Do Funds That Bet on Risk Factors Create Value?

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(Work in Progress)

Abstract

I present the *timing volatility*, a measure of bets on systemic risks that is not affected by bets on idiosyncratic risks. I show that traditional measures of active management are excessively affected by the stock picking behavior of portfolio managers, making the timing volatility a valuable tool to measure how active mutual funds are in terms of bets on risk factors. Funds with high timing volatility have higher performance than funds with low timing volatility. Furthermore, mutual funds active on the dimension of systemic risks can add value through style rotation: the largest component of their alphas is generated by shifts on the exposure to risk factors. Funds with high timing volatility have poor stock picking abilities, suggesting that skilled managers specialize in either timing or stock picking.

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1 Introduction

The asset pricing literature suggests that returns of individual securities are harder to predict than the returns of risk factors (see French and Roll (1986), Andrew W. Lo (1988), Fama and French (1988)). As a consequence, optimal portfolios should be diversified and take advantage of macroeconomic predictors to risk premia (Avramov (2002)). In a seemingly contradiction to this statement, past research about institutional investors documented that managers actively concentrating their portfolios in specific stocks can add value to their clients (i.e., they posses stock picking skills), while managers actively overexposing their portfolios to risk factors (e.g., "SMB" or "HML") don't generate significant alphas (i.e., little evidence of timing skills). In this paper I argue that this apparent inconsistency is caused by the characteristics of the current proxies of active portfolio management, which puts excessive weight on idiosyncratic risks (that can lead to picking) and are unable to measure active bets on risk factors (that can lead to timing) in an appropriate way.

The most widely used measure of active portfolio management by researchers and market participants is the tracking error volatility (TEV), roughly defined as the standard deviation of the difference between the portfolio returns and the benchmark returns. The tracking error is simultaneously affected by active bets on risk factors (e.g., growth stocks vs. value stocks) and on security-specific risks (e.g., Facebook vs. Google). It is of economic importance, however, to understand if managers equipped with different types of skills (picking vs. timing skills), and consequently active in distinct dimensions, can deliver performance in different ways. I address this issue by decomposing the tracking error of each mutual fund in two components. The first component captures the deviation to the fund benchmark in terms of idiosyncratic risks and is intuitively related to existing measures of active stock picking (see Cremers and Petajisto (2009)). The second component, which I call *timing volatility* (TVol), captures the deviation to the fund benchmark in terms of systemic risks risks and is defined as the variance of the projection of the fund overperformance on a set of relevant risk factors[1] (here specified

[1]Benchmarks in this paper are defined as the combination of risk factors (with constant loadings) that better match the returns of each fund in the time series. As a consequence, the timing volatility is not influenced by funds' systematic investment in risk factors (i.e., is not influenced by the fund *style*.)

as the Fama-French three-factors[1]). To my best knowledge, this is the first work proposing a measure of active portfolio management in the systemic dimension that is not affected by funds' exposure to idiosyncratic risks.

My results show that the timing volatility is, for most funds, a small component of the overall tracking error, suggesting that other measures of active management that don't isolate the contribution of timing might also be excessively affected by portfolios' stock picking bets. Furthermore, timing volatility is a concave function of the total tracking error and, as a consequence, the larger the tracking error is, the more it is dominated by the stock picking behavior of the mutual fund. Therefore, previous research that sorts mutual funds based on their tracking error volatilities are, in approximation, ordering portfolios according to their concentrated stock picks. The absence of evidence of timing abilities of highly TEV-active managers is, consequently, not surprising.

I show that portfolios investing on mutual funds that are active on the timing dimension have larger performance than portfolios investing on mutual funds that are passive on the timing dimension. The difference of alphas between high-TVol and low-TVol portfolios with respect to a four factors regression (similarly to Carhart (1997)) is around 19 basis points per month and is significantly positive both before and after fees. High-TVol mutual funds have significantly positive alphas before fees, around .18% per month, while low-TVol funds have significantly negative alphas after fees, around -.10% per month.

One could argue that those results are driven by a cross-sectional correlation between the intensities of picking bets and timing bets. A possible way to overcome this problem would be creating a proxy for the portfolio's exposure to idiosyncratic risks, and then sorting funds in two dimensions of active management (similarly Cremers and Petajisto (2009)). Instead, I employ the simpler approach of directly decomposing the performance of mutual funds in timing and picking, using standard performance attribution techniques designed by previous research. For robustness purposes, I employ two different decomposition techniques.

My first test is based on the assumption that funds' time-varying loadings on risk factors are linear on a set of instruments, which enables estimation of the underlying coefficients through

[1] The Fama-French three-factors are the excess of return of the market, the return of value stocks minus the return of growth stocks, and the return of small cap. stocks minus the returns of large cap. stocks. For more details, see Fama and French (1993).

standard OLS. (see Treynor and Mazuy (1966), Henriksson and Merton (1981) and Ferson and Schadt (1996)). Timing performance of mutual funds can then be calculated as the covariance between the time-varying betas and the risk factor returns. Resulting estimates show that funds in the bottom six TVol decides have (statistically insignificant) losses with timing, while funds in the top three deciles earn around 30 basis points per month with bets on risk factors. The difference in timing between the top 20% and the bottom 20% TVol funds is around 40 basis points monthly ($p < .5$). Interestingly, high TVol funds have worse stock selectivity than low TVol funds. These results strongly support the hypothesis that the superior performance of high-TVol funds comes from their bets on risk factors, and not from an eventual correlation with bets on stock picking.

My second test is based on funds' risk factor loadings calculated with holdings data, similarly to Jiang et al. (2007), Elton et al. (2011a) and Kacperczyk et al. (2014). Timing in this context is defined as the (hypothetical) profit made by a given mutual fund by deviating from its benchmark's betas, assuming that: (i) all trades are made only slightly before portfolios are disclosed (i.e., ignoring interim trades), and that (ii) all trades are made using closing prices (and therefore ignoring liquidity costs). My results show that mutual funds in the bottom five TVol-deciles don't have significant timing abilities. Funds in the sixth decile earn 25 basis points per quarter through timing, value that is both economically significant (more than half of the average expense ratio of .4% per quarter estimated by Wermers (2000)) and statistically significant ($p < .1$). Point estimates of timing performance are increasing in the subsequent TVol groups, reaching 70 basis points per quarter in the ninth decile and 1% per quarter in the tenth decile. In summary, funds that bet on risk factors *do* add value.

This paper builds on the small literature investigating the value added by active portfolio management. Based on the premise that several closet-indexers[1] misleadingly self-report their investment style as active, several papers tried to define proxies of benchmark deviations in order to estimate the performance of effectively active managers. Pioneer in this literature, Kacperczyk et al. (2005) show that mutual funds with higher industrial concentration than their peers can generate alpha through stock picking, with no significant timing abilities. My measure of active portfolio management is related to theirs in the sense that we both use the notion of

[1] i.e., funds investing in portfolios with same weights as their benchmarks.

concentration in sources of systemic risks. By analyzing the dimensions of market exposure, book-to-market and market capitalization I focus on factors whose premia is documented as predictable in the time-series (see Avramov (2002)), so it is natural to expect the existence of TVol-active managers that are skilled in the timing dimension.

Cremers and Petajisto (2009) propose a measure of active management in the picking dimension, called the Active Share, defined as the share of portfolio holdings that differ from the benchmark index holdings. Because covariances between stocks are not considered in this measure, diversified stock picks that cancel out in the tracking error calculation would be accounted by the Active Share. With this intuition in mind, they sort mutual funds based on their tracking error and on their Active Share scores, showing that the Active Share predicts performance more efficiently than tracking error. My findings help to shed light to their result: given that (i) the tracking error is dominated by concentrated stock picks and that (ii) the Active share accounts for both concentrated and diversified stock picks, we can conjecture that diversified stock picks are better predictors of performance than concentrated stock picks. However, given that both measures are marginally affected by factor bets, it's hard to point exactly what can be concluded about the timing abilities of active mutual funds. In this paper I fill this gap by defining a measure of portfolio active management that is not affected by bets on idiosyncratic risks. I also explicitly decompose the performance of mutual funds in timing and picking, showing that active managers can time risk factors.

This paper also contributes to the extensive literature investigating the existence of timing abilities of equity mutual funds managers. Early studies on the subject found evidence of insignificant or even negative timing abilities. Treynor and Mazuy (1966) and Henriksson and Merton (1981) employ non-linear regressions of funds returns on market returns. Ferson and Schadt (1996) estimates conditional betas of mutual funds as a function of macro variables in regression models. Daniel et al. (1997) uses a non-parametric approach, analyzing the value created by shifts between investment styles that better fit the fund portfolio in a given date. Becker et al. (1999) estimates a model of optimal usage of managers' private information about future market returns. Recent research, based on several methodological improvements, found evidence of significant market timing abilities. Jiang et al. (2007) calculates betas from holdings and uses bootstrap to test for the existence of market timing abilities in the cross-section. Mamaysky et al. (2008) employs Kalman filtering techniques to estimate the dynamics of market betas of mutual funds. Elton et al. (2011a) uses higher frequency holdings data to estimate finds' exposure to the market. Kacperczyk et al. (2014) estimates time-varying market timing skills. A limitation of these recent inquires is that, by focusing solely on the market factor, they are unable to estimate the total performance due to timing. To the best of my knowledge, the present work is the first to give evidence of timing abilities based on a multifactor model. My contribution is to show that, in order to estimate significant timing abilities, one should focus on the mutual funds that are betting on risk factors. Closet indexers and funds specialized in stock picking introduce noise in the full sample and make statistical tests reject the existence of timing skills much more easily.

The remainder of the paper proceeds as follows. In section 2 I describe the data used in the subsequent analysis and the criteria of selection of mutual funds. In section 3 I present my measure of timing volatility and its basic properties. In section 4 I present several performance measures of mutual funds sorted by their timing volatilities scores. Section 5 concludes.

2 Data and Mutual Fund Selection

My sample builds upon several databases. I start with a table containing total net assets (TNA), investment objective codes, realized returns, expense ratios, turnover, starting dates and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. I aggregate funds with different share classes investing in the same portfolio[1] into single observations[2].

Data from mutual funds holdings comes from two different sources. First I take data on portfolios weights from CRSP, merging it with my starting table of funds characteristics using portfolio codes (CRSP_PORTNO) and calendar dates to identify observations. CRSP provides the most comprehensive data about U.S. mutual funds holdings in terms of number of portfolios, with the downside that it is available only after 2002. In order to cover a time

[1] i.e., with the same CRSP_PORTNO code.

[2] The aggregated observation have TNA equal to the sum of the TNAs of different classes. Qualitative characteristics of the aggregated observation equals to the average of the characteristic among individual observations, weighted by their total assets. Qualitative characteristics of the aggregated observation equals to the characteristic of the oldest share.

period as large as possible, I also use data from the Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12). Thomson Reuters tables contain data from funds holdings since 1980, when the U.S. Securities and Exchange Commission (SEC) made the disclosure of mutual funds portfolios mandatory. I merge the CRSP database with the Thomson Reuters holdings using the MFLINKS table developed by Wermers (2000) and available on WRDS.

After merging all relevant tables, I apply standard filters to exclude undesirable observations. First I remove all funds not classified as U.S. domestic equity funds[1]. Since self-reported classifications can be misleading, I also exclude funds investing less than 75% of their total assets in U.S. stocks (in average terms). Next I exclude all observations classified as ETFs, ETNs, or passive index funds. In addition, I also exclude sector funds. I address the possibility of incubation bias[2] by excluding small funds (with total net assets smaller than U$ 5 millions) and funds with few stocks in their portfolios (less than 10). Finally, I exclude observations dated before the date when the first shares of the fund were made available to the public.

The final database of mutual funds holdings have quarterly frequency and is composed by 131,266 fund-quarter observations between Mar 1980 and Dec 2014. The number of funds in the sample varies from 51 in 1980 to 2,822 in 2014, while the total number of funds is 4,690. Basic summary statistics can be found in table 1. The average fund is thirteen years old, have total net assets (TNA) of one billion of dollars, receives 0.4% of inflows (as a proportion of TNA) every quarter, have yearly expenses of 1.2% of their TNA, invest 89% of their TNA in stocks and hold 110 stocks in his portfolio.

I collect data on risk factors returns on the Kenneth French's data library[3]. My analysis for the remaining of this paper will be based on the following risk factors: market minus risk free rate, "HML" (value minus growth) and "SMB" (small cap minus large cap). Data on stocks returns, necessary to calculate the betas of individual stocks, were obtained from the CRSP monthly returns file. Monthly data from mutual funds realized net returns, necessary for the calculation of the performance measures, comes CRSP funds tables.

In the next section I give details about the calculation of my measure of active management

[1] I say that an observation is a domestic equity mutual funds if its CRSP investment objective code starts with "ED".

[2] Incubation bias arises when families privately manage several starting funds, discarding the losers and making available to the public only the best tracking records.

[3] Avaliable at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

based on holdings data of the mutual funds in my sample.

3 Measurement of Active Portfolio Management

Mutual funds can deviate from their benchmarks in two ways: by overweighting specific stocks or by increasing the sensitivity of their portfolios' returns to aggregate factors reflecting systemic risks. In this section I propose a novel methodology to measure those two different deviations separately.

I assume that the Fama and French three factors returns (here represented by $\mathbf{f}_{t+1}$) mimic the set of systemic risks relevant to the investment decisions of managers of mutual funds[1]. This is motivated by two well documented facts: first, these factors do a relatively good job in explaining the cross-section of US stocks returns (Fama and French (1993)). Second, they are defined in terms of stocks characteristics that shape the investment strategies of US equity funds, namely size and book-to-market (Chan et al. (2002)).

I define the exposure of a mutual fund portfolio to risk factors in terms of a general model for the conditional performance, projecting funds returns on the returns of risk factors:

$$R_{P,t+1} - R^f_{t+1} = \alpha_{Pt} + \boldsymbol{\beta}^\top_{Pt}\mathbf{f}_{t+1} + \varepsilon_{P,t+1} \tag{3.1}$$

where $R_{P,t+1}$ is the return of the portfolio, R^f_{t+1} is a risk-free rate, α_{Pt} is a constant, $\boldsymbol{\beta}_{Pt}$ is the vector of factor loadings, $\mathbf{f}_{t+1}$ is the return of the risk factors, and $\varepsilon_{P,t+1}$ is the idiosyncratic component of the fund performance, uncorrelated with the risk factors. A natural way to estimate the parameters in equation (3.1) is by running regressions of funds returns on risk factors' returns. However, funds betting on systemic risks have, by definition, time-varying loadings on risk factors, and therefore a special procedure that takes this dynamics into account is needed. I overcome this issue by using data on mutual funds holdings to estimate the conditional betas $\boldsymbol{\beta}_{Pt}$, similarly to Jiang et al. (2007), Elton et al. (2011a) and Kacperczyk et al. (2014)). For each date and each mutual fund, loadings are calculated as the average of the individual stocks' betas, weighted by the percentage that each security represents in the

[1] All results of this paper are robust to the inclusion of the momentum factor.

portfolio. Betas of individual stocks are estimated by running multiple regressions of stock's returns against the Fama-French three factors returns on rolling windows of three years of monthly data[1].

The next step in the definition of my measure of active portfolio management is the adoption of assumptions about funds' bechmarks. I follow the large body of literature assuming that portfolios' benchmarks are linear combinations of risk factors returns with constant loadings, taking the form $\boldsymbol{\beta}_P^{*\top}\mathbf{f}_{t+1}$ for an appropriate constant vector $\boldsymbol{\beta}_P^*$, which I call the mutual fund "objective beta". In this paper I follow Elton et al. (2011a) and estimate $\boldsymbol{\beta}_P^*$ as the average beta within each fund[2]. It is convenient to think that objective betas are related to the stationary investment styles of each mutual fund. For example, funds whose mandate specifies that managers should invest in small cap. growth funds would have negative HML objective betas and positive SMB betas.

Funds that are passive on the systemic risk dimension would always invest in portfolios such that $\boldsymbol{\beta}_{Pt} = \boldsymbol{\beta}_P^*$, while funds making active bets on risk factors would have loadings different from objective betas. The extent to which such active bets (that could be motivated by superior private information or by agency problems) can generate value to the funds' clients is an empirical question. Before addressing this problem, however, a numerical measure for the size of the gap $\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}_P^*$ is needed.

The total tracking error of the mutual fund, defined as the standard deviation of the difference between the portfolio returns and the benchmark returns, can be calculated by combining equations (3.1) and the objective betas $\boldsymbol{\beta}^*$:

$$\begin{aligned}
\mathrm{TEV}_{Pt} &\equiv \sqrt{\mathrm{var}_t[R_{Pt} - \boldsymbol{\beta}_P^{*\top}\mathbf{f}_{t+1}]} && (3.2)\\
&= \sqrt{\mathrm{var}_t[(\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}_P^*)^\top\mathbf{f}_{t+1} + \varepsilon_{t+1}]} && (3.3)\\
&= \sqrt{\mathrm{var}_t[(\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}_P^*)^\top\mathbf{f}_{t+1} + \mathrm{var}_t[\varepsilon_{t+1}]} && (3.4)
\end{aligned}$$

[1]For simplicity, the estimation errors of those regressions are ignored. It is noteworthy, however, that such errors cancel out and get very small when betas are aggregated in funds portfolios. See Elton et al. (2011b) for a more detailed discussion

[2]Another way to estimate the objective betas would be running unconditional regressions of funds returns on risk factors returns. However, as pointed by Admati and Ross (1985), Dybvig and Ross (1985) and Grinblatt and Titman (1989), this procedure generates upwardly biased estimates of the real systematic risks of funds with time-varying betas.

where the last equality comes from the fact that the idiosyncratic disturbance ε_{t+1} is uncorrelated with risk factors. The difference $\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}^*_P$ corresponds to the deviation to the benchmark in terms of systemic risks, while the residual term ε_{t+1} corresponds the deviation from the benchmark in terms of idiosyncratic risks[1]. We can, therefore, interpret equation (3.4) as a decomposition of the square of the total tracking error as the sum of the risk originated from stock selection and the risk originated from factor bets. As a consequence, the total contribution of timing to tracking error, which I call timing volatility (TVol), is given by

$$\text{TVol}_{Pt} \equiv \sqrt{\text{var}_t[(\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}^*_P)^\top \mathbf{f}_{t+1}]} = \sqrt{(\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}^*_P)^\top \boldsymbol{\Sigma}_t (\boldsymbol{\beta}_{Pt} - \boldsymbol{\beta}^*_P)} \tag{3.5}$$

where $\boldsymbol{\Sigma}_t$ is the covariance matrix of the risk factors calculated in a three years rolling window of monthly returns.

Figure 1 plots the cross-sectional empirical distribution of the average timing volatility (TVol) and of the average tracking error across mutual funds. Several conclusions can be made by the simple analysis of the magnitudes of these variables. First, the timing volatility is concentrated in the interval $[0, .05]$, while the tracking error seems to be concentrated in the interval $[0, .1]$, so TEV have magnitude approximately two times larger than TVol. Equation (3.4) tell us that if idiosyncratic risks and systemic risks were the same, then TEV would be equal to TVol multiplied by $\sqrt{2} \approx 1.41$. The observation that the real multiplicative factor found in data seems to be around 2 tell us that idiosyncratic risks are dominating the tracking error volatility. Furthermore, the tracking error distribution clearly have much larger kurtosis, suggesting that funds with extremely large TEV have idiosyncratic risks disproportionately larger than systemic risks.

This intuition is confirmed by the analysis of the correlations between tracking error and timing volatility. In figure 2 I plot the estimated average[2] timing volatility, conditionally on a fixed value of the total tracking error. The straight line represents the set of points such that idiosyncratic risks and systemic risks give the same contribution to the tracking error[3]. It is noteworthy that the fitted curve is always bellow the straight line, indicating that risks created

[1]Note that if the portfolio return were spanned by risk factors, then ε_{t+1} would be zero with probability one.

[2]Estimated using locally weighted scatterplot smoothing, following Cleveland (1979).

[3]Equation (3.4) implies that the slope of this line is $1/\sqrt{2}$.

by stock picking are always the dominant component of the tracking error. Furthermore, the fitted curve is concave, showing that the larger the tracking error is, the more it is dominated by idiosyncratic risks. Therefore, previous research that sorted mutual funds by tracking error (such as Cremers and Petajisto (2009)) were in fact grouping funds depending on their concentrated stock picks. In this paper I overcome this issue by using the TVol, which is not influenced by stock selection, as a measure of active portfolio management in the dimension of systemic risks.

What are the observable characteristics of TVol-active mutual funds? In table 2 I report the average total net assets, age, flows, expenses and turnover of funds sorted on their timing volatilities. Surprisingly, funds that are active on the timing dimension are large: the difference in size of the top 20% and the bottom 20% TVol funds is around 0.6 billions of dollars. Given that previous research found that mutual funds making the larger stock picking allocations are small, this helps to enlighten how different mutual funds characteristics might shape the profile of active bets: small funds usually deviate from their benchmarks in the idiosyncratic dimension, while large funds usually deviate in the systemic dimension. One possible conjecture for the reason of this difference is that large funds have more resources than small funds to invest in macroeconomic research to predict returns of risk factors, while small funds make large purchases of specific stocks by attractive prices when counterparts engage in fire selling (e.g., other funds in need of liquidity because of unexpected outflows). More TVol-active mutual funds are also older, more expensive, receive smaller flows and have higher turnover, coherently with recent research finding that turnover is a predictor manager skills (see Pastor et al. (2014)).

In figure 3 I plot the median timing volatility (calculated across different mutual funds) in each quarter, normalized by the volatility of the market. Apparently, there is a negative trend in the level of active management on the dimension of bets on risk factors, which is coherent with the findings of previous research that the U.S equity funds are becoming less active over time (see Cremers and Petajisto (2009)).

4 Performance Measures

In this section I address the main question of this paper: do mutual funds active in the dimension of bets on risk factors add value to their clients? First, I use the traditional approach of calculating the Jensen's alpha based on an unconditional linear regression of realized funds returns against risk factors (Fama-French three factors plus momentum), similarly to Carhart (1997). Next I use a regression model that enables for time-variation of funds loadings as a function of instruments, following Henriksson and Merton (1981) and Ferson and Schadt (1996). In the last subsection I use a performance measure based on funds betas calculated from mutual portfolio holdings, in the same spirit of Elton et al. (2011a) and Kacperczyk et al. (2014).

4.1 Carhart Four-Factor Measure

In my first performance measure I compute standard unconditional regressions controlling for mutual funds styles (i.e., size and book-to-market). Motivated by previous research that found evidence of systematic investment in winners by mutual with high raw returns (see Jegadeesh and Titman (1993)) I also include momentum in the final regression model, which takes the form

$$\begin{aligned} R_{i,t+1} - R^f_{t+1} &= a_i + b_{i,m}(R^m_{t+1} - R^f_{t+1}) + b_{i,SMB}SMB_{t+1} + b_{i,HML}HML_{t+1} \quad (4.6) \\ &+ b_{i,MOM}MOM_{t+1} + e_{i,t+1} \quad (4.7) \end{aligned}$$

Regression model (4.7) is estimated using returns of portfolios of mutual funds sorted in timing volatility deciles. Given that the data on mutual funds holdings necessary to calculate the TVol measure is available only on a quarterly basis, I rebalance the portfolios of mutual fund in every March, June, September and December. Following the practice of previous research on mutual funds performance, my portfolios equally weights different mutual funds (i.e., one manager, one observation).

Table 3 reports the estimates of the parameter of equation (4.7) using returns before and after fees. Low-TVol funds have significantly negative alphas (around -.1%) after fees, suggesting low overall skills of mutual funds passive on the dimension of systemic risks. Active funds have net alphas statistically indistinguishable from zero. The difference between net returns of the top 20% and the bottom 20% TVol funds is around 17 basis points (p< .1). When gross returns are considered, the losses of Low-TVol become close to zero, while the positive value added by the top 10% TVol funds gets significantly positive (around .19%, with p< .1).

Some noteworthy aspects if table 3 should be highlighted. First, the spreads documented here are smaller than the difference in performance found using proxies for active stock picking, such as industrial concentration (Kacperczyk et al. (2005)) and the Active Share (Cremers and Petajisto (2009)). One possible explanation for this result is that regression models such as (4.7) tend to overestimate the slopes (i.e., betas) of mutual funds that make more aggressive bets on risk factors (see Grinblatt and Titman (1989)), so the real value added could be larger. Second, given that regression model (4.7) doesn't allow for time variation on the slopes, it's hard to say if top TVol funds are adding value with picking or timing. I overcome those two issues in the next section by estimating a regression model that allows for time variation on mutual funds systemic risks.

4.2 Henriksson-Merton Conditional Measure

Following Henriksson and Merton (1981) and Ferson and Schadt (1996) I assume that the conditional performance of (a portfolio of) mutual funds have the form

$$R_{i,t+1} - R^f_{t+1} = \alpha_i + \boldsymbol{\beta}_i(\mathbf{z}_t)^\top \mathbf{f}_{t+1} + \varepsilon_{i,t+1} \tag{4.8}$$

where α_i is the value added by stock picking, $\mathbf{z}_t$ is a set of instruments mimicking the information set of the fund manager up to the quarter t, and $\boldsymbol{\beta}_i(\cdot)$ is a linear function. The objective beta can then be estimated as

$$\boldsymbol{\beta}^*_i = \mathbb{E}[\boldsymbol{\beta}_i(\mathbf{z}_t)] \tag{4.9}$$

The value added by timing (which I call θ_i) is defined as the value created by deviations from the objective beta,

$$\theta_i = \mathbb{E}[(\boldsymbol{\beta}_i(\mathbf{z}_t) - \boldsymbol{\beta}_i^*)^\top \mathbf{f}_{t+1}] \tag{4.10}$$

I follow Henriksson and Merton (1981) and Chan et al. (2002) by using the signal of the realization of the risk factors returns as instruments. This enables for variation of betas depending on positive or negative returns associated with each type of idiosyncratic risks. In mathematical terms,

$$\mathbf{z}_t = \begin{bmatrix} 1(R_{m,t+1} - R_{f,t+1} > 0) \\ 1(SMB_{t+1} > 0) \\ 1(HML_{t+1} > 0) \end{bmatrix}, \ \boldsymbol{\beta}_i(\mathbf{z}_t) = \begin{bmatrix} \beta_{0,i}^{MKT} + \delta_i^{MKT} \times 1(R_{m,t+1} - R_{f,t+1} > 0) \\ \beta_{0,i}^{SMB} + \delta_i^{SMB} \times 1(SMB_{t+1} > 0) \\ \beta_{0,i}^{HML} + \delta_i^{HML} \times 1(HML_{t+1} > 0) \end{bmatrix}$$

I estimate the parameters (α_i, θ_i) for the different deciles of timing volatility using GMM based on the moment conditions (4.8, 4.9, 4.10).

Table 4 reports the resulting estimates of timing and picking performance for the portfolios of mutual funds sorted by timing volatility. Timing abilities are increasing on the timing volatility deciles: low-TVol funds have insignificant timing skills, while the top 30% mutual funds add around 30 basis points of value per month ($p < .05$). The total alpha of funds making active bets on risk factors is partially offset by their losses of 20 basis points with stock selection. The difference in timing between the top 20% and the bottom 20% TVol mutual funds is around 41 basis points, while the difference in selectivity is around negative 13 basis points.

The results largely support the hypothesis that the superior performance in the top TVol funds found in the previous subsection is a consequence of their active bets on risk factors, and not a simple result of the correlation between active bets on systemic risks and on picking of individual stocks. It also indicates that a relevant number of mutual funds have skills to time their exposure to different style of stocks. To the best of my knowledge, previous research found only the existence of funds that can time stocks' market betas (see Jiang et al. (2007), Mamaysky et al. (2008), Kacperczyk et al. (2014)). My finding of the existence of timing abilities in the framework of a multifactor model is, therefore, a novel results.

4.3 Holdings Measure

The methodology employed in the previous subsection to decompose the total alpha of mutual funds in timing and picking surfers from several problems. First, it is based on a non-linear regression of mutual fund returns on risk factors returns, which implicitly assumes that stocks returns are linear on risk factors. However, there is documented evidence that several stocks returns are convex on risk factors returns. Jagannathan and Korajczyk (1986) show that mutual funds passively investing in such stocks would exhibit convex features, and would be classified as funds possessing timing abilities according to the non-linear regression approach, phenomena known as “passive timing”. In order to make sure that the results from last subsection are not a simple consequence of the passive timing bias, in this subsection I employ a test based on mutual funds holdings to identify the existence of funds with timing abilities, following Jiang et al. (2007), Elton et al. (2011a) and Kacperczyk et al. (2014).

The performance decomposition used here relies on the assumption that end-of-quarter holdings represents all relevant trades made by fund managers. In other words, it is assumed all trades are made slightly before portfolios are disclosed. Once the new portfolio is formed, it is kept for the subsequent quarter.

Let $\omega_{P,j,t}$ denote the weight of stock j in the portfolio P in the end of the quarter t. I Assume that returns $r_{j,t+1}$ of individual stocks can be projected on the set of risk factors:

$$r_{j,t+1} - R^f_{t+1} = \mathbf{b}_{j,t}^\top \mathbf{f}_{t+1} + u_{j,t+1},\ \mathbb{E}_t[u_{j,t+1}\mathbf{f}_{t+1}] = \mathbf{0} \tag{4.11}$$

The excess of return of the portfolio P between t and $t+1$, assuming that weights are constant in this period[1], takes the form:

$$R_{P,t+1} - R^f_{t+1} \equiv \sum_j \omega_{P,j,t}(r_{j,t+1} - R^f_{t+1}) = \boldsymbol{\beta}_{P,t}^\top \mathbf{f}_{t+1} + \varepsilon_{P,t+1} \tag{4.12}$$

[1]And also assuming that resources not invested in stocks, $1 - \sum_j \omega_{P,j,t}$, are entirely invested in cash

where $\boldsymbol{\beta}_{P,t} \equiv \sum_j \omega_{P,j,t}\mathbf{b}_{j,t}$ and $\varepsilon_{P,t+1} \equiv \sum_j \omega_{P,j,t}u_{j,t+1}$. Equation (4.12) tell us that managers of mutual funds can add value to their clients by using their private information about the future returns of risk factors (by increasing the slopes $\boldsymbol{\beta}_{P,t}$ if high returns are expected) or about the idiosyncratic returns of individual securities (by increasing the weights of stocks with high expected shock $u_{j,t+1}$).

As in the previous sections, risk adjustment is based on the benchmark of objective betas $\boldsymbol{\beta}^*_P$ multiplied by the risk factors' returns $\mathbf{f}_{t+1}$:

$$R_{P,t+1} - R^f_{t+1} - \boldsymbol{\beta}^{*\top}_P\mathbf{f}_{t+1} = (\boldsymbol{\beta}_{P,t} - \boldsymbol{\beta}^*_P)^\top\mathbf{f}_{t+1} + \varepsilon_{P,t+1} \tag{4.13}$$

Performance decomposition (4.13) motivates the definition of the holding-based measures of timing and picking for the portfolio P between the quarters t and $t+1$ as:

$$\text{Timing}_{P,t+1} \equiv (\boldsymbol{\beta}_{P,t} - \boldsymbol{\beta}^*_P)^\top\mathbf{f}_{t+1} \tag{4.14}$$

$$\text{Picking}_{P,t+1} \equiv \varepsilon_{P,t+1} = \sum_j \omega_{P,j,t}(r_{j,t+1} - R^f_{t+1} - \mathbf{b}^\top_{j,t}\mathbf{f}_{t+1}) \tag{4.15}$$

Timing is the component of the funds' alpha generated by deviations from the benchmark in terms of exposure to risk factors, while picking is the component due to the overweight of stocks with (ideally) higher performance than their peers.

For the calculation of formulas (4.14) and (4.15), betas of individual stocks $\mathbf{b}_{j,t}$ are calculated using rolling regressions of three years of monthly data (including t as last date), while betas of mutual funds are the average of betas of individual stocks weighted by their participation in the total net assets. Objective betas $\boldsymbol{\beta}^*_P$ are the average of betas within each mutual fund. Weights $\{\omega_{P,j,t}\}_j$ used the calculation of the funds' loadings are obtained from mutual funds holdings disclosed in end of quarters (see the data section for more details).

For each quarter I sort mutual funds on timing volatility deciles. Unconditional averages of the timing and picking measures are then calculated across different quarters and funds, using standard errors clustered by time and fund to take possible correlations into account.

Empirical results are displayed in table 5. Funds in the bottom 50% deciles of timing volatility possess no significant timing skills. Their picking performance is economically large (around 50 basis points per quarter), though not significant due to large standard errors. Again, timing abilities are increasing on TVol, reaching significant values (around 50 basis points per quarter) between the top seventh and ninth deciles ($p < .05$). Timing of top 10% TVol funds is very large (1% per quarter), though not significant because of large standard errors. Interestingly, point estimates of picking for funds with large timing volatilities are small, and even negative for the top 10% TVol observations. This suggests that mutual funds specialize in the different tasks of timing or selection, which requires specific skills and research. Overall, results obtained form holdings-based measures of performance are largely coherent with the findings based on the Henriksson-Merton model, showing that the timing volatility is truly a proxy for active bets on risk factors and a predictor for timing abilities in the cross-section of mutual funds.

5 Conclusion

The consensus view of the literature about skills of portfolio managers is that mutual funds making active bets on risk factors don't add value to their clients. Traditional measures of active management predicts only stock picking performance, suggesting that timing skills don't exist in the cross section of mutual funds.

In this paper I argue that traditional measures of active portfolio management (i) heavily overweight stock picking bets, and (ii) strongly underweight systemic risks bets. I overcome this issue by proposing a novel measure of active management in the timing dimension, which I call the *timing volatility* (TVol), given by the contribution of the overexposure to risk factors to the total tracking error. Timing volatility is usually a small component of the tracking error, so such decomposition is fundamental for the identification of mutual funds that are truly active in the style rotation dimension.

Timing volatility predicts performance. Evidence with this respect is found using three different performance measures: a Carhart four-factor measure, a Henriksson-Merton conditional measure and a holdings-based measure. Overall, empirical results shows that the superior performance of TVol-active mutual funds is largely attributed to superior timing skills, and not by stock picking.

The profile of funds that are active on the dimension of risk factors is drastically different from the characteristics of active funds found in previous research using measures of benchmark deviation that are influenced by managers stock picks. Active-TVol funds have high turnover, are expensive, old and large, managing usually more than one billion of dollars. This is coherent with the idea that large institutions have more resources for the development of macroeconomic research required for the prediction of returns of aggregate risk factors.

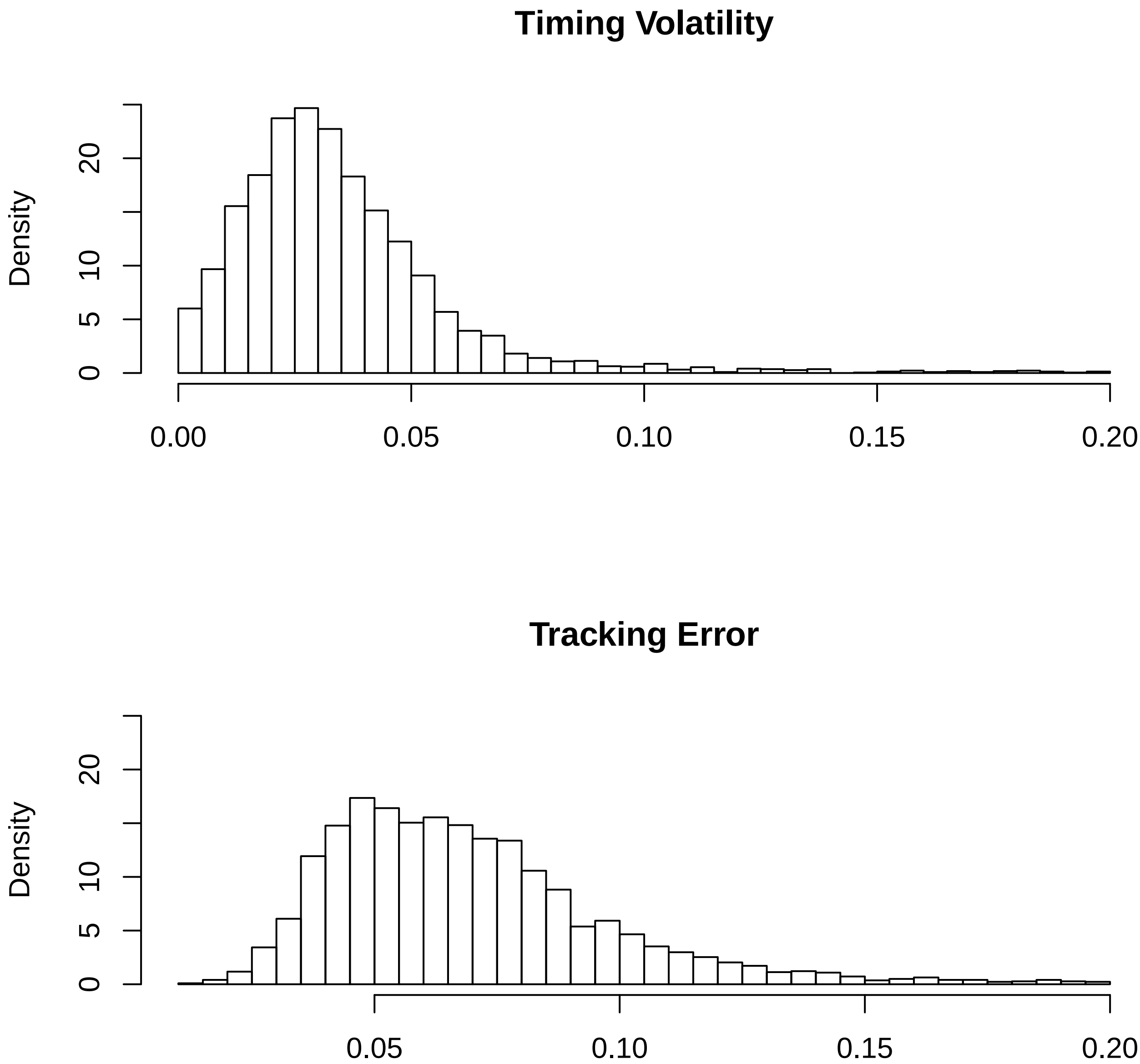
One of the limitations of the present work is that it relies in a parametric measures of exposure to systemic risks. Proxies for active style rotation that are not based on assumptions about the relevant set of risk factors might be a relevant contribution for future research. Another promising direction in which this research could be extended is analyzing the aggregate predictive power of the U.S. equity mutual funds, comparing them with classical predictors for the returns of risk factors.

Table 1: Summary statistics

This table summarizes the characteristics of the funds in my sample over the period from 1980 to 2014. I include fund-quarter observations of U.S. domestic equity funds that are not ETFs, ETNs, passive index funds or sector funds. I also require that (1) the date of the observation is greater than the first offering date of the fund; (2) the total net assets (TNA) are greater than U$ 5 millions; (3) only funds with average investment in stocks (as a percentage of TNA) greater than 75%; (4) holdings data from CRSP or Thomson Reuters are available; and (5) the disclosed portfolio contains at least 10 different stocks. When more than one portfolio is available in a given month, I consider only the portfolio reporting the largest number of stocks.

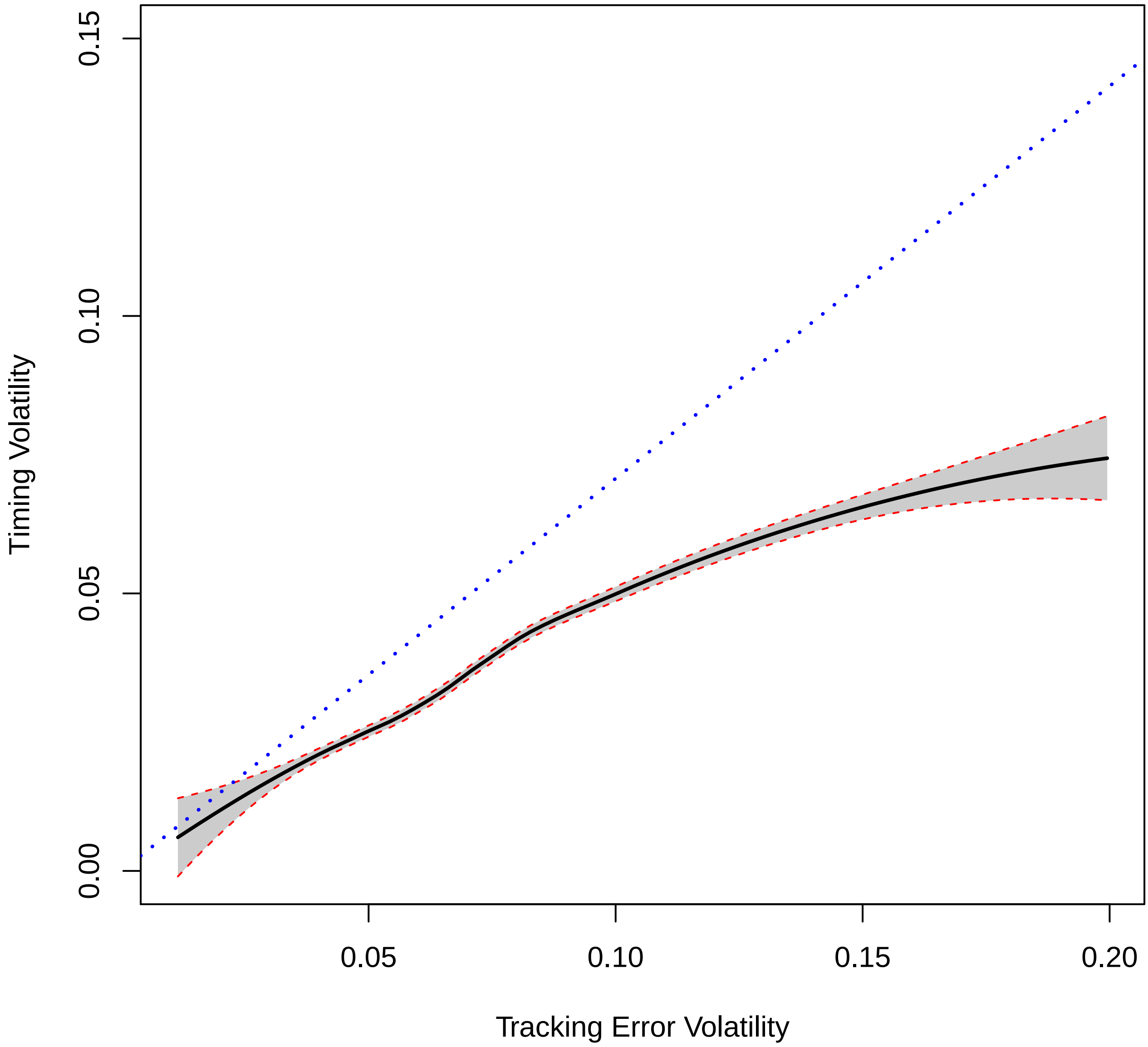
Statistic	N	Mean	St. Dev.	Q(25)	Median	Q(75)
Age (years)	131,266	12.596	12.135	5.167	9.499	15.515
TNA (millions of dollars)	131,266	1,011.485	3,802.058	57.600	200.100	718.800
Flow (proportion of TNA)	131,266	0.043	0.300	−0.039	−0.006	0.046
Expenses (% of TNA)	131,266	0.012	0.004	0.010	0.012	0.015
Turnover (% of TNA)	131,266	0.872	0.852	0.360	0.660	1.140
Stocks (% of TNA)	131,266	88.841	498.591	76.551	86.122	95.140
# of holdings	131,266	109.965	158.283	44	68	109
Number of funds	4,690					
Number of quarters	140					

Figure 1: Cross sectional empirical distribution of the timing volatility measures



Note: this figure plots the cross sectional empirical distribution of the average timing volatility and of the average tracking error measures across different funds, where averages are calculated within each fund. Timing volatility and tracking error for each quarter-fund are defined by equations (3.4) and (3.5).

Figure 2: Fitted average timing volatility conditionally on tracking error



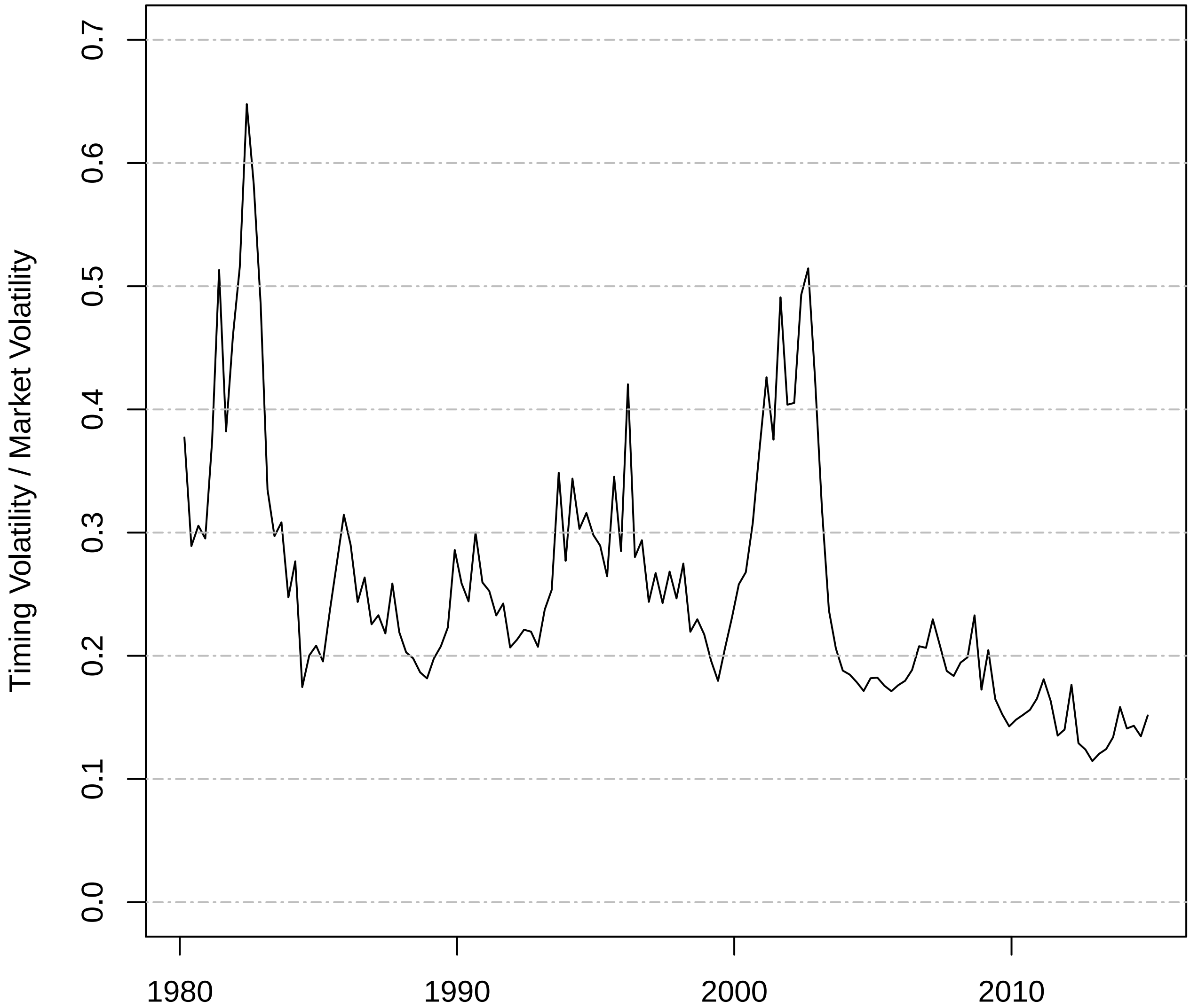
Note: this figure plots the fitted average timing volatility conditionally on tracking error using locally weighted scatterplot smoothing. Red dotted curves are 90% confidence intervals, and the dotted blue straight line is the set of points such that timing volatility and idiosyncratic risks give the same contribution to the total tracking error,

Table 2: Observable characteristics of mutual funds by TVol deciles

This table reports the sample averages of the observable characteristics of mutual funds sorted by deciles of timing volatility. TNA is measured in millions of dollars, age is measured in years, and the other variables are measured in % terms. Standard errors (in parentheses) are clustered by fund and time. * denotes p< 0.1, ** denotes p< 0.05, and *** denotes p< 0.01.

Timing Volatility	Average Characteristics				
Deciles	TNA	Age	Flow	Expenses	Turnover
Decile 1	770.378	10.755	0.051	0.011	0.718
Decile 2	809.515	11.420	0.045	0.012	0.755
Decile 3	872.311	11.794	0.043	0.012	0.764
Decile 4	902.783	12.259	0.042	0.012	0.786
Decile 5	944.776	12.364	0.045	0.012	0.821
Decile 6	1033.041	12.584	0.040	0.012	0.843
Decile 7	998.667	12.707	0.041	0.013	0.881
Decile 8	990.467	12.738	0.044	0.013	0.929
Decile 9	1224.685	13.635	0.041	0.013	1.033
Decile 10	1567.207	15.700	0.038	0.013	1.185
5th quintile - 1st quintile	606.517**	3.584***	-0.009	0.002***	0.373***
	(236.158)	(0.664)	(0.006)	(0.000)	(0.031)
10th decile - 1st decile	796.829**	4.946***	-0.014**	0.002***	0.467***
	(337.325)	(0.880)	(0.007)	(0.000)	(0.043)

Figure 3: Median Timing Volatility Over Time



Note: this figure plots the median timing volatility across different mutual funds in each date, normalized by the volatility of the market (estimated in a rolling window of three years of monthly data).

Table 3: Factor-Based Performance Measures of Decile Portfolios

This table summarizes abnormal returns earned by portfolios of mutual funds sorted by their timing volatility values. Newey–West corrected standard errors (using lags of 36 months) appear in parentheses. * denotes p< 0.1, ** denotes p< 0.05, and *** denotes p< 0.01.

Panel A: Net Returns

Timing Volatility Deciles	Portfolios Factor Loadings Constant	$R_m - R_f$	SMB	HML	MOM	Adj. R^2
Decile 1	-0.101**	1.003***	0.051	0.002	-0.057*	0.953
	(0.047)	(0.019)	(0.046)	(0.048)	(0.030)	
Decile 2	-0.146***	1.019***	0.091*	-0.003	-0.028	0.956
	(0.050)	(0.018)	(0.055)	(0.050)	(0.028)	
Decile 3	-0.104**	1.008***	0.134***	0.009	-0.041	0.952
	(0.053)	(0.017)	(0.051)	(0.045)	(0.026)	
Decile 4	-0.133**	1.029***	0.136**	0.022	-0.016	0.952
	(0.057)	(0.023)	(0.059)	(0.048)	(0.028)	
Decile 5	-0.090	1.007***	0.166***	-0.008	-0.023	0.948
	(0.056)	(0.018)	(0.051)	(0.049)	(0.023)	
Decile 6	-0.131**	1.012***	0.176***	-0.003	-0.001	0.945
	(0.058)	(0.020)	(0.058)	(0.051)	(0.027)	
Decile 7	-0.040	1.004***	0.235***	-0.010	0.025	0.948
	(0.056)	(0.017)	(0.036)	(0.045)	(0.023)	
Decile 8	-0.070	1.004***	0.278***	-0.008	0.035	0.949
	(0.071)	(0.017)	(0.033)	(0.039)	(0.022)	
Decile 9	0.020	1.008***	0.428***	-0.066	0.070**	0.939
	(0.101)	(0.024)	(0.028)	(0.058)	(0.028)	
Decile 10	0.079	1.015***	0.455***	-0.102**	0.084**	0.953
	(0.100)	(0.022)	(0.027)	(0.049)	(0.035)	
5th quintile - 1st quintile	0.173*	0.001	0.370***	-0.084*	0.120***	0.565
	(0.103)	(0.034)	(0.054)	(0.051)	(0.045)	
10th decile - 1st decile	0.181	0.012	0.403***	-0.104**	0.140***	0.576
	(0.110)	(0.035)	(0.053)	(0.049)	(0.052)	

Panel B: Gross Returns

Timing Volatility Deciles	Portfolios Factor Loadings Constant	$R_m - R_f$	SMB	HML	MOM	Adj. R^2
Decile 1	-0.016	1.003***	0.051	0.002	-0.057*	0.953
	(0.047)	(0.019)	(0.046)	(0.048)	(0.030)	
Decile 2	-0.054	1.019***	0.091*	-0.003	-0.028	0.956
	(0.050)	(0.018)	(0.054)	(0.050)	(0.028)	
Decile 3	-0.010	1.007***	0.134***	0.009	-0.042	0.952
	(0.052)	(0.017)	(0.051)	(0.045)	(0.026)	
Decile 4	-0.037	1.029***	0.135**	0.021	-0.016	0.951
	(0.057)	(0.023)	(0.059)	(0.048)	(0.028)	
Decile 5	0.009	1.007***	0.166***	-0.009	-0.023	0.948
	(0.056)	(0.018)	(0.051)	(0.049)	(0.023)	
Decile 6	-0.033	1.012***	0.176***	-0.004	-0.001	0.945
	(0.058)	(0.020)	(0.058)	(0.051)	(0.027)	
Decile 7	0.058	1.004***	0.235***	-0.010	0.025	0.948
	(0.056)	(0.017)	(0.036)	(0.045)	(0.023)	
Decile 8	0.033	1.004***	0.278***	-0.008	0.035	0.949
	(0.071)	(0.017)	(0.033)	(0.039)	(0.022)	
Decile 9	0.124	1.009***	0.428***	-0.067	0.070**	0.939
	(0.101)	(0.024)	(0.028)	(0.058)	(0.028)	
Decile 10	0.181*	1.015***	0.455***	-0.102**	0.083**	0.953
	(0.100)	(0.022)	(0.027)	(0.049)	(0.035)	
5th quintile - 1st quintile	0.188*	0.001	0.370***	-0.084*	0.120***	0.565
	(0.103)	(0.034)	(0.054)	(0.051)	(0.045)	
10th decile - 1st decile	0.197*	0.011	0.404***	-0.104**	0.140***	0.575
	(0.110)	(0.035)	(0.053)	(0.049)	(0.052)	

Table 4: Instrument-Based Performance Measures of Decile Portfolios

This table reports the estimates of the picking (α_i) and timing (θ_i) performance measures defined by equations (4.8, 4.10). All parameters of the model are estimated through GMM based on the moment conditions (4.8, 4.9, 4.10). Net returns of mutual funds were used in calculations. Newey–West corrected standard errors (using lags of 36 months) appear in parentheses. * denotes p< 0.1, ** denotes p< 0.05, and *** denotes p< 0.01.

Timing Volatility	Realized Performance (% per month)	
Deciles	Timing	Picking
Decile 1	-0.039	-0.122
	(0.081)	(0.111)
Decile 2	-0.100	-0.071
	(0.066)	(0.079)
Decile 3	-0.083*	-0.060
	(0.050)	(0.087)
Decile 4	-0.075	-0.071
	(0.077)	(0.096)
Decile 5	-0.069	-0.040
	(0.126)	(0.134)
Decile 6	-0.090	-0.034
	(0.110)	(0.105)
Decile 7	0.074	-0.090
	(0.094)	(0.118)
Decile 8	0.249**	-0.299***
	(0.108)	(0.086)
Decile 9	0.333**	-0.252**
	(0.166)	(0.123)
Decile 10	0.362**	-0.220
	(0.163)	(0.147)
5th quintile - 1st quintile	0.413**	-0.134
	(0.168)	(0.139)
10th decile - 1st decile	0.401**	-0.098
	(0.172)	(0.174)

Table 5: Holding-Based Performance Measures of Mutual Funds

This table presents the sample averages of the timing and picking measures (equations 4.15, 4.14) across different quarter-funds observations. Standard errors (in parentheses) are clustered by fund and time. * denotes p< 0.1, ** denotes p< 0.05, and *** denotes p< 0.01.

Timing Volatility	Holding-Based Performance (% per quarter)	
Deciles	Timing	Picking
Decile 1	-0.006	0.587
	(0.021)	(0.369)
Decile 2	0.024	0.577
	(0.052)	(0.371)
Decile 3	0.050	0.605
	(0.080)	(0.377)
Decile 4	0.128	0.539
	(0.097)	(0.364)
Decile 5	0.160	0.547
	(0.124)	(0.368)
Decile 6	0.252*	0.467
	(0.150)	(0.378)
Decile 7	0.310*	0.472
	(0.179)	(0.389)
Decile 8	0.461**	0.412
	(0.218)	(0.391)
Decile 9	0.691**	0.305
	(0.317)	(0.456)
Decile 10	1.054	-0.228
	(1.506)	(1.245)
5th quintile - 1st quintile	0.864	-0.545
	(0.815)	(0.647)
10th decile - 1st decile	1.060	-0.815
	(1.503)	(1.158)

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