Mutual Fund Market Timing: Daily Evidence

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Abstract

We examine mutual fund market timing based on beta asymmetry from dynamic conditional correlation (DCC) model. We find significant timing using daily returns rather than monthly returns. The sensitivity of our findings to data frequency is consistent with funds altering their market exposure at a greater frequency than can be precisely captured by monthly returns. Timing evidence is stronger during down markets, when the gains associated with market timing are especially meaningful. Successful market timers earn significant abnormal returns and attract greater investor cash flows than non-timers. Holding diversified portfolios and short selling help facilitate market timing.

Key words: timing, mutual fund, dynamic conditional correlation model

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1. Introduction

Active mutual fund management holds the promise of adding value for fund shareholders via stock selection and market timing. Of the two value-enhancing activities, market timing appears to pose the greater challenge for fund managers for two main reasons. First, the empirical asset pricing literature documents a large number of anomalies that are exploitable to varying degrees (see, for example, Novy-Marx and Velikov (2016)). The documented anomalies include many with modest trading frequency requirements, including those based on stock fundamentals, such as value. The existence of such strategies suggests that opportunities exist for mutual funds to increase risk-adjusted performance through active stock selection. Second, Welch and Goyal (2008) find little evidence that an ex-ante identifiable variable can significantly predict the return of the aggregate stock market. Although a reliable market timing signal may exist, it has yet to be recognized as such in the academic literature.

Consistent with Welch and Goyal's (2008) conclusion that it is difficult to predict the market, mutual fund timing studies find little evidence of significant timing ability, with some notable exceptions. Bollen and Busse (2001) identify significant timing ability in a 230-fund sample based on daily fund returns from 1985-1995. They argue that timing tests based on daily returns provide more power to reject the null of no timing regardless of the frequency with which managers alter their portfolios in an attempt to time the market. Consistent with Bollen and Busse (2001), Jiang, Yao, and Yu (2007) find timing skill when they estimate changes in fund risk exposure based on the underlying stocks that funds hold in their portfolios. More recently, Simutin (2013) finds that mutual funds that deviate from the portfolio held by other funds in the same fund family show timing ability. Dass, Nanda, and Wang (2013) show that sole-managed, balanced funds with centralized decision rights exhibit significant market timing ability. Lastly, Ferson and Mo (2016) find that timing components (including factor level timing and volatility timing) dominate the selectivity component in the performance of funds. By contrast to these studies, many others are consistent with little or even perverse market timing ability across the universe of U.S. mutual funds. See, for example, Treynor and Mazuy (1966), Henriksson (1984), Becker, Ferson, Myers, and Schill (1999), Jiang (2003), and Huang, Sialm, and Zhang (2011).

Studies of fund market timing typically estimate the relation between the excess market return and fund systematic risk, i.e., fund beta with respect to the excess market return. If funds show higher market exposure when the market return is relatively high, and conversely when the market return is relatively low, then that is interpreted as market timing skill. The two most common approaches to estimate fund market timing include those of Treynor and Mazuy (TM, 1966) and Henriksson and Merton (HM, 1981). Treynor and Mazuy (1966) examine the extent to which fund beta is positively linearly related to the excess market return, and Henriksson and Merton (1981) examine whether fund beta is greater (lower) when the excess market return is positive (negative). Operationally, estimation proceeds by expressing beta as a function of market return via either of these two specifications, substituting the beta expression into a factor model of fund returns, and then estimating the factor model regression.

Given that fund managers have the flexibility to alter their stock portfolios daily, the ability of an empirical timing model to capture market timing behavior can be sensitive to the frequency of the data utilized in the estimation. For instance, a timing model would have difficulty detecting timing behavior if fund managers alter fund beta at a greater frequency than the return data used in the timing estimation. As an example, Busse, Tong, Tong, and Zhang (2019) examine daily fund trading activity using the ANcerno institutional trade database, finding that the most active quintile of funds transact an average of 1.66 trades per stock per day.

Bollen and Busse (2001) find that, compared to analysis based on monthly returns, analysis of daily returns has greater power to reject the null of no timing. Essentially, Bollen and Busse's (2001) daily analysis detects intra-month movements in fund risk that are not as apparent when returns are observed monthly, a point emphasized by Goetzmann, Ingersoll, and Ivkovich (2000).

In this paper, we improve short-horizon estimates of mutual fund market exposure relative to traditional beta estimates based on monthly fund returns by estimating daily factor loadings via the dynamic conditional correlation (DCC) model (Engle, 2002). Bali and Engle (2010) use the DCC model to estimate the conditional covariance of stocks with the market to test the ICAPM model. The benefit of applying this dynamic model to mutual funds is potentially greater than it is for individual stocks given that fund managers periodically alter their portfolios, leading to fund factor loadings that vary across time. The advantage of using the DCC beta over standard measures of market beta based on rolling regressions is that the DCC beta has a dynamic feature that weighs more heavily recent observations. By contrast, unconditional measures of market beta equally weigh observations within an estimation window and produce one beta estimate for the entire estimation window. Additionally, the DCC beta estimates are allowed to vary each day, such that it would capture daily beta changes more timely than the rolling beta measures. We find that the DCC beta estimate at the end of the estimation period better captures the fund's next period out-of-sample true beta than the rolling regression beta. Another advantage of the DCC approach is that it accounts for potential time-series variation in the covariance between fund and market returns, whereas the traditional rolling regression beta methodology does not. Beyond improvements stemming from the DCC model, we use daily, rather than monthly, fund returns. In the end, the combination of the DCC approach and daily frequency fund returns produce more precise estimates of changes in fund risk that improve market timing inference[1].

To measure fund timing behavior, we propose a measure of fund beta asymmetry (BA), defined as the difference of conditional fund betas during periods of relatively high and relatively low market returns. Greater beta asymmetry is interpreted as more successful timing, consistent with funds taking on more market exposure during up markets than during down markets. Ang and Chen (2002), Hong, Tu, and Zhou (2007), and Jiang, Wu, and Zhou (2018) use related measures in their analyses of individual stocks. Ang and Chen (2002) compare market beta and stock correlations with the market during relatively high and relatively low market return periods. They find that stocks show higher correlations with the market and higher market betas when the market goes down than when it goes up. Thus, in order to successfully time the market, funds would need to overcome the average negative timing pattern inherent in the individual stocks that they hold in their portfolios.

We find large cross-sectional variation with respect to asymmetry in market factor loadings across actively-managed U.S. equity funds, ranging from 0.053 for the decile of funds with the largest asymmetry to -0.054 for the decile of funds with the lowest asymmetry. At one extreme, funds show evidence of skillful market timing. At the other extreme, funds show evidence of perverse timing, which, given Ang and Chen (2002) and Hong, Tu, and Zhou (2007)'s findings for individual stocks, is consistent with what one would expect if funds did not try to time the market. Although the evidence of timing varies across the fund sample, we find evidence of positive market timing skill, on average, in actively-managed funds. That is, actively managed funds show greater market exposure, on average, during market upturns than during

[1] It is not feasible to use monthly return in DCC approach which requires large number of observations, because of the limit number of monthly observations in short measurement period.

market downturns. Moreover, we find no evidence of positive market timing in a sample of passively-managed funds, which suggests that our findings are not driven by a mechanical relation associated with our DCC beta asymmetry methodology.

When we further examine fund timing behavior, we find especially strong timing during periods of poor market returns. Funds show relatively low market exposure during market downturns and even lower market exposure during especially steep market downturns. By contrast, although funds show higher market exposure during upturns than during downturns, they appear unable to discern a good market environment from a great market environment. That is, conditional on a market upturn, funds show no higher market exposure when market returns are especially high. Our findings are consistent with Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), who find evidence of stock picking skill during market booms and evidence of market timing in recessions.

Since the alpha of a standard non-timing performance regression model, such as the Carhart (1997) four-factor model, is the difference between the mean fund return and the risk premium associated with its mean level of market beta, we would expect higher estimates of standard contemporaneous performance (i.e., alpha) to be associated with a fund that shows evidence of successful market timing, which is what we find.[2] Consistent with expectations, we find a positive relation between the non-timing four-factor alpha and standard measures of market timing behavior, with a *t*-statistic between the two of 2.62 for the regression based on the TM timing model and 3.00 for the regression based on the HM timing model.

[2] A fund with positive timing earns relatively high risk premia (driven in part by its higher than average level of market beta) on days with relatively high market returns and relatively low risk premia (driven in part by its lower than average level of market beta) on days with relatively low market returns. By not adjusting for the positive relation between fund market exposure and market return, a standard unconditional performance model controls for the fund's risk premium based on a constant level of market exposure, and the fund's timing skill manifests itself in a relatively high estimate of alpha.

Beyond the expected positive relation between market timing skill and contemporaneous fund alpha, we also find a strong positive relation between market timing skill and future fund performance. When we sort funds into deciles based on beta asymmetry, we find that funds in the top (highest) beta asymmetry decile outperform funds in the bottom (lowest) beta asymmetry decile during the following month based on several performance measures ranging from excess return to several alternative factor model alphas. For example, the Carhart (1997) alpha is 0.45% per month higher for funds in the top beta asymmetry decile than for funds in the bottom beta asymmetry decile. This 5.4% annual performance difference is economically important and robust to controlling for fund characteristics. Since there is no overlap between the measurement interval over which timing skill is estimated and the subsequent measurement interval over which we estimate these alternative measures of performance, the positive correspondence between timing and subsequent performance suggests that our estimates of timing uncover an enduring aspect of fund manager skill. These results are robust to estimating empirical *p*-values for the performance estimates based on the bootstrap method of Fama and French (2010) applied to our daily fund return sample. The bootstrap approach is important in this context because time-varying betas and daily fund returns could impact standard measures of statistical significance. Our analysis further indicates that the bulk of the abnormal performance earned by funds with timing skill occurs during down markets.

We also find that investors differentially value fund market timing relative to other skill that positively impacts fund performance. When we examine fund investor cash flows, we find that, after controlling for the strong relation between alpha and investor flows, investors prefer funds with lower downside beta and better downside performance, and they award those funds with inflows.

Lastly, when we characterize successful market timers, we find that successful timers hold diversified, rather than concentrated, portfolios, possibly because concentrated portfolios are associated with higher trading costs, on average, given the large size of some of their positions. We also find that timing is associated with short selling and a significant reduction in downside risk.

The rest of this paper is organized as follows. Section 2 introduces the beta estimation method and the definition of our beta asymmetry measure, which proxies for market timing. Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes.

2. Beta Estimation and Asymmetry Measures

2.1. Dynamic Conditional Correlation Beta

Fund managers alter their stock portfolios throughout the month in response to investor flows, changes in investment strategy, information, and so on. Changes in portfolio holdings lead to commensurate changes in fund exposure to factors that affect fund returns, especially the market factor. Following the prior literature on fund timing, our paper emphasizes market factor timing, which arguably is the most relevant factor to the investors (Berk and Binsbergen, 2015 and Barber, Huang, and Odean, 2016). To capture the short-term, dynamic feature of fund loadings, we estimate daily market factor loadings via the dynamic conditional correlation (DCC) model (Engle, 2002). Bali and Engle (2010) use the DCC model to estimate the conditional covariance of stocks with the market to test the ICAPM model. They find that the market's risk premium is significantly positive after controlling for other state variables. Bali, Engle, and Tang (2016) use the DCC method to estimate stock betas and present evidence for a significantly positive link between the dynamic conditional beta and the cross-section of daily stock returns.

The advantage of using the DCC beta over traditional measures of market beta estimated based on rolling regressions is the former has a dynamic feature that weighs more heavily recent observations. Unconditional measures of market beta, by contrast, weigh observations equally within an estimation window. Thus, theoretically, the DCC model should capture the true beta more precisely at a given point in time. Another advantage of the DCC beta is that it accounts for time-series correlation in the covariance between fund and market returns and volatility clustering features that characterize time-series return data. Moreover, the DCC model allows beta to vary each day during the estimation period, whereas the traditional rolling model produces a beta estimate that is constant across the entire estimation period. Thus, at a given point in time, the DCC model reflects the portfolios' market exposure more accurately.

We estimate the conditional covariance between the excess returns on fund *i* and the market portfolio *m* based on the mean-reverting DCC model of Engle (2002). To expedite parameter convergence, we follow Bali and Engle (2010) and Engle and Kelly (2012) and use correlation targeting, assuming that the time-varying correlations mean revert to the sample correlation. DCC beta is defined as the ratio of expected conditional covariance between the excess returns of fund and market to the expected variance of the market portfolio:

$$\beta_{i,d+1}^{DCC} = \frac{cov[R_{i,d+1} - r_{f,d+1}, R_{m,d+1} - r_{f,d+1} | \Omega_d]}{var[R_{m,d+1} - r_{f,d+1} | \Omega_d]}, \tag{1}$$

where Ω_d denotes the information set at time d that investors use to form expectations about future returns and betas. To estimate fund DCC beta on day $d + 1$, we use daily returns over the past 252 trading days up to day d, requiring at least 200 observations. Please see the Appendix for a detailed description of the model.

To provide an initial indication of the DCC beta's superior ability to capture changes in fund beta compared to the traditional rolling window OLS approach, we sort funds into deciles based on the difference between beta estimated at the beginning of the calendar year (i.e., January) and estimated at the end of the calendar year (i.e., December). We use daily returns within the month to estimate beta during January or December. We then sort funds into deciles based on the difference in beta estimates, i.e., December beta minus January beta. For each decile, we report the DCC beta and the rolling beta at the end of the year, both estimated based on daily returns from the entire year. We report the results in Table 1. The table shows that the DCC beta moves closely in line with the December beta from decile 1 to decile 10, while the difference in rolling betas across deciles is negligible. The result shows that the DCC beta captures changes in beta far better than the beta based on the rolling window regression estimates.

[Table 1 about here]

Since monthly frequency returns are unable to detect intra-month beta movements, we also compute the standard deviation of a fund's daily beta within the month to provide an indication of the movements in beta that monthly data misses. In particular, we first calculate the standard deviation of daily intra-month beta for each fund in each month. We then compute the cross-sectional mean of the monthly fund beta standard deviations. Across time, the mean of this monthly time series is an economically meaningful 6%. Moreover, the correlation across time between the monthly cross-sectional mean standard deviation in beta and the monthly return of the market is –0.27, consistent with fund betas showing greater intra-month volatility during periods of relatively poor market returns. We thus anticipate that utilizing daily data should provide additional incremental benefits relative to monthly data for estimating fund beta when the market return is negative.

2.2. Measure of Beta Asymmetry

We classify the DCC beta of fund i on day d as downside beta when both the market excess return and the fund excess return on day d are smaller than their respective average returns during month *t*. Similarly, we classify the DCC beta as upside beta when both the market excess return and the fund excess return on day d are larger than their respective average monthly return:

$$\beta_{i,d}^{-} := \beta_{i,d} | r_{M,d} < \mu_{M,t}, r_{i,d} < \mu_{i,t} \tag{2}$$

$$\beta_{i,d}^{+} := \beta_{i,d} | r_{M,d} > \mu_{M,t}, r_{i,d} > \mu_{i,t}, \tag{3}$$

where $r_{i,d}$ ($r_{M,d}$) is fund i's (the stock market's) excess return on day d , and $\mu_{i,t}$ ($\mu_{M,t}$) is fund *i*'s (the stock market's) average excess return during month *t*.

We further define monthly downside and upside betas as the average daily beta across the month:

$$\beta_{i,t}^{-} = \frac{1}{N^{-}} \sum_{d \in t} \beta_{i,d}^{-} \ , \beta_{i,t}^{+} = \frac{1}{N^{+}} \sum_{d \in t} \beta_{i,d}^{+}, \tag{4}$$

where N^{-} and N^{+} denote the number of downside and upside days during month *t*, respectively. To measure a fund manager's market timing ability, we use beta asymmetry (*BA*), defined as:

$$BA_{i,t} = \beta_{i,t}^{+} - \beta_{i,t}^{-}. \tag{5}$$

A fund's beta asymmetry is the difference in its market risk exposure across different market conditions (i.e., up and down markets). A good market-timer has relatively high exposure to the market when the stock market is rising and relatively low market exposure when the market is declining. We thus expect a fund's BA to be positively correlated with its market timing ability.

As robustness checks, we construct two alternative measures, $BA_{robust1}$ and $BA_{robust2}$, to proxy for timing ability. These proxies differ based on how we define downside and upside beta. For $BA_{robust1}$, we classify beta as downside (upside) beta when both the market excess return and the fund excess return are less (greater) than zero, i.e.,

$$\beta^{-}_{i,d\_robust1} := \beta_{i,d} | r_{M,d} < 0, r_{i,d} < 0 \quad (6)$$

$$\beta^{+}_{i,d\_robust1} := \beta_{i,d} | r_{M,d} > 0, r_{i,d} > 0. \quad (7)$$

For $BA_{robust2}$, we classify beta as downside (upside) beta as long as the market excess return is less (greater) than zero, i.e.,

$$\beta^{-}_{i,d\_robust2} := \beta_{i,d} | r_{M,d} < 0 \quad (8)$$

$$\beta^{+}_{i,d\_robust2} := \beta_{i,d} | r_{M,d} > 0. \quad (9)$$

Similar to our main BA definition, we take the average of these alternative upside and downside daily betas to get monthly upside and downside beta, and compute beta asymmetry as the difference between the two. In the Appendix, we prove that our beta asymmetry measure under the second alternative definition ($BA_{robust2}$) equals the Herriksson-Merton (1981) market timing measure.

3. Data

We obtain open-end mutual fund returns and characteristics including the expense ratio, turnover ratio, total net assets, family size, and fund age (of the fund's oldest share class) from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. Fund family size is the sum of total assets under management of all funds in the family excluding the fund itself. Fund level return, turnover ratio, and expense ratio are the averages across all fund share classes (using share class total net assets as the weight). Fund flow is the change of total net assets excluding that attributable to fund return. We base our selection criteria on the investement objective codes from CRSP following Kacperczyk, Sialm, and Zheng (2008).

We drop ETFs, annuities, and index funds based either on their indicator variables or fund names from CRSP. Since we focus on equity funds, we require 70% of assets under management to be invested in stocks. We restrict our sample to funds that are at least one year old and have at least $15 million in assets under management, and we deal with the incubation bias as in Evans (2010).

We obtain fund investment objective codes and portfolio holdings from the Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) database. Following Herfindahl (1950) and Hirschman (1964), we calculate the Herfindahl-Hirschman Index (HHI) to measure portfolio concentration by summing the squared value weight of each stock in a fund's portfolio. We remove funds with investment objective codes 1, 5, 6, 7 and 8 in the Thomson Reuters Mutual Fund Holdings database, which represent International, Municipal Bond, Bond and Preferred, Balanced, and Metals funds. We merge the CRSP Mutual Fund database and the Thomson Reuters Mutual Fund Holdings database using the MFLINKS tables provided by WRDS. The final sample period is from January 1999 to December 2015, where the January start date is largely driven by the availability of daily fund returns from CRSP. Since we need to use the prior one year's return data to estimate DCC beta, the beta asymmetry measure begins January 2000. Table 2 reports summary statistics for the main variables used in the paper.

[Table 2 about here]

4. Empirical Results

4.1. Mutual Fund Market Timing Ability

Although much of the prior literature on mutual fund market timing finds little evidence of timing ability based on the TM and HM market timing models, our analysis utilizes the DCC methodology to estimate beta. As shown earlier in Table 1, the DCC methodology captures changes in beta better than approaches that assume beta does not vary within the month. As such, our evidence of timing ability could substantially differ from what has been reported before.

We estimate DCC fund beta on day d, $\hat{\beta}_{i,d}$, based on the excess returns of fund i and the market from day d – 252 through d – 1, rolling forward one day at a time to produce a daily time series of fund beta estimates. To examine whether market timing ability exists among our sample funds, we estimate the relation between fund beta and the subsequent excess market return following Jiang et al. (2007) as follows:

$$\hat{\beta}_{i,d} = \alpha_i + \gamma_i r_{m,d} + \eta_d \tag{10}$$

and

$$\hat{\beta}_{i,d} = \alpha_i + \gamma_i I_{r_{m,d}>0} + \eta_d, \tag{11}$$

where $r_{m,d}$ is the excess return on the market on day d, and $I_{r_{m,d}>0}$ is an indicator that takes the value of 1 when $r_{m,d}$ is positive and 0 otherwise. We estimate equations (10) and (11) once per fund over its entire time series of daily $\hat{\beta}_{i,d}$ estimates. A significantly positive γ_i is evidence of market timing skill. Though regressions (10) and (11) estimate timing ability in the spirit of the Treynor-Mazuy (1966) and Henriksson-Merton (1981) market timing models, respectively, they differ from TM and HM because they examine the relation directly, rather than by substituting the beta expressions in (10) and (11) into a factor model of fund returns.[3]

We estimate equations (10) and (11) across our sample of actively managed mutual funds and, for comparison purposes, across a sample of passively-managed funds. We then calculate

[3] To control for the effect of passive timing (Jagannathan and Korajczyk, 1986) and artificial timing (Jiang et al., 2007), we add lagged market excess return as a control variable in equations (10) and (11), that is,

$$\hat{\beta}_{i,d} = \alpha_i + \gamma_i r_{m,d} + \varphi_i r_{m,d-1} + \eta_d$$

and

$$\hat{\beta}_{i,d} = \alpha_i + \gamma_i I_{r_{m,d}>0} + \varphi_i I_{r_{m,d-1}>0} + \eta_d.$$

We calculate the cross-sectional statistics for $\hat{\gamma}$ and get similar results as in regressions (10) and (11). The results are available upon request.

cross-sectional statistics for $\hat{\gamma}$ and its t-statistic separately for the active and passive samples. We base statistical inference on bootstrapped p-values following the procedure of Jiang et al. (2007). To the extent that our approach does not induce spurious evidence of market timing ability, passively-managed funds should show no timing ability.

Figure 1 plots the cross-sectional distributions of the t-statistics of the Treynor-Mazuy $\hat{\gamma}$ for active funds (Panel A) and for passive funds (Panel B), while simultaneously showing the distribution of the bootstrapped t-statistics. In Panel A, the sample distribution is right-skewed relative to the bootstrap (zero timing) distribution, consistent with overall positive timing ability among actively-managed funds. Since index funds passively follow pre-specified indices, i.e., they do not attempt to time the market, the index fund results should provide no indication of positive market timing ability. Consistent with this expectation, the distribution of $\hat{\gamma}$ t-statistics for index funds in Panel B closely matches the bootstrap distribution, with no visible shift off center. Beyond confirming that index funds show no systematic market timing ability, the Panel B results also provide an indication that the methodology itself does not mechanically induce spurious evidence of timing ability. Panels C and D depict the density of the cross-sectional distribution of the Henriksson-Merton measure for active funds and passive funds, respectively. The results are similar to the Treynor-Mazuy results, with evidence of market timing ability among the actively-managed funds, but not among the index funds.

[Figure 1 about here]

Table 3 presents statistics associated with the $\hat{\gamma}$ timing coefficient estimates at various percentiles in the Figure 1 distribution plots. The table also reports distribution statistics based on two alternative methodologies, including (i) using rolling betas in equations (10) and (11), and (ii) based on the standard TM and HM factor timing models applied to daily returns. Panel A

(Panel B) reports statistics associated with the Treynor-Mazuy (Henriksson-Merton) timing measure corresponding to Figure 1, Panels A and B (Panels C and D). At each reported percentile, the table reports the timing coefficient $\hat{\gamma}$, the t-statistic associated with the timing coefficient, and the p-values of the $\hat{\gamma}$ and t-statistic relative to the bootstrap distribution.

[Table 3 about here]

Based on the DCC betas, the mean and median of the $\hat{\gamma}$ timing coefficients are positive for actively-managed funds (Panels A1 and B1), consistent with positive timing performance, on average. For the TM results in Panel A1, the 50th, 75th, and 90th percentiles of the timing statistics are all significantly greater than the bootstrap percentiles, consistent with timing ability by active funds at these percentiles of the timing gamma distribution. The HM results in Panel B1 show even stronger evidence of timing ability among actively managed funds, as the 25th, 50th, 75th, 90th, and 95th percentiles of the timing measure coefficient ($\hat{\gamma}$) and t-statistics (t) are significantly greater than the bootstrap statistics.[4] By contrast, in Panels A2 and B2, although the mean and median of the timing measure for index funds are slightly positive, they are statistically insignificant, as expected, since passive funds on average should show no timing ability.

As a point of comparison to the DCC results in Table 3, Panels A1 and B1, we also report in Table 3 results from estimating regression (10) and (11) based on rolling betas (Panels A3 and B3) and results based on estimating standard TM and HM factor model regressions applied to our daily return sample (Panels A4 and B4). Although the rolling beta tests also show positive mean and median timing coefficients, none of the reported percentiles of the timing measure coefficient ($\hat{\gamma}$) or t-statistics (t) are significantly greater than the bootstrap statistics based on regression (10), except for the median. The standard TM and HM timing coefficients based on

[4] We also test the timing ability of actively managed funds by regressing the DCC beta on weekly and monthly returns. Positive timing ability is weaker than when regressing on daily returns, but still exists in general.

daily returns provide limited evidence of market timing skill at the 90th and 95th percentiles, but only based on the t-statistic of the timing coefficient relative to the bootstrap distribution. The results in Figure 1 and Table 3 indicate that, controlling for fund sample, sample period, and sample return frequency, the DCC methodology produces greater evidence of mutual fund market timing skill compared to rolling betas or compared to the standard TM and HM market timing approaches previously explored in the literature.

The results thus far are consistent with significant market timing, on average, across the sample of actively-managed funds. We next examine whether timing evidence is particularly strong during up or down market days by estimating the equation (10) and (11) regressions separately for $r_{m,d} > 0$ and for $r_{m,d} < 0$. In essence, by examining timing ability conditional on market returns being positive or negative, this analysis examines whether funds show especially low market exposure on days with particularly poor market returns and/or especially high market exposure on days with particularly positive market returns.

Figure 2 plots the distribution of t-statistics of the Treynor-Mazuy $\hat{\gamma}$ for active funds (Panel A) and for passive funds (Panel B), estimated separately during up and down market days. In Panel A, the distribution associated with negative market return days indicates that active fund managers show especially strong timing skill during down markets, with the distribution of t-statistics skewed noticeably to the right of zero. By contrast, conditional on a positive market day, fund beta is no higher on large positive market return days than on small positive market return days. In Panel B, both index fund distributions indicate no discernable difference in timing ability conditional on positive or negative returns in the market. Overall, the finding that funds show timing ability mainly when the market goes down is consistent with Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014).

[Figure 2 about here]

Ex ante, we would expect a positive correlation between the market timing $\hat{\gamma}_i$ coefficient and a contemporaneously-measured standard factor model performance estimate (α_i) for the following reason. A fund with positive timing ability earns relatively high risk premia (driven in part by its higher than average level of market beta) on days with relatively high market returns and relatively low risk premia (driven in part by its lower than average level of market beta) on days with relatively low market returns. By not adjusting for the positive relation between fund market exposure and market return, a standard unconditional performance model controls for the fund's risk premium based on a constant level of market exposure, and the fund's timing manifests itself in a relatively high estimate of alpha.

We examine this relation by regressing cross-sectionally standard (non-timing) alpha on market timing gamma, with each fund comprising one observation in the regression. We use the same timing $\hat{\gamma}_i$ coefficients as in Table 3 and estimate four-factor alpha across each fund's entire time series of returns. In untabulated results, we find, as expected, positive, statistically significant relations between the non-timing four-factor alpha and both market timing $\hat{\gamma}_i$ coefficients. The *t*-statistic for the coefficient on the timing $\hat{\gamma}_i$ is 2.62 for the regression based on the TM timing model and 3.00 for the regression based on the HM timing model. These results suggest that, among funds with positive estimates of four-factor alpha, a portion of the skill that they generate stems from their ability to time the market.

The results in Figure 2 indicate that funds show market timing ability conditional on relatively poor market return but not conditional on relatively high market return. Given that a positive relation exists between market timing skill and contemporaneous four-factor alpha, we would therefore expect to find higher mean estimates of four-factor alpha during down markets than during up markets. To examine this hypothesis, we first split the daily return data into two groups depending on whether the market excess return is greater or less than 0. For each fund, we then estimate standard (non-timing) four-factor alpha twice, once based on the data associated with positive market return days and once based on the data associated with negative market return days. Following Fama and French (2010), we use cross-sectional i.i.d. bootstraps to empirically determine whether the performance estimates are statistically significant, accounting for potential non-normality in the data.[5] In our bootstraps, we focus on the *t*-statistic of alpha as in Kosowski et al. (2006), because the *t*-statistic is a pivotal statistic that achieves asymptotic refinement (Horowitz, 2001), i.e. when the sample size is finite, the bootstrapped distribution for a pivotal statistic is closer to the true distribution, compared to the limiting distribution based on central limit theorems.

Consistent with expectations, the results in Figure 3 show that active fund managers on average achieve higher downside alpha (the green line) than upside alpha (the blue line), with a positive difference between downside and upside alpha existing at all cross-sectional percentiles. That is, the cross-sectional distribution of downside alpha first-order stochastically dominates that of the upside alpha.

[Figure 3 about here]

4.2. Market Timing Ability and Future Performance

The above results indicate a statistically significant correspondence between contemporaneous estimates of market timing ability and non-timing alpha. In this section, we empirically investigate the relation between fund market timing skill and future performance.

[5] As an alternative to the bootstrap approach of Fama and French (2010), we use the block bootstrap method of Dong and Massa (2013) to account for potential time-series correlation in fund returns. The results (untabulated) are qualitatively similar and somewhat stronger when based on block bootstraps.

Each month from January 2000 to December 2015, we sort funds into deciles based on beta asymmetry (i.e., proxying for market timing skill), computed using daily fund net returns over the previous 12 months. Decile 1 contains funds with the lowest beta asymmetry, and decile 10 contains funds with the highest beta asymmetry. We then compute equal- and value-weighted (based on fund TNA) fund returns for each decile over the subsequent (i.e., post-sort) month. Lastly, we concatenate the post-sort monthly returns for each decile and estimate several performance measures, including excess return, Fama and French (1993) three-factor alpha, Carhart (1997) four-factor alpha, and Fama and French (2015)'s five- and Fama and French (2018)'s six-factor (adding the momentum factor to Fama and French (2015)'s five-factor model) alpha.

Table 4 reports the results, with Panel A based on equal-weighting fund returns within each decile, and Panel B based on value-weighting the fund returns. Panel A shows that average excess returns increase monotonically from decile 1 to decile 10. The mean monthly return difference between decile 10 and decile 1 is 0.463%, with a *t*-statistic of 2.70. Beyond its statistical significance, this monthly return difference amounts to an economically meaningful annualized 5.6%. The results based on the Fama and French (1993) three-factor alpha, Carhart (1997) four factor alpha, Fama and French (2015) five-factor alpha, and Fama and French (2018) six-factor alpha in Panel A show a similar pattern, with monthly average alpha differences between the top and bottom beta asymmetry deciles of 0.464%, 0.446%, 0.349%, and 0.349% respectively that are all statistically significant at the 5% level or better. The slightly smaller magnitudes for the results based on factor model alphas indicate that commonly used factors explain only a small part of the return difference across the beta asymmetry deciles. In Panel B, the value-weighted results show a similar pattern to the equal weighted results in Panel A, with return differences between the top and bottom deciles of 0.513%, 0.510%, 0.486%, 0.389% and 0.389% per month for excess return, three-factor alpha, four-factor alpha, five-factor alpha, and six-factor alpha respectively. Consistent with the equal-weighted results, the value-weighted top-bottom performance differences in Panel B are statistically significant at the 10% level or better. The value-weighted results thus suggest that the positive relation between past timing ability and subsequent performance is not exclusively associated with relatively small funds.

[Table 4 about here]

As robustness checks, we repeat the beta asymmetry – future performance analysis using the alternative measures of beta asymmetry given by equations (6) - (9). The results, which we show in the Internet Appendix, are qualitatively similar to the results reported in Table 4.

4.3. Market Timing and Downside Risk

We next analyze a slightly different aspect of fund performance and examine whether funds with greater market timing ability take on less risk during market downturns. This is what we expect, on average, given that funds with relatively high beta asymmetry have some combination of high upside beta and/or low downside beta. Alternatively, successful timers could show especially high risk during market upturns combined with moderate risk during market downturns. We examine several alternative measures of downside risk, including downside beta, expected shortfall (ES5, ES10), value-at-risk (VaR5, VaR10), and minimum return (Min). We compute all of the downside risk measures using daily fund returns during a given month. Expected shortfall, value-at-risk, and minimum return are absolute values and measured as percentage returns per day.

Each month from January 2000 to December 2015, we sort funds into deciles based on beta asymmetry, with decile 1 containing the lowest beta asymmetry funds and decile 10 containing the highest beta asymmetry funds. For each beta asymmetry decile, we then compute the equal-weighted average of the various downside risk measures, and we report the averages for each decile in Table 5.

[Table 5 about here]

The results show that downside beta decreases with beta asymmetry, as expected. The difference in downside beta between the highest and the lowest beta asymmetry decile is -0.077 (*t*-stat=-3.65). The expected shortfall, value-at-risk, and minimum return results in Table 5 provide similar inference, that is, an inverse relation between beta asymmetry and all of the alternative downside risk measures. Statistical significance varies depending on the downside risk measure, with the ES5, VaR5, and Min (ES10 and VaR10) decile10 – decile 1 differences statistically significant at the 5% (10%) level. Moreover, the alternative measures also show somewhat lower levels of risk among the moderate deciles rather than in decile 10. Overall, the Table 5 results suggest that market timers have attractive downside risk characteristics.

4.4. Market Timing and Flows

Previous research shows that the relation between performance and investor flows is convex (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Top performing funds attract economically and statistically significant inflows, whereas the relation is weak among low performance ranks, such that poorly-performing funds do not suffer substantial net investor redemptions. In light of the prior performance-flow evidence, we next examine whether investors respond incrementally to market timing skill, i.e., after controlling for standard estimates of non-timing performance. Given our earlier findings that fund market timing is especially evident during market downturns, we might expect investors to respond positively to market timing skill because the cross-sectional standard deviation of fund performance is greater during periods of negative market returns than during periods of positive market returns. For example, the mean cross sectional standard deviation in fund returns is 0.56% per day (2.57% per month) during months with negative market return and 0.53% per day (2.43% per month) during months with positive market return. Consequently, investing in mutual funds with market timing skill is especially beneficial from a risk management or hedging perspective.

We estimate the relation between mutual fund market timing ability and investor flows via Fama and Macbeth (1973) regressions based on monthly data as follows:

$$Net\ inflow_{i,t+1} = \gamma_0 + \gamma_1 BA_{i,t} + \gamma_2 \alpha_{i,t} + \sum_{k=3}^{K} \gamma_k Fund\ Controls_{k,t} + \varepsilon_{i,t+1}, \qquad (12)$$

where $BA_{i,t}$ proxies for fund *i*'s market timing ability during month *t*, and $\alpha_{i,t}$ is fund *i*'s alpha, defined as

$$\hat{\alpha}_{i,t}^{DCC} = \sum_{d \in t} \left(r_{i,d} - \hat{\beta}_{i,d}^{DCC} \cdot r_{M,d} \right), \qquad (13)$$

where $r_{i,d}$ ($r_{M,d}$) is fund *i*'s (the market's) excess return on day d, and $\hat{\beta}_{i,d}^{DCC}$ is the dynamic conditional correlation beta of fund i on day d, estimated using the prior 252 daily returns through day $d - 1$. To estimate monthly alpha, we sum daily risk-adjusted return across the month. We define net investor cash flow as

$$Net\ inflow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{TNA_{i,t-1}}, \qquad (14)$$

where $R_{i,t}$ represents the return of fund *i* during month *t*, and $TNA_{i,t}$ are fund *i*'s total net assets at the end of month *t*. Given prior evidence that the performance-flow relation is asymmetric, for each month $t + 1$, we divide funds into two groups according to their past performance ($\alpha_{i,t}$), and we run the cross-sectional regression in equation (12) separately for each past-performance group. The first performance group consists of funds with positive past single-factor alpha, and the second group consists of funds with negative past single-factor alpha. We run regression (12) separately with and without fund controls, which include log(TNA), past return, expense ratio, turnover ratio, log(age), and family TNA. Lastly, we repeat the performance-flow regressions based on the BA_{robust_1} and BA_{robust_2} beta asymmetry measures in equations (6) - (9).

Table 6 shows the results, with the results in Panel A based on estimating regression (12) without controls, and the results in Panel B based on estimating regression (12) with controls. We focus first on the results based on using the standard measure of beta asymmetry in columns (1), (4), and (7). In Panel A, the coefficient on beta asymmetry is 5.065 (*t*-statistic = 2.44) for high performing funds, consistent with a statistically significant relation between timing ability and investor net flows after controlling for fund alpha. By contrast, among the low performance funds, beta asymmetry is insignificantly related to investor flows. These results suggest that investors are sensitive to fund manager timing ability only when funds generate positive abnormal performance. When past performance is poor, investor flows do not respond to timing ability, as the benefits associated with timing may be offset by relatively poor stock selection ability.

[Table 6 about here]

Comparing the regression coefficients on α for the two past-performance groups, the point estimates and *t*-statistics associated with the high performers are greater than those associated with the low performers, with the high-performer coefficient (0.469) about double that of the low performers (0.235). Thus, flows are much more sensitive to performance when performance is relatively good than when performance is relatively poor. This convex flow-performance relation coincides with evidence documented previously by Sirri and Tufano (1998). Results based on the BA_{robust_1} and BA_{robust_2} beta asymmetry measures shown in columns (2)-(3), (5)-(6), and (8)-(9) of Table 6 are qualitatively similar to the results based on *BA*, as are the results based on including controls in regression (12). Regardless of the specification or beta asymmetry measure, the results suggest that investors only respond to market timing ability when funds generate positive overall performance and that the overall performance-flow relation is convex.

4.5. Holdings of Funds that Time the Market

We next characterize fund attributes that correlate with market timing ability. We first examine whether successful market timers tend to concentrate the positions in their portfolio rather than diversify across holdings. Pastor, Stambaugh, and Taylor (2019) find that, other things equal, funds that diversify their portfolios have lower transaction costs, on average, than funds that concentrate their portfolios among fewer stocks. Price impact has been shown to be positively related with trade size (e.g., Keim and Madhavan, 1997)), and a fund with concentrated positions could be susceptible to large transaction costs in its larger-size, concentrated positions. The possibility of high transaction costs could be problematic if market timing required the fund to liquidate positions.

We analyze the cross-sectional relation between fund market timing and concentration measured via the Herfindahl-Hirsehman Index (HHI) by estimating Fama and MacBeth (1973) regressions that relate beta asymmetry to lagged HHI. Specifically, for each month *t*, we estimate the following cross-sectional regression:

$$BA_{i,t+1} = \gamma_0 + \gamma_1 HHI_{i,t} + \sum_{k=2}^{K} \gamma_k \cdot Fund\ Controls_{k,t} + \varepsilon_{i,t+1}. \quad (15)$$

We run regression (15) using the main beta asymmetry measure as well as the alternative beta asymmetry measures defined in equations (6) - (9). To account for potential autocorrelation in the slope estimates, we base the *t*-statistics on Newey and West (1987) standard errors computed using a lag of three months. We incorporate the same set of controls that we use in the previous tables.

Table 7 shows the results of the equation (15) analysis. The multiple regression results in columns (2), (4), and (6) show significantly negative coefficients for HHI, consistent with market timing ability being associated with diversified, rather than concentrated, portfolios. The univariate slope coefficients in columns (1), (3), and (5) provide largely similar inference. Overall, the results suggest that market timers construct their portfolios in a way that provides them with the flexibility to time the market without bearing unusually steep transaction costs.

[Table 7 about here]

As reflected in our beta asymmetry measure, market timing entails modifying fund beta at opportune times. In addition to altering the mean beta of their long holdings, funds potentially modify portfolio beta via several additional approaches, such as by short selling or by investing in derivatives, including equity or index options. To examine whether a correspondence exists between market timing ability and alternatives to simply holding common stock long, we first hand collect from the Securities and Exchange Commission (SEC) Edgar website data in the N-SAR forms that indicate, based on fund filings, whether or not funds have permission to invest via the alternative approaches. We focus on the following types of investment approaches: short selling, holding equity, debt, or index options and the use of margin.[6] Short selling can help a fund exploit a bearish outlook, whereas a fund could use margin to take a leveraged bet when it is relatively optimistic. Equity, debt, and index options could be used to quickly change a fund's systematic risk profile. The data that we collect from the SEC website are from January 2006 to June 2013.

[6] Additional data are available on whether funds are permitted to invest in foreign stocks, restricted securities, and repos and whether funds borrow.

We combine the permission data with actual portfolio holdings data and run cross sectional regressions as follows:

$$BA_{i,t+1} = \gamma_0 + \gamma_1 Permit * Use_{i,t} + \gamma_2 NoPermit * Use_{i,t} + \gamma_3 Permit * NoUse_{i,t} + \varepsilon_{i,t+1}, \quad (16)$$

where $Permit_{i,t}$ is a dummy variable that equals 1 if fund *i* is permitted to invest via that type of investment approach (e.g., short selling) during month *t*, and 0 otherwise. Similarly, $Use_{i,t}$ is a dummy variable that equals 1 if fund *i* actually invested via the approach during month *t*. $NoPermit_{i,t}$ and $NoUse_{i,t}$ are dummy variables that capture the opposite of $Permit_{i,t}$ and $Use_{i,t}$, taking the value 1 if fund *i* did not have permission to invest via the particular approach and did not invest via the approach during time *t*, respectively. For a given fund, we only include month *t* in regression (16) if the fund reports portfolio holdings for that month in the N-SAR forms. Note that funds typically report N-SAR forms semi-annually.

Table 8 reports the coefficients from estimating regression (16) separately for the four alternative investment approaches. We control for time fixed effects, we cluster standard deviation at the fund and time levels. The strongest results in the table suggest a negative correspondence between timing ability and fund permission to invest in index options, regardless of whether they actually invest in index options. That is, permission to invest in index options is associated with poor market timing ability. One interpretation of this result is that some funds sell covered calls on the market index, which leads to a concave relation between these funds' returns and the market return. The results are also marginally consistent with short selling being positively related to fund market timing.

[Table 8 about here]

4.6 Stock downside risk and market timing: natural experiment

To reduce the possibility that beta asymmetry is attributable to rationale unrelated to fund managers intentionally trying to time the market, we next test whether we can establish a direct link between beta asymmetry and the risk of specific portfolio stocks whose downside risk level changes over time. To do so, we focus on a two-year time period when the SEC enacted a program to study the effects of short sale restrictions. On July 28, 2004, the SEC announced a temporary modification to the Securities Exchange Act of 1934 that suspended price test provisions for a pilot group of stocks that affects the ability to sell those stocks short. Stocks in the pilot group would be expected to have greater downside risk during the period of time associated with the SEC's program, which commenced on January 3, 2005, because they were easier to sell short. We consequently would expect a decrease in beta asymmetry for funds that hold more securities with fewer short sale constraints during this time period. This exogenous event can be viewed as a natural experiment. To analyze the effect associated with this event, we use a difference-in-difference regression as follows:

$$BA_{i,t} = b_0 + b_1 Time_t + b_2 SHO\%_{i,t} + b_3 Time_t \times SHO\%_{i,t} + \sum_{k=4}^{K} b_k Fund\ Controls_{i,t}^{k} + \varepsilon_{i,t}, \quad (17)$$

where *Time* equals 1 if month *t* is between May 2005 and July 2007, and 0 otherwise. *SHO%* is the holding value percentage of stocks whose short sale restriction was lifted (i.e., the pilot group) to facilitate short selling. b_3 is the coefficient of the cross term; it is this coefficient that we are most interested in. We estimate regression (17) with and without the fund characteristic control variables that we use previously.

Table 9 presents the results from the DID regression. The slope of $Time \times SHO\%$ is significantly negative when we define beta asymmetry using equations (6) and (7) (i.e., comparing both the fund and the market return to 0) and equations (8) and (9) (i.e., comparing the market return to 0), while insignificant under the main definition (i.e., comparing both the fund and the market return to their means). Stronger results based on the second and third alternative beta asymmetry measures are sensible to the extent that short sales are more likely to happen during a market downturn, rather than less extreme instances when the market return is less than its median. Overall, the results suggest that beta asymmetry decreases when fund portfolios hold more securities not subject to short sale constraints. This result is consistent with fund managers intentionally trying to time the market via the betas of their stock holdings.

[Table 9 about here]

5. Conclusion

Mutual fund managers have the flexibility to trade positions on any trading day, as they execute their investment strategies while accommodating shareholder flows. Such trading activity can affect intra-month levels of fund risk that could be masked when fund returns are analyzed less frequently. As studies of market timing focus on the relation between fund systematic risk level and the subsequent market return, market timing inference can thus be sensitive to the frequency of the data analyzed.

By estimating mutual fund systematic risk levels daily via the dynamic conditional correlation model, we capture changes in fund systematic risk more frequently and more precisely than standard studies based on monthly returns. Our time-varying estimates of fund betas show strong evidence of fund market timing ability among actively managed mutual funds. Beyond detecting successful market timing in-sample, our timing estimates correlate positively with subsequent fund performance, consistent with our market timing estimates capturing an enduring aspect of fund skill.

We find that market timing is particularly evident during down markets. Investor sensitivity to performance is strong during downturns, because market downturns represent periods during which cross-sectional variation in fund performance is especially large. As expected, we find that successful market timers have relatively low downside risk. As such, we find that flows strongly correlate with market timing skill, even after controlling for standard measures of non-timing performance. Lastly, we examine several fund attributes to characterize funds that time the market. We find a strong inverse relation between market timing and portfolio concentration and some evidence that successful timers short sell stocks.

Appendix

Dynamic Conditional Correlation Model

The mean-reverting DCC model is built by Engle (2002), where the conditional covariance between the excess returns on fund *i* and the market portfolio *m* is estimated as follows:

$$R_{i,d+1} - r_{f,d+1} = \alpha_0^i + \sigma_{i,d+1} u_{i,d+1}, \tag{A1}$$

$$R_{m,d+1} - r_{f,d+1} = \alpha_0^m + \sigma_{m,d+1} u_{m,d+1}, \tag{A2}$$

$$E_d\left(\varepsilon_{i,d+1}^2\right) \equiv \sigma_{i,d+1}^2 = \beta_0^i + \beta_1^i \sigma_{i,d}^2 u_{i,d}^2 + \beta_2^i \sigma_{i,d}^2, \tag{A3}$$

$$E_d\left(\varepsilon_{m,d+1}^2\right) \equiv \sigma_{m,d+1}^2 = \beta_0^m + \beta_1^m \sigma_{m,d}^2 u_{m,d}^2 + \beta_2^m \sigma_{m,d}^2, \tag{A4}$$

$$E_d\left(\varepsilon_{i,d+1} \varepsilon_{m,d+1}\right) \equiv \sigma_{im,d+1} = \rho_{im,d+1} \sigma_{i,d+1} \sigma_{m,d+1}, \tag{A5}$$

$$\rho_{im,d+1} = \frac{q_{im,d+1}}{\sqrt{q_{ii,d+1} q_{mm,d+1}}}, \tag{A6}$$

$$q_{im,d+1} = \bar{\rho}_{im} + a_1\left(u_{i,d} u_{m,d} - \bar{\rho}_{im}\right) + a_2\left(q_{im,d} - \bar{\rho}_{im}\right), \tag{A7}$$

where $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$ denote the excess return on fund *i* and the market portfolio *m*, respectively, on day *d* + 1, and E_d denotes the expectations operator conditional on day *d* information. $\sigma_{i,d+1}^2$ and $\sigma_{m,d+1}^2$ are the expected conditional variance of fund *i* and the market portfolio *m* separately on day *d*+1 conditional on the information set on day *d*. $\sigma_{im,d+1}$ is the day *d* expected conditional covariance between $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$. $u_{i,d} = \frac{\varepsilon_{i,d}}{\sigma_{i,d}}$ and $u_{m,d} = \frac{\varepsilon_{m,d}}{\sigma_{m,d}}$ are the standardized residuals for fund *i* and the market portfolio *m*, respectively. $\rho_{im,d+1}$ is the day *d* expected conditional correlation between $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$, and $\bar{\rho}_{im}$ is the unconditional correlation.

Relation between Beta Asymmetry and the HM Measure

We prove that beta asymmetry ($BA_{robust2}$) equals the Henriksson-Merton (1981) measure γ as follows. Let r_d and $r_{m,d}$ denote the excess fund and market return on day d. The Henriksson-Merton measure γ is the coefficient estimated from the regression

$$r_d = \alpha + \beta_0 r_{m,d} + \gamma \max(r_{m,d}, 0) + \varepsilon_d, \tag{A8}$$

where $\max(r_{m,d}, 0)$ equals $r_{m,d}$ if the market excess return on day d is positive and 0 otherwise. We extract $r_{m,d}$ and rewrite (A8) as

$$r_d = \alpha + (\beta_0 + \gamma I_{r_{m,d}>0}) r_{m,d} + \varepsilon_d, \tag{A9}$$

where $I_{r_{m,d}>0}$ is an indicator that takes the value of one when $r_{m,d} > 0$ and zero otherwise. Thus, for a time-varying fund beta β_d, the relation with the Henriksson-Merton measure is

$$\beta_d = \beta_0 + \gamma I_{r_{m,d}>0} + \eta_d. \tag{A10}$$

Specifically, we write (A10) in the form of conditional expectations:

$$E(\beta_d | r_{m,d} > 0) = \beta_0 + \gamma \tag{A11}$$

$$E(\beta_d | r_{m,d} \leq 0) = \beta_0. \tag{A12}$$

Subtracting equation (A12) from equation (A11), we get the relationship between the Henriksson-Merton measure γ and the beta asymmetry

$$\gamma = E(\beta_d | r_{m,d} > 0) - E(\beta_d | r_{m,d} \leq 0). \tag{A13}$$

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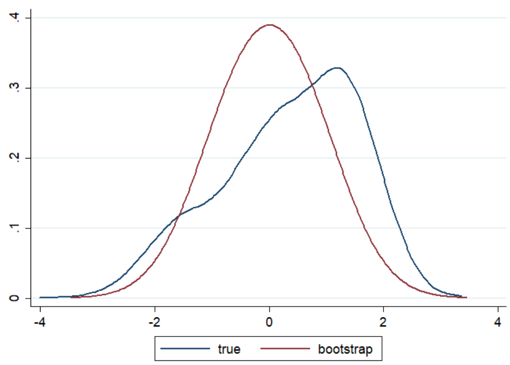
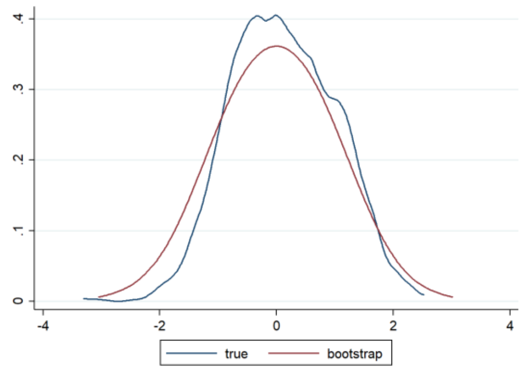
Figure 1. The distribution of *t*-statistics for the DCC-based timing measures γ_i.

The Treynor-Mazuy Measure

Panel A: Active Funds

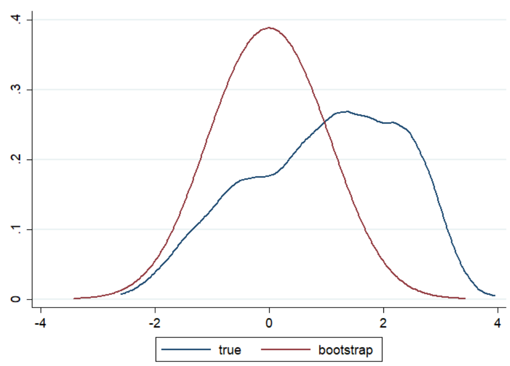


Panel B: Passive Funds

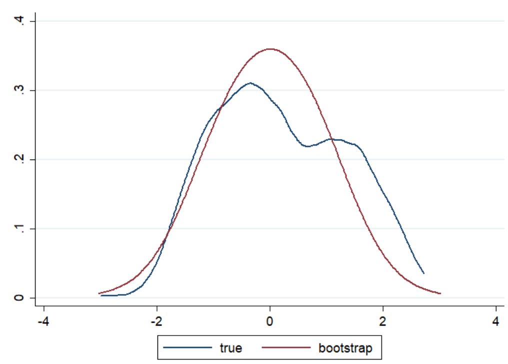


The Henriksson-Merton Measure

Panel C: Active Funds



Panel D: Passive Funds

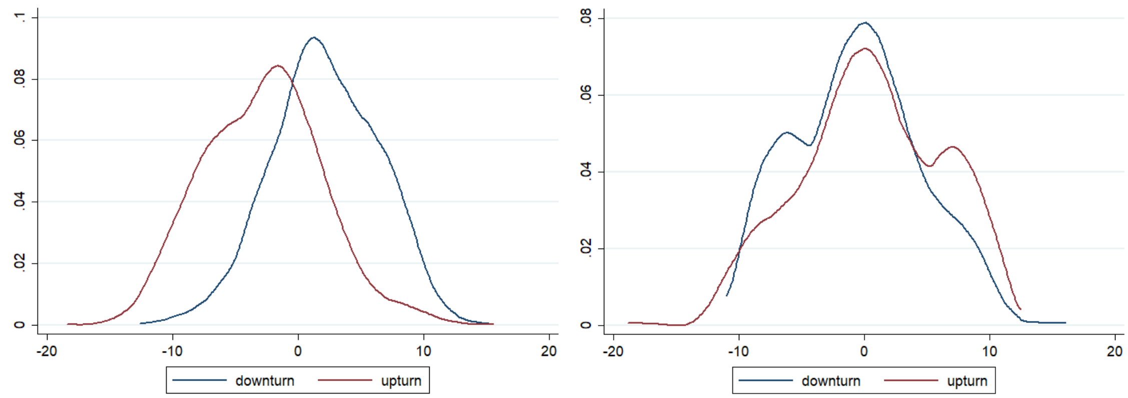


This figure plots the cross-sectional distribution of *t*-statistics (the blue line) for the DCC-based timing measures γ_i (for both active and passive funds), together with that of the bootstrapped distributions (the red line). Panel A and B report the results for timing tests using Treynor-Mazuy Measures. Panel C and D report the results for timing tests using the Henriksson-Merton Measures.

Figure 2. The distribution of t-statistics for the DCC-based timing measures γ_i during up and down markets.

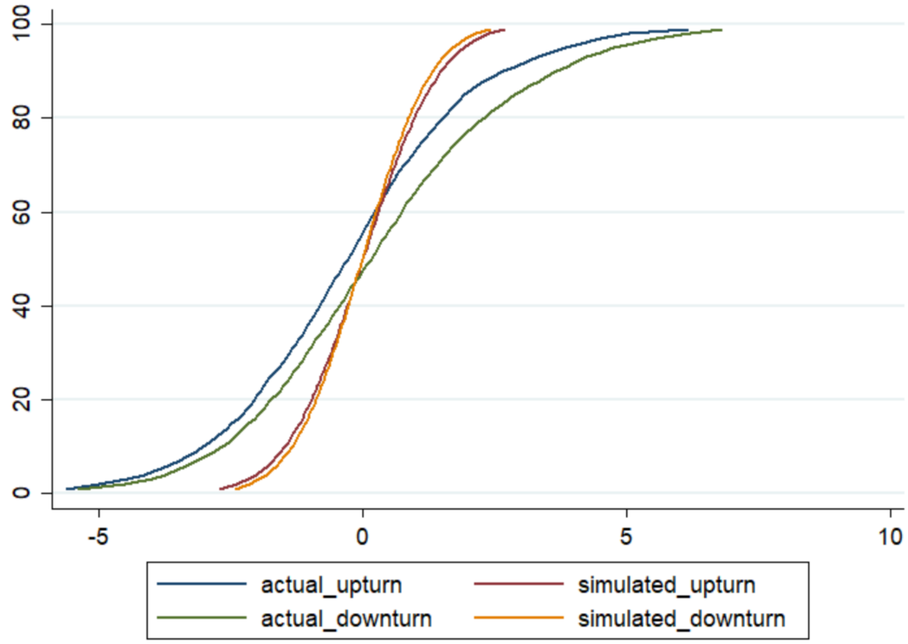
Panel A: Active Funds

Panel B: Passive Funds



This figure plots the cross-sectional distribution of t-statistics for the DCC-based timing measures γ_i, when the market excess return is positive (the blue line) and negative (the red line) for both active and passive funds.

Figure 3. The cumulative distribution of t-statistics for the three-factor alpha.



This figure shows the simulated and actual cumulatve distribution function of three-factor $t(\alpha)$ for updays and downdays. First, we split daily returns into up and down days depending on whether the market excess return is greater or less than 0. Second, following Fama and French (2010), we estimate cross sectional bootstraps separately for market updays and downdays. The sample period is from September 1998 to June 2016 in order to directly compare with Fama and French (2010). The figure shows evidence that active fund managers on average achieve higher downside alpha (the green line) than upside alpha (the blue line).

Table 1. Beta Difference, DCC and Rolling Beta

The table sorts funds into deciles based on difference in beta between the beginning of the year (i.e., January) to the end of the year (i.e., December). We estimate January and December betas using daily fund returns during that particular month. We estimate DCC and rolling betas on the last trading day of the calendar year using the entire year's daily returns.

Decile	Beta Difference	Beta			
	December - January	January	December	DCC	Rolling
1	-0.381	1.229	0.848	0.954	1.028
2	-0.168	1.102	0.934	0.982	1.005
3	-0.096	1.039	0.943	0.975	0.985
4	-0.047	0.989	0.942	0.964	0.966
5	-0.004	0.953	0.949	0.964	0.953
6	0.040	0.927	0.967	0.975	0.952
7	0.091	0.907	0.998	1.000	0.962
8	0.150	0.875	1.025	1.015	0.962
9	0.229	0.848	1.077	1.055	0.978
10	0.441	0.758	1.199	1.138	0.987

Table 2. Summary Statistics

The table reports summary statistics of our full sample from January 2000 to December 2015. At the end of each day, we calculate cross-sectional statistics (mean, standard deviation, minimum, 5^{th} percentile, 25^{th} percentile, medium, 75^{th} percentile, 95^{th} percentile, and maximum) of daily beta and then average the time series statistics. Other than Beta, we report monthly fund characteristics including beta asymmetry (three different measures), excess return (in percentage), the logarithm of TNA, fund age, net flow, expense ratio, and turnover ratio.

	mean	std	min	5%	25%	median	75%	95%	max
Beta	0.978	0.256	-0.314	0.566	0.835	0.973	1.127	1.379	2.230
BA	0.000	0.031	-0.227	-0.047	-0.016	0.000	0.015	0.044	0.229
$BA_{robust1}$	0.000	0.026	-0.166	-0.041	-0.014	0.000	0.014	0.039	0.179
$BA_{robust2}$	0.000	0.028	-0.166	-0.042	-0.014	0.000	0.015	0.042	0.187
Excess Return (%)	0.313	2.374	-12.060	-3.343	-1.031	0.289	1.656	4.025	12.930
Log(TNA)	5.759	1.639	2.156	3.238	4.511	5.676	6.884	8.601	11.660
Age	15.190	12.66	1.184	3.852	7.819	11.940	17.550	41.610	84.290
Net Flow	0.010	0.373	-0.575	-0.048	-0.015	-0.004	0.010	0.068	15.150
Expense Ratio	0.012	0.004	-0.001	0.006	0.010	0.012	0.015	0.019	0.046
Turnover Ratio	0.848	1.037	0.002	0.099	0.331	0.622	1.063	2.181	18.300

Table 3. Timing Tests

The table reports the cross-sectional distribution of the Treynor-Mazuy timing measure (Panel A) and the Henriksson-Merton timing measure (Panel B), i.e., $\hat{\gamma}$, as well as *t*-statistics (*t*). Panels A1, A3, A4, B1, B3, and B4 show the timing measure distribution of active funds; Panels A2 and B2 show the timing measure distribution of index funds. The table reports results based on three alternative methodologies. We base the results in Panels A1, A2, B1, and B2 on DCC betas. We base the results in Panel A3 and B3 on standard betas estimated via rolling windows. We base Panels A1, A2, A3 on regression (10) and Panels B1, B2, and B3 on regression (11). We base the results in Panels A4 and B4 on the standard timing factor models of TM and HM respectively. We report bootstrapped *p*-values for the timing measures and *t*-statistics, respectively, in parentheses underneath. *St.Dev*, *Skew*, and *Kurto* denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	5%	10%	25%	Mean	Median	75%	90%	95%	St.Dev	Skew	Kurto
					Panel A. Treynor-Mazuy						
A1: DCC Active											
$\hat{\gamma}$	-0.83	-0.47	-0.10	0.06	0.10	0.34	0.54	0.67	0.52	-1.72	11.38
p	(0.95)	(0.83)	(0.22)	(0.24)	(0.07)	(0.04)	(0.10)	(0.17)	(0.03)	(0.88)	(0.83)
t	-1.91	-1.47	-0.47	0.36	0.51	1.31	1.81	2.09	1.23	-0.46	2.59
p	(0.83)	(0.76)	(0.26)	(0.98)	(0.41)	(0.04)	(0.07)	(0.10)	(0.07)	(1.00)	(0.87)
A2: DCC Index											
$\hat{\gamma}$	-0.64	-0.26	-0.06	0.03	0.02	0.21	0.38	0.58	0.57	1.16	49.01
p	(0.59)	(0.19)	(0.08)	(0.35)	(0.26)	(0.13)	(0.42)	(0.58)	(0.48)	(0.35)	(0.25)
t	-1.19	-1.00	-0.51	0.12	0.11	0.82	1.30	1.49	0.88	-0.004	2.89
p	(0.05)	(0.15)	(0.24)	(0.28)	(0.31)	(0.32)	(0.48)	(0.66)	(0.82)	(0.49)	(0.55)
A3: Rolling Active											
$\hat{\gamma}$	-0.52	-0.30	-0.07	0.04	0.06	0.21	0.36	0.46	0.31	-1.42	9.34
p	(0.81)	(0.64)	(0.23)	(0.30)	(0.10)	(0.15)	(0.23)	(0.33)	(0.26)	(0.89)	(0.71)
t	-1.54	-1.22	-0.45	0.29	0.42	1.09	1.54	1.75	1.02	-0.36	2.33
p	(0.53)	(0.53)	(0.26)	(0.12)	(0.07)	(0.13)	(0.21)	(0.30)	(0.35)	(0.94)	(0.89)
A4: Standard Active											
$\hat{\gamma}$	-1.86	-1.21	-0.73	-0.36	-0.29	0.11	0.50	1.02	1.05	-1.69	18.90
p	(0.92)	(0.90)	(0.90)	(0.81)	(0.78)	(0.60)	(0.51)	(0.35)	(0.05)	(0.74)	(0.67)
t	-5.58	-4.75	-3.34	-1.37	-1.50	0.59	2.35	3.22	2.77	0.48	3.03
p	(1.00)	(1.00)	(1.00)	(0.97)	(0.97)	(0.38)	(0.03)	(0.01)	(0.00)	(0.03)	(0.83)

Table 3 continued.

	5%	10%	25%	Mean	Median	75%	90%	95%	St.Dev	Skew	Kurto
					Panel B. Henriksson-Merton						
B1: DCC Active											
$\hat{\gamma}$	-0.013	-0.007	-0.000	0.007	0.006	0.014	0.022	0.027	0.013	-0.663	7.164
p	(0.45)	(0.27)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)	(0.68)	(0.98)
t	-1.40	-0.96	-0.06	0.96	1.10	2.05	2.64	2.89	1.34	-0.31	2.25
p	(0.28)	(0.17)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.97)	(0.99)
B2: DCC Index											
$\hat{\gamma}$	-0.009	-0.005	-0.002	0.003	0.000	0.007	0.014	0.021	0.016	4.562	77.318
p	(0.04)	(0.02)	(0.19)	(0.04)	(0.46)	(0.02)	(0.10)	(0.14)	(0.18)	(0.06)	(0.05)
t	-1.53	-1.29	-0.71	0.19	0.02	1.16	1.84	2.11	1.16	0.14	2.09
p	(0.36)	(0.49)	(0.52)	(0.17)	(0.46)	(0.04)	(0.07)	(0.10)	(0.19)	(0.22)	(0.99)
B3: Rolling Active											
$\hat{\gamma}$	-0.015	-0.009	-0.002	0.004	0.004	0.010	0.017	0.021	0.011	-0.745	6.259
p	(0.91)	(0.80)	(0.18)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.72)	(0.95)
t	-1.910	-1.493	-0.440	0.678	0.954	1.849	2.362	2.586	1.430	-0.472	2.176
p	(0.81)	(0.78)	(0.24)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.04)	(0.99)	(0.96)
B4: Standard Active											
$\hat{\gamma}$	-0.158	-0.110	-0.059	-0.029	-0.021	0.010	0.043	0.075	0.079	-1.820	16.388
p	(0.89)	(0.85)	(0.80)	(0.75)	(0.69)	(0.62)	(0.60)	(0.55)	(0.12)	(0.84)	(0.49)
t	-4.75	-3.99	-2.72	-1.07	-1.08	0.54	1.99	2.74	2.32	-0.06	2.89
p	(1.00)	(1.00)	(1.00)	(0.94)	(0.91)	(0.44)	(0.07)	(0.01)	(0.00)	(0.52)	(0.86)

Table 4. Monthly Performance of Mutual Fund Sorted on Beta Asymmetry

The table reports excess return, Fama-French three-factor alpha, Carhart four-factor alpha, Fama-French five-factor alpha, and Fama-French (2018) six-factor alpha of portfolios of mutual funds sorted on beta asymmetry. Each month from January 2000 to December 2015, we sort funds into deciles based on beta asymmetry computed using daily fund net returns from the prior year. Beta asymmetry is the difference between upside beta and downside beta. Decile 1 contains funds with the lowest beta asymmetry, and decile 10 contains funds with the highest beta asymmetry. Return and alphas are monthly and reported in percentage. *t*-statistics are in parentheses. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively. Panel A shows equal-weighted portfolios, and Panel B shows value-weighted portfolios.

Panel A: Equal-weighted

	BA	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low *BA*	-0.055	0.149	-0.288***	-0.278***	-0.171	-0.171
2	-0.026	0.217	-0.201***	-0.200***	-0.225***	-0.225***
3	-0.016	0.277	-0.126**	-0.127**	-0.172***	-0.172***
4	-0.009	0.316	-0.080	-0.083	-0.132**	-0.132**
5	-0.003	0.338	-0.053	-0.056	-0.103**	-0.103**
6	0.002	0.347	-0.049	-0.055	-0.105**	-0.105**
7	0.008	0.400	-0.001	-0.010	-0.050	-0.051
8	0.015	0.451	0.030	0.019	0.011	0.010
9	0.025	0.537	0.106	0.099	0.081	0.081
High *BA*	0.053	0.612	0.176	0.168	0.178	0.178
High-Low		0.463***	0.464***	0.446***	0.349**	0.349**
t-statistic		(2.70)	(2.81)	(2.70)	(2.02)	(2.02)

Panel B: Value-weighted

	BA	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low *BA*	-0.050	0.021	-0.363***	-0.347***	-0.204*	-0.204*
2	-0.026	0.109	-0.264***	-0.266***	-0.235***	-0.235***
3	-0.016	0.224	-0.130*	-0.129*	-0.121*	-0.121*
4	-0.009	0.284	-0.067	-0.070	-0.074	-0.074
5	-0.003	0.308	-0.037	-0.038	-0.055	-0.055
6	0.002	0.316	-0.037	-0.040	-0.065	-0.065
7	0.008	0.408	0.041	0.027	0.018	0.018
8	0.015	0.453	0.069	0.056	0.080	0.080
9	0.024	0.457	0.077	0.072	0.079	0.079
High *BA*	0.051	0.534	0.147	0.139	0.185	0.185
High-Low		0.513***	0.510***	0.486***	0.389*	0.389*
t-statistic		(2.64)	(2.70)	(2.57)	(1.96)	(1.96)

Table 5. Beta Asymmetry and Downside Risk

The table shows equal-weighted measures of downside beta (β^{-}), expected shortfall (ES5, ES10), value-at-risk (VaR5, VaR10), and minimum return (Min) for deciles of mutual funds sorted based on beta asymmetry (BA). Decile 1 contains funds with the lowest beta asymmetry, and decile 10 contains funds with the highest beta asymmetry. We rebalance the deciles each month. *t*-statistics are in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Variable	BA	Downside Beta	ES5	ES10	VaR5	VaR10	Min
Low BA	-0.055	1.060	2.802	2.369	2.361	1.768	2.543
2	-0.026	1.012	2.562	2.169	2.160	1.620	2.320
3	-0.016	0.990	2.484	2.103	2.094	1.569	2.243
4	-0.009	0.969	2.433	2.058	2.047	1.534	2.192
5	-0.003	0.958	2.406	2.036	2.023	1.517	2.162
6	0.002	0.953	2.404	2.034	2.020	1.514	2.157
7	0.008	0.961	2.430	2.058	2.045	1.534	2.182
8	0.015	0.970	2.469	2.090	2.076	1.557	2.220
9	0.025	0.981	2.526	2.139	2.124	1.596	2.269
High BA	0.053	0.983	2.695	2.279	2.264	1.698	2.421
High-Low		-0.077***	-0.107**	-0.090*	-0.097**	-0.071*	-0.122**
t-statistic		(-3.65)	(-1.99)	(-1.95)	(-2.04)	(-1.92)	(-2.24)

Table 6. Market Timing and Flow

The table reports the coefficients and their t-statistics for regressions of fund flows on beta asymmetry (BA, BA_{robust_1}, BA_{robust_2}) and alpha (α) in two cases. The sample period is from January 2000 to December 2015. We report time-series averages of cross-sectional OLS estimates. Alpha, flow, expense ratio, and turnover ratio are in percentage. The standard errors were adjusted using Newey-West procedure with 3 lags. *t*-statistics are in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Without Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			Alpha>0			Alpha<0		
BA	1.549			5.065**			-0.010		
	(0.74)			(2.44)			(-0.00)		
BA_{robust_1}		3.190			8.084***			1.658	
		(1.37)			(3.05)			(0.47)	
BA_{robust_2}			4.212			10.716***			-0.235
			(1.44)			(2.74)			(-0.07)
$alpha$	0.278***	0.280***	0.284***	0.469***	0.472***	0.476***	0.235**	0.236**	0.236**
	(4.58)	(4.60)	(4.63)	(10.53)	(10.54)	(10.87)	(2.34)	(2.37)	(2.36)
Constant	0.363***	0.367***	0.352***	0.095	0.099	0.087	0.329***	0.329***	0.322***
	(4.04)	(4.04)	(3.86)	(1.19)	(1.25)	(1.11)	(3.05)	(3.02)	(2.98)
Fund-month obs	362,566	362,647	362,607	178,546	178,602	178,582	184,020	184,045	184,025
Average Rsq	0.011	0.011	0.011	0.014	0.014	0.015	0.009	0.009	0.009
Time periods	191	191	191	191	191	191	191	191	191

Table 6 continued.

Panel B: With Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			alpha>0			alpha<0		
BA	0.524			4.743**			-1.068		
	(0.19)			(2.39)			(-0.26)		
BA_{robust_1}		1.920			7.373***			0.559	
		(0.61)			(2.88)			(0.12)	
BA_{robust_2}			2.848			10.347***			-1.742
			(0.78)			(2.61)			(-0.39)
$alpha$	0.219***	0.219***	0.223***	0.368***	0.369***	0.373***	0.156	0.155	0.157
	(4.16)	(4.08)	(4.12)	(9.41)	(9.24)	(9.76)	(1.31)	(1.31)	(1.31)
Log(TNA)	-0.119**	-0.120**	-0.120***	-0.162***	-0.163***	-0.160***	-0.048	-0.048	-0.050
	(-2.60)	(-2.60)	(-2.61)	(-5.52)	(-5.53)	(-5.59)	(-0.58)	(-0.58)	(-0.60)
Lagged flow	0.273***	0.274***	0.274***	0.321***	0.321***	0.321***	0.223***	0.223***	0.223***
	(17.73)	(17.80)	(17.81)	(18.14)	(18.15)	(18.16)	(9.30)	(9.32)	(9.32)
Expense ratio	-0.000	0.006	-0.009	-0.304***	-0.303***	-0.320***	0.172	0.184	0.196
	(-0.00)	(0.03)	(-0.05)	(-2.91)	(-2.92)	(-2.93)	(0.56)	(0.60)	(0.64)
Turnover ratio	0.002**	0.002**	0.002**	0.003***	0.003***	0.003***	0.003	0.003	0.003
	(2.30)	(2.29)	(2.33)	(3.14)	(3.07)	(3.28)	(1.28)	(1.27)	(1.27)
Log(age)	-1.078***	-1.079***	-1.079***	-0.645***	-0.644***	-0.645***	-1.473*	-1.475*	-1.477*
	(-2.66)	(-2.66)	(-2.66)	(-8.99)	(-8.93)	(-8.98)	(-1.89)	(-1.89)	(-1.89)
TNA_family	0.055***	0.055***	0.054***	0.036***	0.036***	0.034***	0.057**	0.057**	0.057**
	(3.20)	(3.25)	(3.19)	(3.50)	(3.50)	(3.40)	(2.00)	(2.01)	(2.02)
Constant	2.956***	2.956***	2.957***	2.329***	2.339***	2.338***	3.235***	3.233***	3.219***
	(4.71)	(4.70)	(4.71)	(6.65)	(6.68)	(6.66)	(2.81)	(2.80)	(2.79)
Fund-month obs	357,177	357,218	357,193	175,874	175,896	175,885	181,303	181,322	181,308
Average Rsq	0.079	0.079	0.079	0.109	0.109	0.110	0.085	0.085	0.085
Time periods	191	191	191	191	191	191	191	191	191

Table 7. Market Timing and Portfolio Concentration

The table reports the estimates and t-statistics for regressions of fund timing (BA, BA_{robust_1}, BA_{robust_2}) on the degree of concentration of fund portfolios. The sample is from January 2000 to December 2013. We report time-series averages of cross-sectional OLS estimates. The magnitude of beta asymmetry is much small compared to the independent variables; thus, we scale the coefficients by 100 for the ease of reading. The standard errors were computed using Newey-West procedure with 3 lags. T-statistics are in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	BA		BA_{robust_1}		BA_{robust_2}	
HHI	-0.447	-0.637**	-0.696***	-0.812***	-0.550**	-0.806***
	(-1.44)	(-2.11)	(-2.61)	(-3.01)	(-2.06)	(-3.14)
Return		6.253*		4.728		5.129
		(1.82)		(1.55)		(1.55)
Log(TNA)		-1.346		-0.590		0.244
		(-1.30)		(-0.85)		(0.31)
Expense ratio		3.083		0.865		3.613
		(0.69)		(0.21)		(0.92)
Turnover ratio		0.014		0.020		0.046*
		(0.53)		(0.82)		(1.92)
Flow		-0.042		0.043		0.150
		(-0.24)		(0.29)		(0.96)
Log(Age)		-0.026		-0.63		-0.925
		(-0.02)		(-0.44)		(-0.61)
TNA_family		0.304		-0.214		-0.240
		(0.74)		(-0.74)		(-0.71)
Constant	6.804	7.692	7.0924	11.651	13.908*	10.563
	(0.87)	(0.48)	(0.93)	(0.83)	(1.85)	(0.67)
Fund-month obs	297,899	292,774	297,929	292,799	297,892	292,778
Average Rsq	0.018	0.099	0.018	0.106	0.018	0.107
Time periods (month)	168	168	168	168	168	168

Table 8. Beta Asymmetry and Portfolio Holding Types

The table reports coefficients and *t*-statistics for regressions of fund beta asymmetry on the interaction terms of Permit and Use dummies. We control for time fixed effects and standard deviation is clustered at the fund and time level. The magnitude of beta asymmetry is much small compared to the independent variables; thus, we scale the coefficients by 100 for the ease of reading. *t*-statistics are in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Short Sell	(2) Equity Option	(3) Debt Option	(4) Index Option	(5) Margin
Permit*Use	0.459**	-0.136	-0.693**	-0.658***	0.485
	(2.09)	(-1.39)	(-2.04)	(-4.16)	(1.49)
NoPermit*Use	-1.042***	-1.971**	-1.936***	-2.064***	-1.521***
	(-4.56)	(-2.13)	(-19.59)	(-18.88)	(-4.77)
Permit*NoUse	0.079	-0.099	0.101*	-0.061	0.078
	(1.55)	(-1.28)	(1.85)	(-0.78)	(1.38)
Intercept	0.093***	0.241***	0.079**	0.211***	0.131***
	(2.90)	(3.55)	(2.20)	(3.14)	(8.70)
Fund-month obs	19,320	19,320	19,320	19,320	19,320
Average Rsq	0.071	0.070	0.071	0.071	0.070
Time periods (month)	84	84	84	84	84

Table 9. Timing and Stock Holdings

The Securities and Exchange Commission established a pilot program wherein a subset of securities from the Russell 3000 was chosen for a short sale price test. The pilot program was effective from May 2, 2005 to August 6, 2007. Beta asymmetry is expected to increase for fund portfolios that hold more securities without the short sale constraint. We use a difference-in-difference regression as follows:

$$BA_{i,t} = b_0 + b_1 Time_t + b_2 SHO\%_{i,t} + b_3 Time_t \times SHO\%_{i,t} + \sum_{k=4}^{K} b_k \cdot Fund\ Controls_{i,t}^{k} + \varepsilon_{i,t}$$

where *Time* equals 1 if month *t* is during the period from May 2005 to July 2007. SHO% is the percentage holding value of stocks without the short sale restriction (i.e., the pilot group) to facilitate short selling. Fund characteristics are control variables. The magnitude of beta asymmetry is much small compared to the independent variables; thus, we scale the coefficients by 100 for the ease of reading. *t*-statistics are in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	BA		BA_{robust_1}		BA_{robust_2}	
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.282***	0.259***	0.446***	0.467***	0.473***	0.399***
	(4.56)	(4.14)	(8.26)	(8.56)	(8.29)	(6.93)
SHO%	0.809***	0.582***	0.734***	0.778***	1.292***	0.761***
	(7.29)	(5.01)	(7.59)	(7.70)	(12.64)	(7.12)
$Time \times SHO\%$	-0.025	0.055	-0.345*	-0.405**	-0.640***	-0.448**
	(-0.11)	(0.25)	(-1.81)	(-2.10)	(-3.17)	(-2.20)
Log(TNA)		-0.100***		-0.059***		-0.024***
		(-10.26)		(-7.01)		(-2.67)
Expense ratio		28.501***		19.485***		37.661***
		(6.64)		(5.21)		(9.54)
Turnover ratio		-0.014*		-0.017**		-0.005
		(-1.68)		(-2.45)		(-0.61)
Flow		-0.040*		-0.025		-0.032
		(-1.70)		(-1.21)		(-1.48)
Log(age)		0.001		0.112***		-0.159***
		(0.04)		(7.24)		(-9.73)
TNA family		-0.000***		-0.000***		-0.000***
		(-5.80)		(-5.41)		(-7.66)
Fund-month obs	321,189	316,677	321,222	316,702	321,189	316,685
R-squared	0.001	0.002	0.002	0.003	0.002	0.003

Table IA.1. Monthly Performance of Mutual Fund Sorted on Alternative Beta Asymmetry Measures

$$BA_{robust\_1} = Beta_{mkt>0,ret>0} - Beta_{mkt<0,ret<0}$$

$$BA_{robust\_2} = Beta_{mkt>0} - Beta_{mkt<0}$$

The table reports excess return, Fama-French three-factor alpha, Carhart four-factor alpha, Fama-French five-factor alpha, and Fama-French (2018) six-factor model of portfolios of mutual funds sorted on beta asymmetry alternative measures BA_{robust_1} (Panel A and Panel B) and BA_{robust_2} (Panel C and Panel D). Each month from January 2000 to December 2015, we sort funds into deciles based on BA_{robust_1} or BA_{robust_2} computed using daily fund net returns from the prior year. BA_{robust_1} is the difference between upside beta and downside beta determined based on whether the market return and the fund return are both above or below 0. For BA_{robust_2}, downside (upside) beta is determined based on whether the market return is below (above) 0. Decile 1 contains funds with the lowest beta asymmetry, and decile 10 contains funds with the highest beta asymmetry. Return and alphas are monthly and reported in percentage. Panel A and panel C show the equal-weighted portfolios; panel B and panel D show the value-weighted portfolios. *t*-statistics are in parentheses. *, **, *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A: Equal-weighted

	BA_{robust_1}	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low BA_{robust_1}	-0.047	0.098	-0.342***	-0.333***	-0.211*	-0.210*
2	-0.023	0.235	-0.186***	-0.191***	-0.200***	-0.200***
3	-0.014	0.317	-0.098	-0.104*	-0.129**	-0.129**
4	-0.008	0.344	-0.063	-0.070	-0.106*	-0.106*
5	-0.003	0.345	-0.054	-0.060	-0.123**	-0.123**
6	0.002	0.378	-0.021	-0.026	-0.085	-0.085
7	0.008	0.415	0.013	0.005	-0.037	-0.037
8	0.014	0.447	0.036	0.025	-0.015	-0.015
9	0.022	0.514	0.097	0.092	0.054	0.054
High BA_{robust_1}	0.045	0.553	0.133	0.138	0.162	0.162
High-Low		0.455**	0.475***	0.471***	0.373**	0.372**
t-statistic		(2.53)	(2.80)	(2.76)	(2.09)	(2.09)

Panel B: Value-weighted

	BA_{robust_1}	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low BA_{robust_1}	-0.045	-0.039	-0.432***	-0.418***	-0.287**	-0.287**
2	-0.023	0.176	-0.198***	-0.205***	-0.173**	-0.174**
3	-0.014	0.264	-0.102	-0.101	-0.056	-0.056
4	-0.008	0.290	-0.069	-0.083	-0.064	-0.065
5	-0.003	0.339	-0.020	-0.025	-0.069	-0.069
6	0.002	0.337	-0.023	-0.032	-0.058	-0.058
7	0.008	0.389	0.036	0.029	-0.013	-0.013
8	0.014	0.424	0.050	0.044	0.016	0.016
9	0.022	0.451	0.071	0.065	0.062	0.062
High BA_{robust_1}	0.043	0.501	0.123	0.125	0.174	0.174
High-Low		0.539***	0.555***	0.543***	0.461**	0.461**
t-statistic		(2.79)	(3.03)	(2.95)	(2.40)	(2.39)

Table IA.1 continued.

Panel C: Equal-weighted

	BA_{robust_2}	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low BA_{robust_2}	-0.048	0.142	-0.297**	-0.275**	-0.223*	-0.222*
2	-0.024	0.250	-0.175**	-0.171**	-0.220***	-0.220***
3	-0.015	0.288	-0.119*	-0.119*	-0.176***	-0.176***
4	-0.008	0.342	-0.059	-0.063	-0.126**	-0.126**
5	-0.002	0.339	-0.057	-0.065	-0.131**	-0.132**
6	0.003	0.378	-0.018	-0.024	-0.072	-0.072
7	0.008	0.427	0.016	0.004	-0.010	-0.011
8	0.015	0.463	0.046	0.032	0.026	0.025
9	0.024	0.503	0.081	0.068	0.073	0.072
High BA_{robust_2}	0.049	0.513	0.098	0.090	0.171	0.171
High-Low		0.371*	0.395*	0.365*	0.394*	0.393*
t-statistic		(1.70)	(1.89)	(1.75)	(1.79)	(1.79)

Panel D: Value-weighted

	BA_{robust_2}	Excess return	3-factor alpha	4-factor alpha	5-factor alpha	6-factor alpha
Low BA_{robust_2}	-0.046	0.034	-0.360**	-0.334**	-0.271*	-0.270*
2	-0.024	0.212	-0.168**	-0.165**	-0.171**	-0.171**
3	-0.015	0.207	-0.155**	-0.149**	-0.131*	-0.131*
4	-0.008	0.305	-0.057	-0.062	-0.105*	-0.105*
5	-0.002	0.311	-0.046	-0.051	-0.101**	-0.101**
6	0.003	0.316	-0.044	-0.049	-0.077	-0.077
7	0.008	0.375	0.010	-0.005	-0.017	-0.018
8	0.015	0.408	0.048	0.034	0.051	0.051
9	0.024	0.435	0.053	0.039	0.089	0.088
High BA_{robust_2}	0.046	0.455	0.087	0.079	0.171	0.170
High-Low		0.422*	0.447*	0.413*	0.441*	0.440*
t-statistic		(1.75)	(1.91)	(1.78)	(1.79)	(1.79)