Downside Risk Timing by Mutual Funds

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JEL classification: G10, G11.

Keywords: downside risk, market timing, mutual funds, risk management

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"Our team maintains a strict focus on downside risk management as we remain fully invested in the equity markets."

Jerry Miccolis, CIO of Giralda Advisors

1. Introduction

The financial economics literature has firmly established that investors do not treat upward and downward price movements symmetrically, but exhibit greater sensitivity to losses than to gains. Loss-averse investors require a premium for holdings assets which returns correlate greatly with the market when the market goes down. Thus, securities which pose high downside risk have higher average returns, i.e., they deliver abnormally positive returns in good times to compensate investors for losses sustained during market declines (Ang, Chen, and Xing, 2006).

The important implication of this phenomenon for asset management is that mutual fund managers can achieve superior returns by shifting funds between high and low downside risk stocks in anticipation of broad market movements. In our paper we examine whether mutual funds systematically manage downside risk of their portfolios in ways that improve their (risk-adjusted) performance.

Management of portfolio's downside risk is inherently related to managers' market timing skills as both strategies rely on the ability to predict the direction of future market price movements. A fund manager engaged in market timing would increase fund's exposure to the market by shifting funds from cash and bonds to stocks as well as increase fund's holdings of high regular beta stocks prior to market advances and would decrease exposure to the market prior to market declines. The abnormal performance relative to the passive benchmark is, thus, achieved by switching to assets, which returns correlate strongly with the market in general, before markets go up.[1]

[1] Earlier evidence (Treynor and Mazuy, 1966, Henriksson and Merton, 1981, Becker, Ferson, Myers, and Schill, 1999, Jiang, 2003) suggested that fund managers on average do not have market timing skills. More recent studies (e.g., Chance and Hemler, 2001, Bollen and Busse, 2001, Jiang, Yao, and Yu, 2007), however, find positive market timing ability.

In contrast, if a manager engaged in downside risk timing (hereafter DRT) anticipates the market to go up (down), she would increase (decrease) the fund's ownership of stocks which stand to lose in bad times, i.e., *high downside risk* stocks. Hence, the abnormal value created by this strategy accrues to loading on stocks, which stand to lose a lot in a down market, prior to upward market movements. These two strategies – market timing and downside risk timing – would be identical if stock returns' comovements with market returns were symmetric; but they need not be the same if stocks comove more with the market when the market goes down than when it goes up (Hong, Tu, and Zhou, 2007).

Which of these strategies would a manager pursue? Market timing and downside risk timing are not mutually exclusive strategies, but could rather be used to complement each other. Indeed, if a manager anticipates the market to go up, he may move funds from safer to riskier assets (market timing) and within these riskier assets choose stocks with higher downside beta (downside risk timing). Additionally, mutual funds' mandates in general restrict funds from holding large cash positions which inhibits their ability to take bets on the direction of market movement.[2] Indeed, Yan (2006) shows that aggregate cash holdings by mutual funds do not forecast future returns implying that cash management is not a good indicator of market timing skills by the managers. By actively managing downside risk of a fund's portfolio, a manager can benefit from his ability to predict market returns without violating this restriction. This suggests that downside risk timing is likely to be of first order importance.

Though our paper is the first formal academic investigation of the downside risk timing activities by mutual funds, the financial industry itself has long recognized the importance of managing downside risk for serving clients' needs and improving performance. For example, Janus Orion fund described its investment goals in 2006 prospectus as "seek[ing] to outperform the benchmark index while managing

[2] The following quote from the Oppenheimer Equity Income Fund's prospectus provides an example of such restriction on cash holdings: "It [the fund] will invest at least 80% of its net assets, plus borrowings for investment purposes, in equity securities". Simutin (2014) concludes that cash holdings while imposing drag on performance, allow managers to make quick investments in attractive stocks and satisfy outflows without costly fire sales.

downside risk."[3] A simple Factiva search identifies close to one thousand mutual funds discussing management of downside risk in their 2013 prospectuses.[4]

To organize our thinking of the concept of downside risk timing, we extend Henriksson and Merton (1986) model of market timing. We show that managers which do not possess forecasting abilities about future direction of the market choose optimally not to engage in market timing of any kind. Managers with intermediate abilities engage in classical market timing. Finally, managers with higher forecasting ability are more likely to follow downside risk timing strategies.

To evaluate downside risk timing of mutual funds, we follow the approach of Jiang, Yao, and Yu (2007) and construct a measure based on observed mutual fund portfolio holdings. Specifically, for each fund we estimate its relative beta as the weighted average of downside market betas of the individual stocks held in the portfolio net of the weighted average of their regular market betas. We then test whether the covariance between the abnormal changes in fund's relative beta and holding period market returns – which we denote as Downside Risk Timing or DRT – is significant. Since we focus on changes in downside beta net of changes in regular beta this covariance measures downside risk timing in excess of market timing by construction.

Our holdings-based measure of downside risk timing skills has several advantages over traditionally used returned based measures which are derived from nonlinear regressions of realized fund returns against contemporaneous market returns (e.g., Henriksson and Merton, 1981, Treynor and Mazuy, 1966). First, any non-linear relation between fund returns and market returns may not reflect the timing abilities of the managers, but instead could be induced by certain dynamic trading strategies or option-like features embedded in returns of some portfolio stocks (Jagannathan and Korajczyk, 1986). Second, return-based measures suffer from look-ahead bias as they rely on ex-post realized returns to estimate beta shifting. Holdings-based measures use only ex-ante information on portfolio holdings.

[3] At the beginning of 2006, the fund was ranked in the 89th percentile in terms of downside risk timing skills estimated over the previous 60 month window.
[4] The reported number includes fixed income funds as well as multiple classes of shares by equity mutual funds.

We conduct our analysis on a sample of 4,921 actively managed U.S. equity mutual funds over the period from 1982 and 2011. We demonstrate that, on average, mutual funds have significant positive DRT ability over three and six month horizons. This result is robust to explicitly accounting for funds' market timing activities and most pronounced in more actively managed funds as measured by "active share" (Cremers and Petajisto, 2009).

Downside risk timing ability does not depend on fund size, expense ratio, or turnover. However, funds which tend to invest in large-cap and value stocks appear to have stronger downside risk timing skills. Managers also adjust funds' downside risk exposure in response to macroeconomic information, in particular to the level of both short-term and long-term interest rates, credit premium, and aggregate earning-to-price ratio. Our results, however, remain strong even after controlling for both fund-specific and macroeconomic variables.

Funds skilled in downside risk timing tend to increase their ownership of small stocks and are less inclined to move into growth stocks prior to market increases; they are also less eager to unload momentum stocks prior to market declines. The observed differences in portfolio reallocations, however, are relatively small in magnitude suggesting that changes in downside risk exposure are achieved by shifting funds between stocks with similar characteristics, but different downside betas.

Finally, we assess the economic consequences of downside risk timing. We demonstrate that funds which are more skilled in timing downside risk outperform those who do not: zero-cost strategies based on funds' DRT abilities generate abnormal performance of 13.8 bp per month (or 1.67 percent per year). This performance is stronger during the down markets; however, it is still economically and statistically meaningful in upmarkets.

The paper which is most complementary to ours is Polkovnichenko, Wei, and Zhao (2015). They argue that actively managed mutual funds respond to investors' demand to curtail tail risk by reducing downside risk of their portfolios while at the same time still trying to capture upside potential. Polkovnicheko et al. (2015) show that returns of actively managed value funds exhibit stronger downside hedging properties than passive benchmarks. Our results indicate that funds not only limit their downside risk exposure, but also manage it in value enhancing ways.

The remained of the paper is organized as follows. Section 2 describes measures of downside risk timing and the nature of our tests. Section 3 presents descriptive statistics of our data. In Section 4, we examine mutual fund downside risk timing. Section 5 explores the characteristics of downside risk timers. In Section 6 we explore how down risk timing relates to public information about the state of the economy. Section 7 investigates the mechanisms of downside risk timing. In Section 8 we quantify the economic impact of DRT. A brief conclusion follows.

2. Measures of Downside Risk Timing

Mutual funds can take advantage of anticipated movements in stock market prices by changing their ownership of assets which strongly comove with the market (market timing) and/or by varying their ownership of securities which value is very sensitive to market declines (downside risk timing). [5] These two strategies are not necessarily independent of each other; in fact, they would be identical if stock returns' comovements with market returns were symmetric, i.e., upside and downside betas of the assets were the same. Hong et al. (2007), however, show that stocks comove more with the market when the market goes down than when it goes up, implying that stocks' downside betas are larger than their regular and upside betas.

Assessment of downside risk management by mutual funds is complicated by the fact that the correlation between downside beta and regular beta is on average high 0.77.[6] Fund manager aiming to change the downside beta of his portfolio would be simultaneously affecting its regular beta as well. We

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[5] Fund managers can also use derivative instruments to take directional bets on the market. Trading of derivatives, however, seem to be an exception rather than the rule. For example, Almazan, Brown, Carlson, and Chapman (2004) report that even though over 70% of actively managed funds do not have restrictions on trading options, only 12.4% of those which are permitted to do so trade them. Deli and Varma (2002) show that mutual funds use derivatives primarily to reduce transaction costs, not to manipulate fund's level of risk; funds tend to permit investment only in those derivatives that offer transaction-cost benefits.

[6] Ang et al. (2006) report the correlation of 0.78 at the individual stocks level.

therefore measure downside risk timing activities of mutual funds as changes in downside beta spurring from active trading in excess of changes in regular beta.

In doing so, we follow the approach of Jiang et al. (2007) and derive our measure of downside risk timing ability from fund's portfolio holdings. As the first step, we estimate fund's relative downside beta as the weighted average of the downside betas of the individual stocks held in fund's portfolio net of the weighted average of the regular betas. Active Change in Relative Beta or ACRB then is defined as the change in fund's relative beta due to active trading from quarter $t-1$ to t.

$$ACRB_t = \Delta\left(\hat{\beta}_t^- - \hat{\beta}_t\right) = \sum_{i=1}^{N_t} \omega_{it}\left(\hat{b}_{it}^- - \hat{b}_{it}\right) - \sum_{i=1}^{N_{t-1}} \omega_{it}^{t-1}\left(\hat{b}_{it}^- - \hat{b}_{it}\right). \tag{1}$$

where $\omega_{it}$is the fund portfolio weight of asset i at quarter t, $\hat{b}_{it}^-$ and $\hat{b}_{it}$ are downside and regular beta estimates of asset i at quarter t, N_{t-1} and N_t is the number of assets held in the fund portfolio at quarter $t-1$ and t, and ω_{it}^{t-1} is the passive portfolio weight of asset i at quarter t inferred from fund portfolio holdings at quarter $t-1$.

Downside and regular betas of asset i at time t are estimated from monthly stock returns over the prior 36 months. We use monthly instead of, for example, daily returns as they are more appropriate for capturing investment horizon and performance evaluation periods of fund managers. Daily fluctuations in portfolio value should have little impact on decisions of managers whose performance is evaluated over much longer time intervals. For cash and non-equity holdings, we assume a monthly rate of return equal to the one-month T-bill rate; correspondingly, they are assigned both regular and downside beta values of zero. For stocks with less than 36 months history of returns we assign regular and downside betas of the stock in the same SIC2-industry most similar in terms of market capitalization; our results are not affected if we limit our analysis to funds with holdings of such stocks below 5% of total assets under management. ACRB is equal to zero if a fund maintains its portfolio constant between quarters $t-1$ and t. The ACRB is positive if the most recently disclosed holdings have larger relative beta, i.e., downside beta less regular beta, than holdings observed a quarter before.

An important feature of our analysis is that we use identical time periods to estimate betas applied to both past and current portfolio holdings. In this way we ensure that when measuring fund's downside risk timing activities we capture changes in downside risk exposure induced by active changes in the portfolio composition rather than changes in market conditions.

In the second step, we relate active changes in relative beta over the past quarter to the future monthly market returns. The coefficients γ_1 and γ_2 from the following fund-by-fund time series regressions provide estimates of fund's downside risk timing ability:

$$ACRB_t = \alpha + \gamma_1 r_{m,t+1,k} + \eta_{t+1,k} \tag{2}$$

$$ACRB_t = \alpha + \gamma_2 \mathrm{I}_{r_{m,t+1,k}>0} + \eta_{t+1,k} \tag{3}$$

where $r_{m,t+1,k}$ is the monthly market return in the month $k \in (1,2,3)$ in the quarter $t+1$ and $\mathrm{I}_{r_{m,t+1},k>0}$ is an indicator that takes the value of one when monthly market return $r_{m,t+1,k} > 0$ and zero otherwise. The specifications of these regressions are similar to those of Jiang et al. (2007) in their analysis of mutual fund market timing skills.

The loading estimates γ_1 and γ_2 describe the sensitivity of each $ACRB_t$ to the latent factor driving the forecast target. As Kelly and Pruitt (2013, p. 1727) point out, in this type of forecasting regressions, each $ACRB_t$ is a function of only the expected portion of future returns and is uncorrelated with unanticipated future shocks. Therefore, time-series regression coefficients of $ACRB_t$on $r_{m,t+1,k}$ and $\mathrm{I}_{r_{m,t+1,k}>0}$ describe how each fund's active change in relative beta depends on the true expectation of future market return.

The γ_1 and $\gamma_2$coefficients estimated from (2) and (3) could be interpreted as the Treynor-Mazuy (1966) and Henriksson-Merton (1981) type measures of DRT ability, respectively. A significant positive γ indicates positive downside risk timing and implies that a fund increases its exposure to securities, which stand to lose a lot in a down market, prior to upward market movements.

3. Data and Summary Statistics

We use several data sources in our analysis. CRSP mutual fund data base provide information about fund performance as well as a host of fund characteristics such as assets under management, expenses, age, and investment style. Mutual fund portfolio holdings come from Thomson Financial CDS/Spectrum database; it contains long positions in domestic common stock holdings. Though prior to 2004 funds were required to disclose their holdings semiannually, over 80% of observations are updated quarterly. We merge these two datasets using the MFLINKS files based on Wermers (2000) and available through Wharton Research Data Services. Individual stock returns come from CRSP monthly stock files. CRSP value-weighted index return is used as a proxy for the market return. We use one-month T-bill yields to measure risk-free rate. Our sample covers the time period between 1982 and 2011.

Since our focus is on active portfolio decisions of fund managers, we exclude index funds from our analysis. Additionally, we remove foreign-based funds, U.S.-based international funds, fixed income and balanced funds, real estate funds, precious metal funds, and money market funds. We also exclude funds that manage less than $10 million; funds with missing portfolio ownership over two quarters are also removed. For funds with multiple share classes, fund-level variables are computed as value-weighted averages.

Table 1 reports the summary statistics of the main fund attributes. Our sample includes 4,921 distinct funds and 123,810 fund-quarter observations with valid abnormal changes in relative beta, ACRB. The number of funds ranges from a minimum of 193 in 1982 to a maximum of 1881 in 2011. By averaging first over time series for each fund and then across funds, we obtain the following characteristics: the average total net assets (TNA) of the funds in our sample is $718 million, with quarterly return of 2.13%, an annual turnover ratio of 90.6%, and an annualized expense ratio of 1.18%. The funds invest 91.2% of their assets in common stocks. The average age of the fund, calculated as the time between the first and the last return observation in CRSP Mutual fund data set, is 12.7 years. The mean number of stocks held is 106. Overall descriptive statistics of our sample of mutual funds is very similar to other studies analyzing managerial portfolio decisions and mutual fund performance (e.g., Kacperczyk, Sialm, and Zheng, 2008, Huang, Sialm, and Zhang, 2011).

The average and median active changes in holdings based relative downside beta (ACRB) are close to zero. In contrast, the average and median changes in regular beta (ACB) are significantly negative -0.090 and -0.063, correspondingly, which is consistent with the fact that the number of mutual funds have increased dramatically toward the end of our sample which overlapped with the recent financial crisis. Both ACRB and ACB exhibit significant variation – the respective standard deviations are 0.186 and 0.163.

4. Downside Risk Timing by Mutual Funds

In the Appendix we lay out our intuition for manager's willingness to engage in downside risk timing by extending Henriksson and Merton (1981) model. In our stylized model the manager can choose either between high- and low-beta symmetric securities, or between high-beta asymmetric security (high sensitivity to downside risk) and low-beta symmetric security. We assume that managers can imperfectly forecast future market movements. We depart from Henriksson and Merton (1981) set-up by allowing the manager to optimally decide on the extent of his involvement in market timing strategies. Manager's choice is driven by simple loss-aversion utility function

$$U = (1+\delta)qE(R|R<0) + (1-q)E(R|R>0)$$

where q is the unconditional probability of market going down, and δ is loss aversion parameter. One can think of loss aversion parameter as coming out of higher risk of being fired if manager underperform.

The basic trade-off in the model is between obtaining higher returns in good state of the world versus probability of making wrong forecast and being stacked with high risk sensitivity security in bad state of the world. We show that if quality of forecast is low, then managers choose not to be involved in market timing of any kind. For intermediate levels of forecasting ability managers choose to be involved in classical market timing. If quality of forecast improves further, then instead of market timing managers are involved in downside risk timing. Managers who make perfect forecast are always involved in DRT. Furthermore, we show that willingness to engage in DRT is larger if compensation for downside risk is higher and loss aversion parameter is lower.

We perform downside risk timing tests as specified in equations (2) and (3). We focus on the ability of active changes in fund's relative beta to forecast market returns over the first and the second quarter following its measurement; that is we relate ACRB over the previous quarter to future monthly market returns in months one through three and four through six. We require that a fund has at least five observation-quarters of ACRB to ensure the robustness of inferences.

Table 2 reports the cross-sectional statistics of DRT ability of the mutual funds: γ_1 and γ_2. We focus on the following cross-sectional statistics: the mean, median, standard deviation, skewness, kurtosis, 25% and 75% quartiles, and 5%, 10%, 90%, and 95% extreme percentiles.

The literature discussed a number of issues related to statistical inferences of mutual fund performance tests including data snooping (Lo and MacKinlay, 1990, Sullivan, Timmermann, and White, 1999), non-normality in fund's alphas (Kosowski, Timmerman, Wermers, and White, 2006), managerial luck (Barras, Scaillet, and Wermers, 2010, Fama and French, 2010), cross-sectional correlations in fund returns (Wermers, 1999) etc. To address these concerns, we follow a bootstrapping approach proposed by Kosowski et al. (2006). In the bootstrapping procedure, we randomly resample the data under the null hypothesis of no downside risk timing while maintaining the covariance structure across fund returns. In particular, in each bootstrap we keep $ACRB_t$ unchanged, but randomly sample market returns. We estimate γ_1 and γ_2 for each fund and calculate bootstrapped cross-sectional p-values based on 2,000 replications. Statistical inference is then based on whether the empirical distribution of downside risk timing statistics is significantly different from what one would expect under the null hypothesis that no fund engages in downside risk timing in economically profitable ways. We refer to the corresponding papers for the details of bootstrapping procedure.[7]

[7] Newey-West adjusted p-values (unreported) indicate stronger statistical significance for all of our estimates.

Mean and median DRT measures are positive and strongly significant at the one quarter horizon, both if we consider Treynor-Mazuy and Henrikson-Merton type measures. The predictive ability of the average and median fund over the second quarter is marginally significant at best. For γ_1, for an average (median) fund, a one standard deviation larger monthly market return in the subsequent quarter is related to a 0.0062 (0.0045) larger active change in the relative beta which corresponds to 3.4% (2.4%) of its standard deviation. For γ_2, a positive future monthly market return is associated with a 0.015 (0.012) larger ACRB for an average (median) fund or 8.8% (6.5%) of its standard deviation.

Funds at the 75th, 90th, and 95th percentiles of the distribution, however, have positive downside risk timing ability over both horizons. For example, for γ_1, a one standard deviation larger monthly return in the subsequent quarter is related to 0.0164 (0.0319, 0.0455) larger ACRB for a fund at the 75th (90th, 95th) percentile of downside risk timing skill distribution which corresponds to a 8.8% (17.2%, 24.5%) of ACRB standard deviation. The strength of the relationship between changes in relative beta and monthly market returns in the second quarter decreases by about 15%. These results are consistent with the evidence on positive market timing ability for holdings based measures by Jiang et al. (2007).

Even though we measure changes in downside risk exposure in excess of changes in regular market exposure it is important to establish that our results are robust to controlling for market timing activities directly. In Table 3 we re-estimate downside risk timing tests controlling for contemporaneous active changes in (regular) beta (ACB) by mutual funds defined as

$$ACB_t = \Delta\hat{\beta}_t = \sum_{i=1}^{N_t} \omega_{it}\hat{b}_{it} - \sum_{i=1}^{N_{t-1}} \omega_{it}^{t-1}\hat{b}_{it}. \tag{4}$$

In particular, we estimate the following regressions

$$ACRB_t = \alpha + \delta_1 ACB_t + \gamma_1 r_{m,t+1,k} + \eta_{t+1,k} \tag{5}$$

$$ACRB_t = \alpha + \delta_2 ACB_t + \gamma_2 \mathrm{I}_{r_{m,t+1,k}>0} + \eta_{t+1,k} \tag{6}$$

We report mean and median values for the coefficients on regular beta changes (δ_1 and δ_2), mean, median, 75th, and 90th percentiles of downside market timing abilities (γ_1 and γ_2) as well as bootstrapped p-values. In this instance, when performing bootstrap estimations we keep $ACRB_t$ and ACB_t unchanged, while randomly sampling market returns.

The results indicate that DRT ability of average, median, top quartile, and top decile funds continues to remain strong over the three months horizon, but becomes mostly insignificant over the second quarter. Interestingly, the coefficient on changes in regular beta is negative (though small) suggesting that funds increasing their exposure to market do not increase their downside beta to the same extent. This does not, however, imply that changes in relative beta and changes in regular beta are correlated with future market returns in opposite ways; we provide evidence on this in Section 7.2.

Actively managed funds vary considerably in how active their strategies are, i.e., to what extent their portfolios differ from benchmark portfolios. Petajisto (2013) finds that closet indexing has become increasingly popular since 2007 currently accounting for about one-third of all mutual fund assets. We would expect that funds that are classified as actively managed, but do not engage much in any type of active management should, on average, show little DRT ability. Likewise, we expect there to be less variation in DRT ability across closet indexers.

We test this conjecture in Table 4. Funds are divided into three groups by their sample-average “active share” (Cremers and Petajisto, 2009, Petajisto, 2013) which measures the percentage of the fund’s portfolio that differs from the fund’s benchmark index. We re-estimate regressions (2) and (3) for each of “active share” terciles of funds and present descriptive statistics of downside risk timing measures.

Most actively managed funds, on average, exhibit most positive DRT abilities. Moreover, they are the only group for which changes in relative beta robustly predict future market returns both over the first and the second quarters. In contrast, closet indexers show the lowest DRT abilities; statistical significance of the inferences is also significantly weaker. Additionally, we also observe that variation in downside risk timing skills is also largest among most actively managed funds.

5. Characteristics of Downside Risk Timers

The results of previous section suggest that mutual funds on average possess positive downside risk timing ability. We now proceed to explore the characteristics of successful downside risk timers.

We consider two dimensions: characteristics of the fund (total net assets, the expense ratio, and turnover) and characteristics of fund's portfolio (size, book-to-market ratio, momentum, and industry concentration of stocks in fund's portfolio). To remove the impact of time trends, for all variables, but industry concentration, we use percentile ranks. Following Jiang et al. (2007) and Huang et al. (2011), percentile ranks for net assets, expense ratio, and turnover are computed as follows: every year we obtain percentile rank of each variable across funds; the annual percentile ranks are then averaged over time for each fund.

The percentile ranks for characteristics of stocks in fund's portfolio (size, book-to-market ratio, and momentum) are derived by obtaining percentile ranks for all stocks in CRSP in each quarter; we then compute the weighted average of percentile ranks for each fund, where the weights are proportional to the values of stock positions in the portfolio. These quarterly measures are subsequently averaged over time for each fund. Industry concentration index (ICI) is computed following Kacperczyk, Sialm, and Zheng (2005) based on the Fama-French 12-industry SIC classification. All variables are demeaned relative to cross-sample fund averages to facilitate the interpretation of results.

We then perform the following panel regressions to gauge the relation between various fund characteristics and the downside risk timing measure:

$$ACRB_{it} = \alpha_i + (b_0 + bC_i)r_{m,t+1,k} + \delta_i + \theta_{tk} + e_{itk} \tag{7}$$

$$ACRB_{it} = \alpha_i + (b_0 + bC_i)\mathrm{I}_{r_{m,t+1}>0} + \delta_i + \theta_{tk} + e_{itk} \tag{8}$$

where C_i is the vector of fund characteristics, δ_i and $\theta_{tk}$are fund and time (quarterly) fixed effects; standard errors are clustered at the fund level.

The results are reported in Table 5. First thing to notice is that the coefficients on market return itself are positive and statistically significant over the 3 month horizon, but turn insignificant for the second quarter. This corroborates our findings from Fama-MacBeth regressions performed in Table 2 that mutual funds on average load more on downside risk prior to upward market movements, i.e., have positive downside risk timing skills, and that this relationship weakens over time.

Downside risk timing ability does not depend on fund's size, expense ratio, or turnover in a systematic way, but relates to fund's investment style. Funds investing in large-cap stocks and value stocks appear to be better at downside risk timing over one quarter horizon. The impact of all fund's characteristics on downside risk timing skills in the second quarter is not statistically significant.

6. Public Information and Downside Risk Timing

The extensive literature has established that macroeconomic variables are useful for predicting stock market movements (e.g., Chen, Roll, and Ross, 1986, Fama and French, 1989, Ferson and Harvey, 1991). We therefore proceed to investigate whether these variables are helpful at explaining downside risk timing by mutual funds. We consider four macro-variables: short-term interest rate, term premium, credit premium, and aggregate earnings-to-price ratio. We use the one-month T-bill yield as the short-term interest rate (obtained from Ken French website). The term premium is the yield spread between the 10-year T-bond and one-month T-bill; the credit premium is the average yield spread between Moody's Baa-rated and Aaa-rated corporate bonds (both obtained from St. Louis Fed website). The aggregate earnings-to-price ratio is based on the S&P 500 index and is estimated as the cyclicality adjusted ratio of aggregate earnings of S&P500 constituents divided by their average price (obtained from Robert Shiller website).[8]

To investigate whether fund managers rely on macroeconomic information to manage downside risk of their portfolios we perform the following fund-by-fund regressions:

[8] In unreported specifications we also used dividend yield. However, since correlation between earnings-to-price ratio and dividend yield is over 90%, we dropped dividend yield from reported specifications. It does affect only coefficients for Earnings/price.

$$ACRB_{it} = \alpha_i + bM_{t-1} + e_{it} \tag{9}$$

where M_{t-1} is the vector of macroeconomic variables at the end of the previous quarter. We report mean and median coefficients as well as bootstrapped p-values.

The results in Table 6, Panel A, indicate that fund managers take into account public information about the state of the economy when adjusting their exposure to the market downside risk. In particular, they tend to decrease their exposure to stocks with a high likelihood of losing value in the down markets when short term rate is high and term premium and credit premium is large. They also increase the downside risk of their portfolios at times when earnings are high relative to prices. One standard deviation larger short term rate (term spread, credit spread) results in a 0.075 (0.028, 0.026) smaller active change in relative beta (ACRB) or 40% (14.9%, 14.1%) of its standard deviation. Similarly, a one standard deviation larger Earnings-to-Price ratio is associated with 0.081 larger ACRB (or 43.5% of its standard deviation).

It is also important to verify that downside risk timing ability remains in place after controlling for macroeconomic variables. The remaining predictive power of active changes in relative beta on future market returns may relate to the private information possessed by managers.[9] To investigate this issue we augment regressions (2) and (3) with macro variables in the spirit of Ferson and Schadt (1996):

$$ACRB_t = \alpha + bM_{t-1} + \gamma_1 r_{m,t+1,k} + \eta_{t+1,k} \tag{10}$$

$$ACRB_t = \alpha + bM_{t-1} + \gamma_2 \mathrm{I}_{r_{m,t+1,k}>0} + \eta_{t+1,k} \tag{11}$$

As before, we report the cross-sectional distribution of holding based Treynor-Mazuy (γ_1) and Henrikson Merton (γ_2) type downside risk timing measures with bootstrapped p-values.

The results reported in Table 6, Panel B, show that though after controlling for macroeconomic variables our estimates of fund's downside risk timing ability decrease by between 10% and 30%, they are still economically and statistically significant. This indicates that macroeconomic information alone cannot

[9] Alternatively, it may also attribute to the public information unaccounted by the macroeconomic variables that we considered.

fully explain fund’s downside risk timing skills. It points out that when adjusting downside risk of their portfolios, managers use not only macroeconomic variables, but also other, possibly private, information as well. We now proceed to investigate changes in portfolio characteristics ensuing management of downside risk.

7. Mechanisms of Downside Risk Timing

Mutual funds have several mechanisms through which they can manage the downside risk of their portfolios. First, they can move funds between equity holdings and cash. However, since we consider changes in funds’ downside risk exposure in excess of changes in exposure to the regular market risk, these portfolio reallocations would not have an effect on relative betas. Second, within equities, funds can switch between low downside beta and high downside beta stocks. This could result in significant adjustments to the characteristics of funds’ portfolios such as the exposure to the market risk, the number of stocks or the concentration of their portfolios, or considerable reallocation of resources between stocks belonging to different investment styles. These are the subject of our analysis reported in Table 7.

Since downside risk timing rests on the ability of managers to predict market movements, we break down our sample into the quarters followed by positive market returns over the subsequent three months (Panel A) and quarters followed by the negative market returns over the subsequent three months (Panel B). In each partitioning, every quarter we sort mutual funds based on their downside risk timing ability γ_1 estimated from the regression (2) over the entire sample and explore quarterly changes in characteristics of funds’ portfolios.[10]

In Panel A we study portfolio reallocations prior to upward market movements. As expected, we observe that in quarters preceding market appreciation funds with high downside risk timing skills increase relative betas of their portfolios while funds with low (negative) downside risk timing ability decrease them. The spread in average (median) changes in relative beta between funds in the top and bottom deciles of

[10] Analysis based on sorting done on γ_2 yields qualitatively similar results.

downside risk timing abilities is 0.074 (0.058). At the same time, both skilled and non-skilled downside risk timers adjust their exposure by similar magnitudes; similar observation can be made when we consider changes in cash holdings, number of stocks, and portfolio concentration of funds' portfolios. Prior to aggregate stock market appreciation, funds with high DRT skills tend to shift their resources toward smaller stocks and do not move funds into growth stocks to the same degree as funds with low DRT skills; all funds, however, make similar portfolio adjustments with respect to the momentum and industry concentration of portfolio stocks and how active they are relative to benchmark portfolios.

In Panel B we find that prior to market declines funds with high downside risk timing skills decrease relative betas of their portfolios while funds with low skills, on the opposite, increase their exposure to the downside market risk. The difference in average (median) changes in relative beta between funds in the top and bottom deciles of downside risk timing abilities is -0.083 (-0.051) which is very similar in magnitude to the corresponding mean (median) difference in changes in relative beta observed prior to the upward market movements reported in Panel A. Funds with high DRT abilities also decrease their exposure to the overall market risk to a larger degree. These funds also increase their portfolio concentration which is achieved, however, by keeping the number of stocks in the portfolio relatively unchanged. Finally, skilled downside risk timers are also less eager to move out from momentum stocks than non-skilled funds.

Besides pronounced differences in management of downside risk exposure, any other observed differences in portfolio reallocations by skilled and non-skilled downside risk timers in both sub-periods, however, are relatively small in magnitude: for example, for all portfolio characteristics measured as percentile scores (size, B/M, momentum) differences in average changes in these variables for top 10% and bottom 10% of funds ranked by DRT skill are within one percentage point – suggesting that variation in downside risk timing activities across funds accrues mostly to shifting funds between stocks with similar characteristics, but different downside betas.

8. Economic Value of Downside Risk Timing

In this section we explore economic consequences of downside risk timing. We approach it from two perspectives. First, we compare the performance generated by funds which are successful in downside risk timing to the performance of those which are not. Second, we evaluate whether the observed action of mutual funds constituting downside risk timing – i.e., active changes in relative beta – can predict fund performance.

7.1. Mutual Fund Performance and Downside risk timing

Positive downside risk timing ability displayed by mutual funds on average should improve their performance. To assess its magnitude we exploit the cross-section variation in the DRT ability by funds established in Section 4. In particular we consider performance of zero-cost portfolios based on fund's DRT. Each quarter funds are sorted into ten groups based on their downside risk timing ability evaluated on a rolling basis over the previous sixty months with the help of Equation (2), coefficient $\gamma_1$being our measure of DRT skill.[11] Zero-cost portfolios are constructed by going long in funds with the highest downside risk timing ability (highest γ_1 group) and going short in funds with the lowest ability (lowest γ_1 group); portfolios are rebalanced quarterly.[12]

In Panel A of Table 8 reports average portfolios returns as well as risk-adjusted returns according to CAPM, Fama-French, Carhart, and Pastor-Stambaugh models. All coefficients are multiplied by 100; p-values are reported in parentheses.

We observe that funds that possess highest DRT ability consistently outperform funds with lowest DRT ability: for example, last specification reports that zero-cost portfolio delivers alpha of 13.8bp per month or 1.67 percent per year (Specification 5). To put these results into a perspective, Jiang et al. (2007) estimate that for an average fund the economic value of market timing is about 0.60% per year.[13]

[11] We anticipate that funds' relative ability to manage downside risk demonstrated over the preceding sixty months persists over the subsequent quarter.

[12] The performance of portfolios based on $\gamma_2$as a measure of downside risk timing ability is very similar (unreported).

[13] It is important to notice that Jiang et al. (2007) estimates were achieved using contingent claim valuation using average estimates of mutual fund market timing abilities, whereas ours are calculated by comparing performance of funds in the top 20% and bottom 20% groups by downside risk timing abilities.

When does downside risk timing pays off best? In Panel B of Table 8 we explore this issue by conditioning our analysis on the state of the economy. In particular, we re-estimate our calendar portfolio analysis by allowing both the intercept and factor loadings to vary across the business cycle. Recession dummy is set to be equal to one if the month of observation falls into the recession period as defined by NBER and zero otherwise and, therefore, measures the incremental abnormal performance during the recession. For exposition purposes, we report only estimates of intercepts and coefficients on recession dummy with corresponding p-values.

The downside risk timing appears to work well both in economic expansions and downturns. At the same time we observe that most of the gains to this strategy accrue to the periods of recession. This is perhaps unsurprising given that a) market return volatility is larger during recessions; b) success of downside risk timing strategy hinges on the ability to predict the direction of the market.

How does performance attributed to downside risk management vary across fund's market timing abilities? This is the focus of our analysis reported in Table 9. At the end of each quarter we run a regression similar to the regression (2) with active change in regular beta, or ACB, as the dependent variable; regression is run over the previous sixty month time interval. The slope coefficient on this regression is used as a contemporaneous measure of fund's market timing ability.

Each quarter we sort funds into three categories by market timing and, within each of these groups, into ten groups by downside risk management measure. Zero-cost portfolios going long in funds in the top 10% of downside risk timing group and shorting funds in the bottom 10% downside risk timing category are then formed and performance evaluation analysis performed.

We find that funds with high downside risk timing skills outperform those with low downside risk timing skills in all market timing skills categories. The economic and statistical differences in returns to downside risk timing between different market timing groups are negligible. We attribute this result to the fact that we measure downside risk timing activity is orthogonal to market timing by construction.

7.2. Active Changes in Relative Beta and Fund Performance

Finally, we explore whether observed actions of mutual funds constituting downside risk timing, i.e., active changes in relative beta, are helpful at predicting fund's performance. In particular, we estimate whether active changes in fund's relative beta are related to future returns after controlling for fund's characteristics. We run multivariate Fama-Macbeth regressions; the dependent variable in each cross-section is a performance measure in a particular month. The independent variables are holdings based measure of fund's active changes in relative beta (ACRB), holdings based relative beta, active change in regular beta (ACB), portfolio beta, return over the previous quarter, the logarithm of the assets of the fund, logarithm of the total assets in the fund family, the expense ratio of the fund, the turnover ratio, the growth rate in new money over the previous quarter, the logarithm of fund's age, fund's active share and tracking error measures.

To adjust for risk and style we use four different performance measures; (1) 1-factor adjusted return; (2) four-factor adjusted return; (3) fund's return in excess of the fund's size weighted average return of the funds in the same style category; and (4) the return gap; the latter is computed following Kacperczyk, Sialm, and Zheng (2008) as the difference between the fund return and the holdings return after adjusting for fund expenses.

The results are reported in Table 10. They show that across all performance measures and sets of controls changes in fund's relative beta resulting from active trading are positively associated with future performance. From specification 3 (6, 9, 12) we see that a one standard deviation variation in ACRB is related to a 0.15bp (0.17bp, 0.39bp, 0.26bp) larger risk-adjusted monthly return in the next three months or 0.18% (0.20%, 0.47%, 0.31%) annualized.

These regressions also show that active changes in regular beta, ACB, also related to future performance with the expected sign and that the economic magnitude of this relationship is similar to that between changes in relative beta and performance. A one standard deviation variation in ACB is associated with 0.29bp (0.08bp, 0.35bp, 0.17bp) larger risk adjusted monthly returns.

When we consider control variables, we observe that the signs of the coefficients are consistent with findings in the literature. Funds with better performance over the previous quarter continue to do well

(Carhart, 1997), so do more actively managed funds (Cremers and Petajisto, 2009) and funds with larger inflows (Zheng, 1999, Lou, 2012). High expense funds are delivering lower performance (Gil-Bazo and Ruiz-Verdu, 2009).

Conclusion

Previous research finds that securities which returns correlate greatly with market when markets go down (high downside risk securities) deliver on average higher abnormal returns. This suggests that mutual fund managers can achieve superior returns by shifting funds between high and low downside risk stocks in anticipation of broad market movements. We study whether mutual funds systematically manage downside risk of their portfolios in ways that improve their performance. We find that mutual funds on average possess positive downside risk timing ability. Funds with different characteristics are equally likely to engage in strategies consistent with downside risk timing. Managers adjust funds' downside risk exposure in response to macroeconomic information. Funds more skilled in timing downside risk outperform those who are not by 13.8bp per month (or 1.67 percent per year).

Appendix: The Model

The model in this appendix is an extension of Henriksson and Merton (1981). Let us assume that economy consists of three securities and manager can hold only one of them at a time.

1. Symmetric high beta security ($\beta_+=\beta_-=\beta_H$). Assume $E(R_1)= \beta_H\lambda$ where λ is risk premium. Assume throughout r_F=0 and all returns are already excess ones.
2. Symmetric low beta security ($\beta_+=\beta_-=\beta_L$). Assume $E(R_2)= \beta_L\lambda$.
3. Asymmetric security ($\beta_+=\beta_H<\beta_-$). Assume $E(R_3|R_m>0)= \beta_H R_m +\Delta\lambda$ and $E(R_3| R_m <0)= (\beta_H+\Delta\beta) R_m$. $\Delta\lambda$ is additional risk premium associated with downward movements.

Managers are price takers. They cannot short sale, borrow or lend and have to be fully invested at each moment of time. Each manager is endowed with \$1. We assume simple piece-wise utility function for managers:

$$U= (1+\delta)E(R|R<0)+ E(R|R>0) \qquad \text{(A1)}$$

This is simplest version of Kahneman-Tversky utility function. It can be interpreted either via normal behavioral finance argument, or by increased chances of getting fired in case of underperformance.

Assume manager forecast returns correctly with probability p. It is reasonable to assume that $0.5\leq p\leq 1$. Probability of 0.5 corresponds to totally uninformative forecast, and p=1 corresponds to perfect forecasting ability.

Portfolio of two symmetric securities

Note that this case is just classical Henriksson-Merton (1981) market timing. We assume that managers jump between low and high beta security based on her forecast. In this case expected returns are given by

$$E(R) = q[p\beta_L + (1-p)\beta_H]E(R_m|R_m \leq 0) + (1-q)\,[p\beta_H + (1-p)\beta_L]E(R_m|R_m > 0)$$

where q is unconditional probability of market going down. It can be rewritten as:

$$E(R) = q(2p-1)(\beta_H - \beta_L)E(R_m|R_m \leq 0) + (p\beta_L + (1-p)\beta_L)\lambda,$$

where second part is average market exposure compensation, and first term is coming via market timing. The first term is zero if manager has no forecasting ability.

Manager's utility function for market timing regime is

$$U_{MT} = \delta\big(\beta_H + p(\beta_L - \beta_H)\big)\,E(R_m|R_m \leq 0) + q(2p-1)(\beta_L - \beta_H)E(R_m|R_m \leq 0) +$$

$$+(\beta_L + p(\beta_H - \beta_L)\lambda. \qquad \text{(A2)}$$

First term is penalty for wrong forecast. Utility function for no market timing case (assuming manager holds low-risk security)

$$U_{not\ MT} = \beta_L\lambda + \delta q\beta_L E(R_m|R_m \leq 0) \qquad \text{(A3)}$$

Comparing utility with the case where there is no market timing, we get the condition for market timing:

$$U_{MT} > U_{not\ MT} \iff p[\lambda + (\delta+2)q|E(R_m|R_m \leq 0)|] > q(1+\delta)|E(R_m|R_m \leq 0)|$$

Thus, for any p> p* managers choose market timing over having lower risk security. p* is given by

$$p^* = \frac{q(1+\delta)|E(R_m|R_m \leq 0)|}{\lambda + (2+\delta)|E(R_m|R_m \leq 0)|}\ , \qquad (A3)$$

It is easy to show that

$$\frac{\partial p^*}{\partial \delta} > 0, \frac{\partial p^*}{\partial q} > 0.$$

Thus, higher low aversion δ (higher risk of downside market movement) leads to higher precision of forecast necessary for manager to be engaged in market timing.

Downside Risk Timing case (choice between low and asymmetric security)

In this case, expected returns

$$E(R) = q[p\beta_L + (1-p)(\beta_H + \Delta\beta)]E(R_m|R_m \leq 0) + (1-q)[p\beta_H + (1-p)\beta_L]E(R_m|R_m > 0) + (1-q)p\,\Delta\lambda.$$

Utility of the manager who is involved in downside risk timing is

$$U_{DRT} = U_{MT} + (1+\delta)\,q\,(1-p)\,\Delta\beta + (1-q)\,p\,\Delta\lambda.$$

Thus, managers would prefer to execute downside risk timing strategy over market timing strategy if

$$(1+\delta)\,q\,(1-p)\,\Delta\beta + (1-q)\,p\,\Delta\lambda > 0.$$

Thus, if $p > p^{**}$, then manager would prefer to execute downside risk timing strategy over market timing strategy, where

$$p^{**} = \frac{(1+\delta)\,q\,\Delta\beta\,|E(R_m|R_m \leq 0)|}{(1+\delta)\,q\,\Delta\beta\,|E(R_m|R_m \leq 0)| + (1-q)\Delta\lambda}\,. \qquad (A4)$$

One can characterize the equilibrium as:

$$\frac{\partial p^{**}}{\partial \delta} > 0, \frac{\partial p^{**}}{\partial \Delta\lambda} < 0, \frac{\partial p^{**}}{\partial \Delta\beta} > 0.$$

Thus, downside risk timing strategy is more likely if payment for downside risk is higher and if forecast is better. It is possible to show that if

$$\Delta\beta(\lambda + q|E(R_m|R_m \leq 0)|) > (1-q)\Delta\lambda, \qquad (A5)$$

then $p^{**} > p^{*}$. Also, from Eq. (A4) $p^{**} < 1$. Thus, in (p-δ) space there exist three distinctive regimes: if precision is low, manager choose not to be engaged in market timing. As precision increases, managers choose to be engaged in portfolio shifting between low and high beta securities. Finally, if $p>p^{**}$, managers are involved in downside risk timing. We plot this space in Figure A1.

If condition (A5) is not satisfied (for example, because compensation for downside risk is very high), then $p^{*}>p^{**}$. In that case, $U_{DRT}>U_{not\ MT}$, which is satisfied if $p>p^{***}$, where

$$p^{***} =$$

$$= \frac{q|E(R_m|R_m \leq 0)|(1+\delta)[\beta_H - \beta_L + \Delta\beta] + \lambda(\beta_H - \beta_L)}{q|E(R_m|R_m \leq 0)|(1+\delta)[\beta_H - \beta_L + \Delta\beta] + \lambda(\beta_H - \beta_L) + \lambda(1-q) + q(\beta_H - \beta_L)|E(R_m|R_m \leq 0)|}$$

p^{***} satisfies the following conditions:

$$\frac{\partial p^{***}}{\partial \delta} > 0, \frac{\partial p^{***}}{\partial \Delta\lambda} < 0, \frac{\partial p^{***}}{\partial \Delta\beta} > 0.$$

Thus, for the case if condition (A5) is not satisfied, only two regimes exist, no market timing and downside risk timing.

Figure A1:

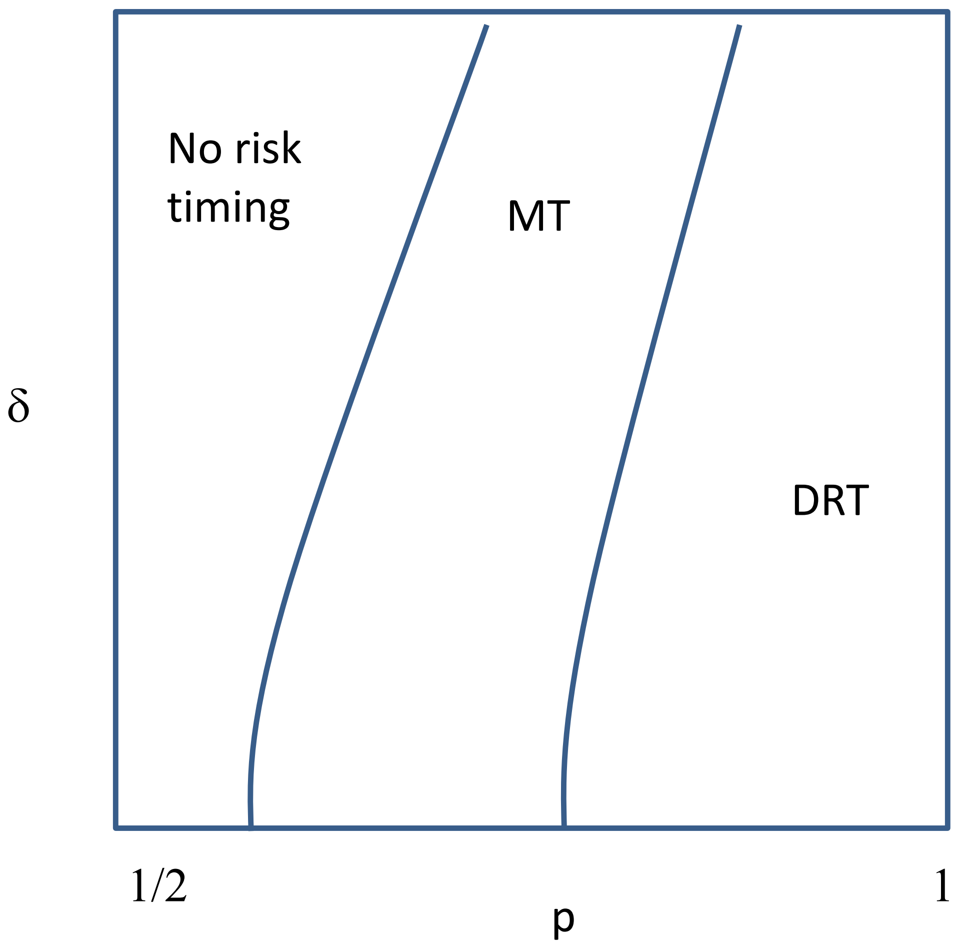

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Table 1. Descriptive Statistics

We report the summary statistics of the main fund attributes. Our sample includes 4,921 distinct funds and 123,810 fund-quarter observations with valid active changes in relative beta, ACRB. The number of funds ranges from 193 in 1983 to 1881 in 2006. By averaging first over time series for each fund and the across funds, we obtain the following characteristics: the average total net assets (TNA) of the funds in our sample is $718 million, with an quarter return of 2.13%, an annual turnover ratio of 90.6%, and an annualized expense ratio of 1.18%. The funds invest 91.2% of their assets in common stocks. The average age of the fund, calculated as the time between the first and the last return observation in CRSP Mutual fund data set, is 12.7 years. The mean number of stocks held is 106.

	Mean	Median	Std. Dev.	Q1	Q3
Total Net Assets (TNA) (in Millions)	717.598	142.658	2800.000	46.300	479.400
Age (in Years)	12.667	9.750	9.291	6.000	16.167
Expense Ratio (in Percent)	1.182	1.120	0.478	0.900	1.400
Turnover Ratio (in Percent)	90.593	65.000	118.617	34.000	112.000
Common Stock Proportion (in Percent)	91.165	95.350	50.576	89.490	98.140
Cash Proportion (in Percent)	5.409	3.000	8.915	0.830	6.760
Bond Proportion (in Percent)	0.417	0.000	3.021	0.000	0.000
Preferred Stock Proportion (in Percent)	0.511	0.000	4.138	0.000	0.000
Other Securities Proportion (in Percent)	0.570	0.000	48.898	0.000	0.000
Flow (in Percent per Quarter)	1.059	-0.934	17.815	-4.334	3.552
Investor Return (in Percent per Quarter)	2.126	3.123	10.816	-2.886	8.405
Holdings Return (in Percent per Quarter)	5.432	5.593	11.549	-0.519	11.687
Number of Stock Positions	105.996	69.000	161.906	46.000	108.000
Industry Concentration Index (in Percent)	11.617	4.111	20.156	2.085	8.480
Size Score	89.380	93.524	10.964	84.858	97.543
Value Score	35.892	34.687	11.888	27.083	43.539
Momentum Score	57.563	57.450	12.693	49.194	65.884
Active Change in Relative Beta, ACRB	-0.001	0.000	0.186	-0.068	0.067
Active Change in (Regular) Beta, ACB	-0.090	-0.063	0.163	-0.168	0.008

Table 2. Downside Risk Timing

We report the cross-sectional distribution of holding based Treynor-Mazuy (γ_1) and Henrikson Merton (γ_2) type mutual fund's downside risk timing measures; regression specifications are presented by equations (2) and (3). Estimations are performed using fund active relative downside beta changes, which are defined in equation (1). The bootstrapped p-values (p) are reported in parentheses underneath. "Stdev", Skew", and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis respectively.

	5%	10%	25%	mean	median	75%	90%	95%	stdev	Skew	Kurto
Months 1-3											
γ_1	-0.609	-0.378	-0.112	0.137	0.098	0.360	0.699	1.003	0.583	0.753	12.800
p	(0.38)	(0.29)	(0.16)	(0.04)	(0.06)	(0.03)	(0.02)	(0.02)	(0.00)	(0.12)	(0.20)
γ_2	-0.049	-0.029	-0.009	0.015	0.012	0.037	0.065	0.090	0.047	0.499	5.376
p	(0.13)	(0.06)	(0.08)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.06)	(0.19)	(0.89)
Months 4-6											
γ_1	-0.677	-0.385	-0.127	0.084	0.077	0.311	0.602	0.858	0.554	0.101	18.305
p	(0.54)	(0.27)	(0.19)	(0.13)	(0.10)	(0.06)	(0.08)	(0.08)	(0.02)	(0.44)	(0.07)
γ_2	-0.055	-0.034	-0.013	0.009	0.007	0.028	0.054	0.076	0.043	0.373	6.805
p	(0.28)	(0.20)	(0.22)	(0.12)	(0.09)	(0.07)	(0.09)	(0.10)	(0.06)	(0.26)	(0.59)

Table 3. Downside Risk Timing: Controlling for Fund's Market Timing Activities

We report the results of the relationship between fund's downside risk timing and future market return controlling for fund's market timing ability (regressions are presented by equations (5) and (6). Estimations are performed using fund active relative downside beta changes, which are defined in equation (1), and active changes in fund's regular beta (equation (4)). The bootstrapped p-values (p) are reported in parentheses underneath.

	ACB_t		$r_{m,t+1}$			
	mean	median	mean	median	75%	90%
Months 1-3						
γ_1	-0.098	-0.106	0.122	0.088	0.336	0.658
p	(0.04)	(0.17)	(0.04)	(0.05)	(0.01)	(0.01)
γ_2	-0.098	-0.104	0.013	0.010	0.034	0.061
p	(0.03)	(0.05)	(0.01)	(0.02)	(0.01)	(0.02)
Months 4-6						
γ_1	-0.097	-0.101	0.065	0.051	0.272	0.541
p	(0.01)	(0.11)	(0.16)	(0.16)	(0.08)	(0.10)
γ_2	-0.098	-0.101	0.006	0.005	0.026	0.052
p	(0.03)	(0.10)	(0.19)	(0.14)	(0.04)	(0.10)

Table 4. Downside Risk Timing: by Fund's Active Share.

We report the cross-sectional distribution of holding based Treynor-Mazuy (γ_1) and Henrikson Merton (γ_2) type mutual fund's downside risk timing measures by fund's active share. Each quarter funds are ranked into 3 groups by active share (Cremers and Petajisto, 2009, Petajisto, 2013); funds are then assigned to three active share categories (low, middle, and high) based on which of three groups they fall most frequently. We then re-estimate the analysis reported in Table 2 for each active share group. The bootstrapped p-values (p) are reported in parentheses underneath. "Stdev", Skew", and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis respectively.

Active Share Category		5%	10%	25%	mean	median	75%	90%	95%	stdev	Skew	Kurto
	Months 1-3											
low	γ_1	-0.383	-0.264	-0.090	0.098	0.050	0.259	0.513	0.755	0.422	0.502	7.788
	p	(0.39)	(0.47)	(0.33)	(0.10)	(0.22)	(0.04)	(0.02)	(0.01)	(0.01)	(0.28)	(0.37)
middle	γ_1	-0.581	-0.346	-0.118	0.099	0.087	0.288	0.600	0.838	0.471	0.838	12.505
	p	(0.63)	(0.38)	(0.24)	(0.09)	(0.07)	(0.05)	(0.02)	(0.02)	(0.01)	(0.90)	(0.06)
high	γ_1	-0.659	-0.449	-0.143	0.120	0.112	0.368	0.656	0.860	0.607	1.181	15.776
	p	(0.31)	(0.33)	(0.19)	(0.11)	(0.09)	(0.08)	(0.09)	(0.12)	(0.04)	(0.05)	(0.07)
low	γ_2	-0.035	-0.022	-0.007	0.012	0.007	0.029	0.053	0.068	0.035	0.660	4.692
	p	(0.38)	(0.30)	(0.24)	(0.05)	(0.12)	(0.02)	(0.00)	(0.01)	(0.00)	(0.18)	(0.65)
middle	γ_2	-0.042	-0.025	-0.009	0.012	0.008	0.032	0.055	0.077	0.038	0.250	5.119
	p	(0.18)	(0.08)	(0.12)	(0.03)	(0.06)	(0.01)	(0.02)	(0.02)	(0.05)	(0.31)	(0.34)
high	γ_2	-0.055	-0.033	-0.011	0.016	0.014	0.039	0.069	0.090	0.051	0.553	5.432
	p	(0.16)	(0.07)	(0.09)	(0.04)	(0.04)	(0.04)	(0.06)	(0.09)	(0.08)	(0.17)	(0.49)
	Months 4-6											
low	γ_1	-0.469	-0.292	-0.078	0.065	0.055	0.223	0.407	0.569	0.388	-0.341	18.993
	p	(0.65)	(0.55)	(0.23)	(0.18)	(0.17)	(0.09)	(0.10)	(0.12)	(0.01)	(0.64)	(0.06)
middle	γ_1	-0.610	-0.370	-0.112	0.062	0.054	0.248	0.509	0.696	0.503	-0.948	14.623
	p	(0.70)	(0.46)	(0.46)	(0.30)	(0.17)	(0.12)	(0.09)	(0.11)	(0.00)	(0.94)	(0.02)
high	γ_1	-0.654	-0.384	-0.130	0.138	0.128	0.379	0.708	0.993	0.533	0.007	4.903
	p	(0.28)	(0.12)	(0.12)	(0.07)	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.50)	(0.61)
low	γ_2	-0.032	-0.021	-0.007	0.008	0.006	0.022	0.040	0.051	0.030	0.971	10.811
	p	(0.22)	(0.27)	(0.24)	(0.14)	(0.15)	(0.08)	(0.08)	(0.17)	(0.09)	(0.10)	(0.11)
middle	γ_2	-0.049	-0.034	-0.015	0.008	0.006	0.020	0.042	0.055	0.057	0.034	-0.092
	p	(0.45)	(0.48)	(0.44)	(0.30)	(0.28)	(0.26)	(0.20)	(0.29)	(0.11)	(0.59)	(0.51)
high	γ_2	-0.063	-0.042	-0.014	0.011	0.012	0.038	0.066	0.083	0.058	-0.316	3.821
	p	(0.36)	(0.29)	(0.17)	(0.11)	(0.06)	(0.05)	(0.08)	(0.16)	(0.05)	(0.75)	(0.66)

Table 5. Characteristics of Downside Risk Managers

This table reports the coefficient estimates ($\hat{b}_0$ and $\hat{b}$) of fund characteristics in regression (7) and (8). The regression is performed jointly for all funds with a vector of fund characteristics. Fund betas are computed from stock betas estimated using the past 5 year monthly returns. TNA, EXPENSE, and TURNOVER denote the average percentile cross-fund percentile ranks of total net assets (TNA), the expense ratio and the turnover for each fund. SIZE, B/M RATIO, and MOMENTUM denote the average cross-sectional percentile ranks of stock characteristics in fund portfolios based on market capitalization, book-to-market, and momentum. ICI is the average industry concentration index for each fund computed following Kacperczyk, Sialm, and Zheng (2005). All fund characteristics are demeaned relative to the sample averages. Fund and quarter fixed effects are also included. Fund and time (quarter) clustered p-values are reported in parentheses.

	mkt	mkt × TNA	mkt × Expense	mkt × Turnover	mkt × Size	mkt × B/M ratio	mkt × Momentum	mkt × ICI	Adj R^2
Months 1-3									
$r_{m,t+1}$	0.258	-0.062	-0.039	0.008	0.676	0.635	0.156	-14.839	0.1499
	(0.03)	(0.20)	(0.42)	(0.14)	(0.01)	(0.01)	(0.55)	(0.22)	
$I_{rm,t+1>0}$	0.018	-0.003	-0.003	0.001	0.038	0.020	0.011	-0.822	0.1499
	(0.03)	(0.58)	(0.50)	(0.89)	(0.02)	(0.09)	(0.22)	(0.42)	
Months 4-6									
$r_{m,t+1}$	0.031	-0.035	-0.012	-0.062	0.039	0.193	0.096	-6.596	0.1464
	(0.15)	(0.52)	(0.83)	(0.32)	(0.82)	(0.26)	(0.74)	(0.63)	
$I_{rm,t+1>0}$	0.007	0.001	0.001	-0.005	-0.016	-0.011	0.005	1.100	0.1466
	(0.36)	(0.85)	(0.90)	(0.38)	(0.31)	(0.25)	(0.10)	(0.29)	

Table 6. Public Information and Downside Risk Timing

Panel A reports the average and median coefficient estimates of the macroeconomic variables in regression (9). The regression is performed for each fund with a vector of four macroeconomic variables – short-term rate (short Rate), term premium (term Premium), credit premium (Credit Premium), and aggregate earnings-to-price ratio (Earnings-to-Price). Panel B reports the cross-sectional distribution of holding based Treynor-Mazuy (γ_1) and Henrikson Merton (γ_2) type mutual fund's downside risk timing measures estimated with regressions (10) and (11). Bootstrapped p-values (p) are reported in parentheses.

Panel A: Macroeconomic Variables

	short rate		term premium		credit premium		earnings-to-price	
	mean	median	mean	median	mean	median	mean	median
estimate	-25.933	-17.386	-0.024	-0.019	-0.054	-0.058	2.820	1.774
p	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Panel B: Downside risk timing Controlling for Public Information

	5%	10%	25%	mean	median	75%	90%	95%	stdev	Skew	Kurto
Months 1-3											
γ_1	-0.612	-0.399	-0.132	0.107	0.070	0.322	0.622	0.901	0.540	1.133	11.012
p	(0.62)	(0.56)	(0.30)	(0.05)	(0.09)	(0.02)	(0.01)	(0.01)	(0.01)	(0.06)	(0.50)
γ_2	-0.049	-0.032	-0.011	0.010	0.007	0.030	0.056	0.076	0.042	0.557	5.668
p	(0.25)	(0.25)	(0.17)	(0.03)	(0.06)	(0.01)	(0.01)	(0.03)	(0.06)	(0.16)	(0.93)
Months 4-6											
γ_1	-0.658	-0.406	-0.148	0.067	0.064	0.280	0.600	0.734	0.513	0.571	28.208
p	(0.75)	(0.56)	(0.37)	(0.12)	(0.09)	(0.08)	(0.09)	(0.10)	(0.01)	(0.16)	(0.04)
γ_2	-0.051	-0.034	-0.015	0.010	0.006	0.025	0.040	0.059	0.037	0.451	9.497
p	(0.33)	(0.34)	(0.27)	(0.13)	(0.09)	(0.08)	(0.10)	(0.27)	(0.29)	(0.31)	(0.37)

Table 7. Mechanics of Downside Risk Timing

We report the changes in the characteristics of mutual funds ensuing to the downside risk timing. We break down our sample into the quarters followed by positive market returns over the subsequent three months (Panel A) and quarters followed by the negative market returns over the subsequent three months (Panel B). In each sub-sample, we sort mutual funds based on their downside risk timing ability $\gamma_1$estimated from the regression (2) over the entire sample and explore changes in characteristics of funds' portfolios. To remove the impact of time trends, for size, B/M, and momentum we use percentile ranks. Following Jiang et al. (2007) and Huang et al. (2011), The percentile ranks for these variables are derived by obtaining percentile ranks for all stocks in CRSP in a given year; we then compute the weighted average of percentile ranks for each fund. The fund's characteristics score is then calculated as the average score over time. Industry concentration index (ICI) is computed for each fund following Kacperczyk, Sialm, and Zheng (2005) based on the Fama-French 12-industry SIC classification.

Panel A: Changes in Portfolio Characteristics Prior to Upward Market Movements

	bottom 10%		bottom 25%		top 75%		top 90%		(90)-(10)		(75)-(25)	
	mean	median	mean	median	mean	median	mean	median	t-test	Wilcoxon	t-test	Wilcoxon
ACRB	-0.0266	-0.0143	-0.0164	-0.0075	0.0362	0.0322	0.0473	0.0441	(0.01)	(0.01)	(0.01)	(0.01)
ACB	0.0184	0.0116	0.0167	0.0115	0.0175	0.0118	0.0196	0.0133	(0.56)	(0.68)	(0.42)	(0.60)
ΔN	0.0030	0.0000	0.0031	0.0000	0.0027	0.0000	0.0023	0.0000	(0.70)	(0.44)	(0.72)	(0.70)
ΔCash	-0.1238	0.0000	-0.1578	0.0000	-0.0968	0.0000	-0.1361	0.0000	(0.84)	(0.88)	(0.10)	(0.20)
ΔPortfConc	-0.0118	0.0108	-0.0147	0.0053	-0.0162	-0.0006	-0.0150	-0.0008	(0.78)	(0.02)	(0.80)	(0.02)
ΔSize Score	0.0503	0.1118	0.0920	0.1343	-0.0244	0.0293	-0.0400	0.0216	(0.01)	(0.01)	(0.01)	(0.01)
ΔB/M Score	-0.3405	-0.3738	-0.2577	-0.3198	-0.0370	-0.1488	-0.1158	-0.1591	(0.01)	(0.01)	(0.01)	(0.01)
ΔMOM Score	0.1664	0.1465	0.3116	0.3095	0.2393	0.2085	0.3487	0.3954	(0.09)	(0.14)	(0.18)	(0.23)
ΔICI	-0.0288	-0.0055	-0.0165	-0.0071	-0.0048	-0.0016	-0.0138	0.0117	(0.72)	(0.56)	(0.58)	(0.74)
ΔActiveShare	-0.1163	-0.0121	-0.1435	-0.0296	-0.0658	-0.0087	-0.0054	0.0013	(0.22)	(0.15)	(0.11)	(0.13)

Panel A: Changes in Portfolio Characteristics Prior to Downward Market Movements

	bottom 10%		bottom 25%		top 75%		top 90%		(90)-(10)		(75)-(25)	
	mean	median	mean	median	mean	median	mean	median	t-test	Wilcoxon	t-test	Wilcoxon
ACRB	0.0203	0.0144	0.0068	0.0033	-0.0436	-0.0268	-0.0630	-0.0366	(0.01)	(0.01)	(0.01)	(0.01)
ACB	0.0004	0.0029	0.0013	0.0033	-0.0025	-0.0011	-0.0026	-0.0006	(0.30)	(0.11)	(0.01)	(0.01)
ΔN	-0.0018	0.0000	0.0004	0.0000	-0.0027	0.0000	-0.0032	0.0000	(0.60)	(0.54)	(0.04)	(0.11)
ΔCash	-0.1622	0.0000	-0.0917	0.0000	-0.0376	0.0000	-0.0439	0.0000	(0.25)	(0.22)	(0.39)	(0.12)
ΔPortfConc	-0.0056	0.0017	-0.0057	0.0042	0.0214	0.0122	0.0389	0.0209	(0.03)	(0.01)	(0.01)	(0.01)
ΔSize Score	-0.1172	-0.0992	-0.1248	-0.0902	-0.0593	-0.0502	-0.0585	-0.0524	(0.10)	(0.15)	(0.01)	(0.01)
ΔB/M Score	-0.1779	-0.3828	-0.1619	-0.3293	-0.2488	-0.4311	-0.1492	-0.4158	(0.78)	(0.81)	(0.10)	(0.06)
ΔMOM Score	-0.7910	-0.8436	-1.0506	-0.8136	-0.0781	0.1940	-0.0155	0.0758	(0.01)	(0.01)	(0.01)	(0.01)
ΔICI	-0.0993	-0.0329	-0.0786	-0.0109	-0.0377	0.0078	-0.0443	0.0093	(0.41)	(0.30)	(0.20)	(0.22)
ΔActiveShare	-0.0168	-0.0560	-0.0605	-0.0250	-0.1370	-0.0612	-0.1062	-0.0871	(0.48)	(0.65)	(0.23)	(0.26)

Table 8. Downside Risk Timing and Mutual Fund Performance: Calendar Portfolios

We report the performance of zero-cost portfolios based on downside risk timing ability of mutual funds. Each quarter funds are sorted into ten groups based on their downside risk timing ability (coefficient γ_1 from regression (2) estimated over the previous sixty months on a rolling basis). Zero-cost portfolios are constructed by going long in funds with the highest downside risk timing ability (highest γ_1 group) and going short in funds with the lowest ability (lowest γ_1 group); portfolios are rebalanced quarterly. Panel A reports the results for the overall sample. Panel B reports performance conditional on the state of the economy. Recession dummy takes the value of one if a month is a recession month; zero otherwise. Months are split into recession and expansion month according to NBER classification. We allow factor loadings to vary across expansion and recession periods. All coefficients are multiplied by 100. P-values are reported in parentheses.

Panel A: unconditional performance

	Average Return	CAPM	Fama-French	Carhart	Pastor-Stambaugh
A	0.148	0.145	0.119	0.141	0.138
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MKTRF		0.361	1.963	1.100	1.141
		(0.73)	(0.07)	(0.32)	(0.30)
SMB			-6.244	-6.734	-6.704
			(0.01)	(0.01)	(0.01)
HML			4.273	3.618	3.711
			(0.01)	(0.03)	(0.03)
UMD				-2.953	-2.970
				(0.01)	(0.01)
LIQ					0.518
					(0.66)

Panel B: by state of the economy

	Average Return	CAPM	Fama-French	Carhart	Pastor-Stambaugh
A	0.095	0.100	0.068	0.085	0.086
	(0.04)	(0.04)	(0.15)	(0.08)	(0.08)
Recession	0.298	0.331	0.412	0.389	0.401
	(0.09)	(0.04)	(0.02)	(0.02)	(0.02)

Table 9. Downside Risk Timing and Mutual Fund Performance: by Fund's Market Timing Ability

We report the performance of zero-cost portfolios based on downside risk timing ability of mutual funds conditional on the degree of their Market timing skills. Each quarter funds are sorted into three groups based on market timing ability estimated over the previous sixty months; within each group funds are then sorted into ten groups based on their downside risk timing ability (coefficient $\gamma_1$from regression (2) estimated over the previous sixty months on a rolling basis). Zero-cost portfolios are constructed by going long in funds with the highest downside risk timing ability (highest γ_1 group) and going short in funds with the lowest ability (lowest γ_1 group); portfolios re rebalanced quarterly. Average portfolios returns as well as risk-adjusted monthly abnormal returns according to CAPM, Fama-French, Carhart, and Pastor-Stambaugh models are reported. For expositional purposes we do not report factor loadings. All coefficients are multiplied by 100; p-values are reported in parentheses.

Market Timing Ability Category	Average Return	CAPM	Fama-French	Carhart	Pastor-Stambaugh
low	0.112	0.117	0.103	0.104	0.105
	(0.07)	(0.06)	(0.09)	(0.09)	(0.09)
middle	0.100	0.078	0.079	0.082	0.086
	(0.12)	(0.16)	(0.16)	(0.15)	(0.14)
high	0.108	0.102	0.099	0.108	0.107
	(0.08)	(0.09)	(0.10)	(0.09)	(0.09)

Table 10. Changes in Relative Beta and Mutual Fund Performance: Multivariate Regressions

To investigate the relation between changes in relative beta and subsequent fund performance, we run multivariate Fama-Macbeth regressions. The dependent variable in each cross-section is a performance measure in a particular month. The independent variables are holdings based measure of fund's active changes in relative beta (ACRB), holdings based relative beta, active change in regular beta (ACB), portfolio beta, return over the previous quarter, the logarithm of the assets of the fund, logarithm of the total assets in the fund family, the expense ratio of the fund, the turnover ratio, the growth rate in new money over the previous quarter, the logarithm of fund's age, fund's active share and tracking error measures. To adjust for risk and style we use four different performance measures; (1) 1-factor adjusted return; (2) four-factor adjusted return; (3) fund's return in excess of the fund's size weighted average return of the funds in the same style category; and (4) the return gap. The return gap is computed following Kacperczyk, Sialm, and Zheng (2005) as the difference between the fund return and the holdings return after adjusting for fund expenses. All coefficients are multiplied by 100.

	1-factor adjusted			4-factor adjusted			style-adjusted			return gap		
ACRB	0.197	0.151	0.081	0.083	0.080	0.089	0.136	0.173	0.210	0.185	0.144	0.140
	(6.30)	(6.12)	(4.30)	(4.71)	(5.81)	(6.06)	(1.45)	(1.77)	(1.86)	(2.88)	(2.22)	(2.14)
Portfolio Relative Beta	-0.018	-0.002	-0.030	-0.058	-0.034	-0.062	-0.016	-0.009	-0.125	-0.062	-0.075	-0.181
	(-0.76)	(-0.12)	(-1.65)	(-2.57)	(-1.65)	(-3.56)	(-0.19)	(-0.12)	(-1.03)	(-1.04)	(-1.26)	(-2.35)
ACB	0.216	0.198	0.180	0.041	0.033	0.049	0.183	0.220	0.216	0.144	0.127	0.102
	(8.99)	(9.32)	(8.07)	(2.04)	(2.05)	(2.18)	(1.61)	(1.77)	(1.76)	(2.24)	(2.07)	(1.72)
Portfolio Beta	-0.244	-0.269	-0.313	0.073	0.069	0.027	-0.013	0.006	0.077	-0.759	-0.684	-0.860
	(-7.29)	(-8.48)	(-9.69)	(4.08)	(3.73)	(1.20)	(-0.10)	(0.05)	(0.43)	(-12.44)	(-10.59)	(-11.67)
Lagged Return		3.188	3.112		1.963	2.090		2.119	2.506		0.689	0.728
		(18.31)	(20.36)		(21.48)	(20.46)		(3.71)	(3.94)		(2.24)	(2.70)
Log(Size)		0.042	0.039		0.034	0.035		-0.014	-0.029		-0.012	-0.019
		(25.44)	(20.64)		(28.06)	(21.07)		(-2.31)	(-3.43)		(-3.05)	(-3.70)
Log(Family Size)		-0.012	-0.011		-0.011	-0.012		0.008	0.009		0.006	0.009
		(-14.81)	(-13.03)		(-14.21)	(-12.45)		(1.91)	(1.97)		(2.75)	(1.52)
Expense Ratio		-3.914	-8.555		-4.993	-6.705		-8.356	-12.428		-11.746	-13.168
		(-5.41)	(-12.77)		(-11.55)	(-14.50)		(-4.55)	(-5.02)		(-8.35)	(-5.91)
Turnover		-0.008	0.011		-0.035	-0.033		0.019	0.025		-0.008	0.000
		(-2.25)	(2.23)		(-11.99)	(-8.47)		(1.28)	(1.39)		(-0.81)	(0.35)
Flow		1.086	1.192		0.870	1.006		0.117	0.098		0.099	0.055
		(41.57)	(37.68)		(39.35)	(39.63)		(1.25)	(0.78)		(1.90)	(1.16)
Log(Age)		-0.069	-0.055		-0.056	-0.040		0.000	0.006		0.028	0.035
		(-20.58)	(-14.86)		(-25.02)	(-12.16)		(0.00)	(0.34)		(3.90)	(3.21)
Active Share			0.382			0.216			0.123			0.532
			(8.04)			(11.63)			(1.70)			(6.29)
Tracking Error			0.340			0.553			-0.304			0.051
			(4.46)			(7.63)			(-0.63)			(0.18)
Constant	0.306	0.407	0.116	-0.072	0.082	-0.125	-0.004	-0.049	-0.115	0.065	0.034	0.601
	(9.59)	(10.13)	(2.11)	(-4.35)	(4.04)	(-4.44)	(-0.02)	(-0.28)	(-0.53)	(1.23)	(0.52)	(5.87)
Nobs	271612	242051	102179	271769	241930	101998	271033	241023	101998	271693	241524	101998
Average R^2	0.0043	0.0234	0.0355	0.0001	0.0008	0.0242	0.0001	0.0012	0.0015	0.0114	0.0188	0.0203