	-2.662	-1.983	-1.253	-.3134	0.5911	1.5184	2.1681	3.5588
	0.9365	0.9015	0.8304	0.8639	0.7824	0.6923	0.5003	0.3507	0.2606
40	-4.055	-2.546	-1.955	-1.158	-.2611	0.5306	1.3990	2.0917	3.0012
	0.9005	0.8624	0.8279	0.8039	0.7249	0.7349	0.5868	0.3842	0.5218
t and p-values (σ_{const})									
min obs	1%	5%	10%	25%	50%	75%	90%	95%	99%
8	-4.864	-2.771	-2.085	-1.141	-.2361	0.8145	1.7744	2.5339	5.5118
	0.2366	0.4342	0.5918	0.7299	0.8454	0.7479	0.8024	0.8279	0.5783
16	-4.304	-2.606	-2.031	-1.144	-.2839	0.6751	1.4911	2.0679	3.7198
	0.9020	0.9115	0.9110	0.8709	0.8584	0.7029	0.6518	0.5898	0.3547
24	-3.965	-2.454	-1.943	-1.117	-.3266	0.5746	1.4050	1.9246	3.5025
	0.9510	0.9195	0.9145	0.8659	0.8719	0.7439	0.6003	0.5368	0.2066
32	-3.544	-2.271	-1.851	-1.064	-.3105	0.5558	1.3754	1.7914	3.1018
	0.9070	0.8464	0.8719	0.8259	0.8399	0.7204	0.5663	0.5908	0.2841
40	-2.837	-2.062	-1.713	-1.027	-.3313	0.5122	1.1658	1.6585	2.3170
	0.5183	0.6878	0.7669	0.7879	0.8314	0.7279	0.7524	0.6748	0.8064

Table 10: 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 $r^e_{t+1} = \hat{\zeta}_i \sigma^2_{pt} w_{it} + \hat{\gamma}_{i1} \sigma^2_{pt} r_{it-1} + \hat{\gamma}_{i2} \sigma^2_{pt} r^2_{it-1} + \hat{\delta}_i \sigma^2_{pt} f_{it} + \hat{\tau}_i \sigma^2_{pt} + \hat{\epsilon}_{it+1} + \text{const}_i$, with a 3-month forecasting horizon. 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 11: 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
${\sigma^2}_{\text{vox}}$	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 12: 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 13: 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	p	σ^2_{GARCH} ρ	p	σ^2_{vox} ρ	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	1	0.08	0.44	0.07	0.45	0.13	0.23
Stock	4	0.08	0.40	0.11	0.27	0.22	0.05
pickers	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	1	0.14	0.14	0.11	0.26	0.13	0.23
Stock	4	-0.07	0.48	-0.05	0.65	0.06	0.59
pickers	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	1	0.19	0.04	0.14	0.16	0.20	0.07
Neutral	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 14: 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 15: 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 given a null hypothesis that managers have no ability. The bootstrap consists of 2000 replications.