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Artificial Market Timing in Mutual Funds

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Abstract

We document statistically significant relations between mutual fund betas and *past* market returns driven by fund feedback trading. Against this backdrop, evidence of "artificial" market timing emerges when standard market timing regressions are estimated across periods that span time variation in fund systematic risk levels, as is typical. Artificial timing significantly explains the inverse relation between timing model estimates of market timing and stock selectivity. A fund's feedback trading relates to its past performance and remains significant after accounting for trading on momentum. Fund flows suggest that investors value feedback trading, which helps hedge downside risk during bear markets.

I. Introduction

Since its inception dating back to Treynor and Mazuy (1966), the mutual fund market timing literature has regularly documented a set of results that are difficult to rationalize in the context of a well-specified test of market timing. First, studies often find that estimates of market timing skill are negatively cross-sectionally correlated with contemporaneous estimates of stock selection skill. That is, funds that show the ability to skillfully time the market during a given time period also show lower stock selection skill during that same time period. See, for example, Kon (1983), Henriksson (1984), Jagannathan and Korajczyk (1986), and Goetzmann, Ingersoll, and Ivkovich (2000). The reason this result seems peculiar is that there is no ex ante reason to expect market timing skill to inversely relate to contemporaneous stock selection skill. For

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instance, Kacperczyk et al. (2014) find that market timing skill and stock selection skill are *positively* correlated when estimated across different time periods: funds that time the market well during recessions tend to show stock selection skill during nonrecessionary periods. The tendency for market timing skill to be positively cross-sectionally correlated with stock selection skill is consistent with priors that either an inherent cognitive ability or effort underlie outperformance via both approaches.

Second, studies such as Chang and Lewellen (1984), Henriksson (1984), Grinblatt and Titman (1988), and Ferson and Schadt (1996) find that mutual funds have perverse market timing skill, on average. That is, funds show higher market exposure during periods with relatively poor market returns, and vice versa, that is, a significant *negative* correlation between market exposure and contemporaneous market returns. To the extent that an estimate of market timing ability emanates from deliberate fund manager behavior, it is difficult to rationalize why a fund manager would perversely time the market, given its negative impact on fund shareholder returns. Moreover, it seems no less a feat for a fund to time the market poorly than for it to time the market well. Evidence of market timing skill suggests that fund managers respond to a signal that reliably forecasts market returns, with perverse timers taking action that is contrary to what the signal would suggest. However, studies such as Lettau and Van Nieuwerburgh (2008) and Welch and Goyal (2008) document no evidence of an ex ante identifiable variable that significantly forecasts aggregate stock market returns. Since we are unable to identify how a fund might time the market, it seems unlikely that funds are able to, but they intentionally do so perversely.

We show that an inverse relation between empirical estimates of alpha and market timing stems largely from an important mismatch between the estimation periods typically examined in market timing analyses and the frequency with which a fund executes its investment strategy. Whereas most mutual fund market timing studies are based on monthly fund returns and multi-month estimation periods that span at least 2–3 years,[1] mutual funds operate intraday, as they respond to daily investor flows and the nonstop flow of information that affects their universe of current and potential stockholdings.[2]

The idea behind our analysis dates to Pfleiderer and Bhattacharya (1983) and can be illustrated with a simple example. Suppose a mutual fund responds to negative realized market returns by reducing its market exposure after the fact, possibly as part of an overarching process to manage risk. If the market shows negative returns during July, for example, the mutual fund lowers its systematic risk level during August. If one were to estimate a market timing model over an estimation period that spans July and August, as is typical (even in studies based on daily fund returns), the fund would appear to have timed the market well, as its average market exposure during the estimation period was relatively low, but only because it reduced its market exposure after the market dropped.[3] These types of

[1]Although Bollen and Busse (2001) use daily fund returns, they estimate timing regressions across 11 years.

[2]See, for example, Busse, Tong, Tong, and Zhang (2019), who report that, in 2009, institutional investment funds execute an average of 0.88 trades per day for each stock in their portfolio.

[3]Jiang, Yao, and Yu (2007) relate the betas of fund portfolio holdings at the end of quarter *t* to market returns following quarter *t*. As such, their market timing tests are not susceptible to this issue. Since they base their fund betas on quarterly holdings, however, they are unable to analyze the relation between

effects, where the estimated parameters of the market timing model are consistent with an interpretation of market timing ability, even though the fund's reduction in systematic risk does not reflect an ability to time future market returns, are referred to as "artificial timing" in the literature (e.g., Jagannathan and Korajczyk (1986), Jiang et al. (2007)).[4,5] In our setting, evidence of timing is an artifact of the fund manager operating at a higher frequency than is captured by the estimation period used in the empirical market timing model. Moreover, as the fund displayed no genuine skill, its artificial timing skill would be offset in an empirical timing model, such as that of Treynor and Mazuy (1966), by an equivalent but opposite (i.e., negative) artificial stock selection skill, thereby leading to a negative cross-sectional correlation between market timing and stock selectivity.

We use fund transaction-level data, daily fund returns, and short estimation periods to study how mutual funds respond to market returns at a greater frequency than previously examined in the literature. We focus on the ramifications to inference when market timing estimates are based on the multi-month estimation periods that typify market timing studies, including studies of monthly and daily fund returns. Our findings show that funds significantly respond to market returns at a lag, rather than in a predictive sense, that is, they feedback trade with respect to the stock market. We find strong evidence of positive feedback trading, where funds increase their beta after relatively positive market returns and decrease their beta after relatively negative market returns.

Funds trading based on past market returns leads to statistically significant estimates of market timing that have nothing in common with standard notions of skillful market timing. Moreover, we find that feedback trading results in an inverse relation between market timing and stock selectivity estimates, as expected. Analyzing transaction-level data shows that funds incur higher transaction costs when they feedback trade (as predicted by Pfleiderer and Bhattacharya (1983)), which further exacerbates the negative relation between artificial timing and fund performance. Finally, since no significant relation exists between the betas of traded stocks and future near-term market returns (i.e., up to 10 trading days), our results indicate that mutual funds have no genuine short-horizon market timing ability. Overall, we are the first to provide comprehensive analyses of feedback trading, artificial timing, and genuine short-horizon timing ability based on actual fund trades. As such, we shed light on a long-standing puzzle surrounding regression model estimates of mutual fund market timing (i.e., the inverse relation between market timing and stock selectivity), while proposing a new trade-based approach to assess fund managers' ability to time future market returns.

Our evidence of a positive relation between fund beta and past market returns stems, in part, from momentum trading (Grinblatt, Titman, and Wermers (1995)), Carhart (1997)), since winning stocks show relatively high betas after an increasing market. Nonetheless, significant feedback trading exists even after controlling for

higher-frequency, intra-quarterly fund activity (Kacperczyk, Sialm, and Zheng (2008), Puckett and Yan (2011)) and market returns.

[4]Jagannathan and Korajczyk (1986) use "artificial timing" to describe the effect of portfolio holdings with option-like features on market timing estimates.

[5]Our explanation relies on market returns showing low autocorrelation, consistent with our in-sample, monthly-frequency estimate of 0.06 from Sept. 1998 to Dec. 2018.

momentum trading and the disposition effect (Shefrin and Statman (1985)). We also find that a fund's feedback trading relates to its past performance, with poorly performing funds showing significantly greater positive feedback trading than top performers. As such, our findings relate to analyses of mutual fund tournaments (e.g., Brown, Harlow, and Starks (1996))), which examine how funds change their risk as a function of past performance as they compete for investor flows. Lastly, flows suggest that investors value feedback trading, possibly because it helps hedge downside risk during extended market drawdowns, such as the global financial crisis of 2008. The positive relation between fund feedback trading and investor flows provides fund managers with an incentive to feedback trade, since a fund's fees relate to its assets under management.

The focus of our study relates to previous work that posits alternative explanations for the perplexing empirical market timing findings documented in the literature. Ferson and Schadt (1996) and Ferson and Warther (1996) attribute the negative relation between fund systemic risk and subsequent market returns to effects related to investor cash flows. In his analysis of higher frequency daily data, Edelen (1999) identifies a related phenomenon arising because mutual funds offer investors the option to invest or redeem daily, that is, daily liquidity, with the resulting flows showing negative correspondence to the market return. However, a shortcoming of the investor flow explanation for the appearance of perverse timing is that there is little evidence to suggest that the stock market is predictable.[6] Our findings suggest that artificial timing contributes to the evidence of perverse market timing among certain funds.

We also contribute to the mutual fund literature that criticizes analyzing market timing ability using monthly frequency returns. Goetzmann et al. (2000) find that tests based on monthly returns produce downward biased timing estimates when funds time the market daily. Bollen and Busse (2001) find that tests based on monthly returns have less power to detect timing ability compared to tests based on daily returns. Jiang et al. (2007) and Ferson and Mo (2016) use fund portfolio holdings to test market timing, where they estimate fund betas based on the daily returns of fund stock holdings. Beyond using daily mutual fund returns, we go one step further and advocate using the actual trades of mutual funds to examine how funds alter the betas of their portfolios, a potentially important methodological improvement relative to the daily frequency timing studies given that Busse et al. (2019) find that the most active 20% of institutional investors execute an average of 1.66 trades per day for each stock in their portfolio.

The article proceeds as follows: We discuss our methodology in Section II. Section III describes the mutual fund data that we use. We present our empirical analysis in Section IV. Section V concludes.

II. Artificial Market Timing

The two most used approaches to estimate mutual fund market timing are those of Treynor and Mazuy (1966) and Henriksson and Merton (1981), estimated as

[6]Moreover, Barber, Odean, and Zhu (2009)) find that individual investors are relatively poor market timers with respect to their investments.

$$R_i - r_f = \alpha_i + \beta_i \left(R_m - r_f\right) + \gamma_i \left(R_m - r_f\right)^2 + \varepsilon_i, \tag{1}$$

and

$$R_i - r_f = \alpha_i + \beta_i \left(R_m - r_f\right) + \gamma_i \max\left(R_m - r_f,\, 0\right) + \varepsilon_i, \tag{2}$$

respectively, where R_i denotes the return of fund i, R_m is the market return, r_f is the risk-free rate, and γ_i represents fund i's market timing coefficient. In the TM specification, the market timing coefficient measures the extent to which fund beta is positively linearly related to the excess market return.[7] In the HM specification, it measures whether fund beta is greater (lower) when the excess market return is positive (negative). The relation between fund systematic risk and market return measured in equations (1) and (2) is contemporaneous, in line with the goal of these specifications to capture the ability of funds to show higher market exposure when the market return is relatively high and vice versa, thereby creating value for fund shareholders.

However, in situations where the time period across which the timing model is estimated is long relative to the frequency with which fund managers alter their portfolios, which is almost always the case, factors other than deliberate attempts by the fund manager to time the market could induce a significant relation between fund beta and market returns. To illustrate these effects, consider a simple case in which a mutual fund trades during each period t, with t in half-month increments (as an example), but returns are observed at a lower frequency, say every 2 periods (via monthly returns). Suppose a fund manager has no genuine market timing ability but adjusts fund beta during the second period conditional on the realized market return during the first period, that is, the fund manager feedback trades with respect to the stock market. Behavior of this sort induces a contemporaneous nonlinear relation between the realized 2-period fund return and the market return. The associated effects on the market timing results in equations (1) and (2) are referred to as "artificial timing."

For example, a fund manager who increases market exposure after positive market returns, that is, a positive feedback fund manager, would exhibit positive artificial timing, and a manager who decreases market exposure after positive market returns, that is, a negative feedback fund manager, would exhibit negative or perverse artificial timing. If we take the spurious timing gamma estimate and compute its return contribution in a monthly timing regression (e.g., in a TM regression, the timing gamma comes in as $\gamma_i \left(R_m - R_f\right)^2$), then, assuming the market return is not autocorrelated, that contribution represents the artificial return that the alpha of the timing model needs to offset. It is this type of dynamic that could explain the empirical evidence of a negative cross-sectional correlation between the market timing alpha (α_i) and gamma (γ_i) in equations (1) and (2).[8]

[7]For instance, the TM specification results from specifying fund i's market risk as $\beta_i' = \beta_i + \gamma_i \left(R_m - r_f\right)$ and then substituting this expression into a single-factor model of fund returns.

[8]For example, Henriksson (1984) finds that when using a nonlinear model to test the timing ability of mutual funds, the timing coefficients are inversely related to the alphas. Bollen and Busse (2001) confirm this evidence.

To illustrate this effect empirically, consider a simple case in which a fund manager with no ability to forecast the market responds to the market with a lag. For instance, express fund beta on day d as

(3) $$\beta_d = \beta_p + \lambda \frac{1}{11} \sum_{s=1}^{11} r_{m,d-s},$$

where $r_{m,\mathrm{d}}$ is the market excess return on day d, and there are approximately 11 daily returns per half month. Thus, the daily return of this hypothetical fund is

(4) $$r_{p,d} = \alpha_p + \beta_p r_{m,d} + \lambda \left(\frac{1}{11} \sum_{s=1}^{11} r_{m,d-s} \right) r_{m,d} + \epsilon_d.$$

If funds behave as described in equations (3) and (4) with $\alpha_p = 0$, $\beta_p = 1$, and $\lambda = 5$, and we were to analyze their timing ability via estimation periods that were incapable of capturing the dynamic relation between fund betas and past market returns, we would estimate a positive market timing gamma, γ. The inference would be that funds skillfully time the market, even though they were not timing the model in a predictive sense, since their betas are based only on *past* market returns.

For instance, when we compute equations (3) and (4) over the 5-year time period from 2014 to 2018 based on 1,257 daily return observations using the SPY ETF as the market proxy, and then estimate the TM market timing model (equation (1)) after aggregating the daily returns to a monthly frequency, we estimate γ to be 0.14. As mentioned above, the artificially positive timing gamma is offset by a negative timing model alpha, which we estimate in this example as $\alpha_p = -0.03\%$ per day.[9] Since there is no positive correlation between $r_{m,d}$ and the average market excess return from $d-11$ to $d-1$ (the correlation is -0.06 in this example), the evidence of positive market timing ability is spurious, and the return associated with this spurious evidence of timing ability is offset by the negative alpha.

III. Data

We use two distinct samples based on data from three sources. First, we obtain open-end mutual fund daily and monthly 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 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 investment objective codes from CRSP following Kacperczyk et al. (2008). We exclude ETFs, annuities, and index funds

[9]When the variance of ϵ_d in (4) approaches 0, the t-statistics for γ and α_p approach 2.90 and -4.45, respectively. γ and α_p are statistically significant at the 5% level when $\lambda > 2.3$.

TABLE 1

Market Timing Coefficient Estimates

Table 1 shows alpha, gamma, and beta estimated based on the Treynor and Mazuy (1966) and Henriksson and Merton (1981) market timing models (equations (1) and (2)) using monthly returns. Alpha is in percentage per month. The sample includes 3,383 actively-managed funds across a Sept. 1998 to Dec. 2018 sample period.

Panel A. Distribution of Market Timing Coefficients

	TM			HM		
	Alpha	Beta	Gamma	Alpha	Beta	Gamma
p5	−0.664	0.635	−2.767	−0.854	0.608	−0.463
p10	−0.437	0.737	−1.604	−0.524	0.734	−0.281
p25	−0.197	0.883	−0.671	−0.228	0.889	−0.120
p50	−0.019	0.997	−0.128	−0.022	1.007	−0.015
p75	0.172	1.132	0.293	0.215	1.158	0.071
p90	0.440	1.277	0.889	0.553	1.347	0.192
p95	0.710	1.430	1.520	0.948	1.536	0.311
Mean	−0.002	1.012	−0.266	0.010	1.032	−0.034
Std. Dev.	0.594	0.267	1.922	0.887	0.361	0.356

Panel B. Relationship Between Market Timing Alpha and Gamma

	TM			HM		
	$\gamma < 0$	$\gamma > 0$	Total	$\gamma < 0$	$\gamma > 0$	Total
$\alpha < 0$	22.49	31.33	53.83	16.23	36.51	52.73
$\alpha > 0$	35.53	10.64	46.17	38.81	8.45	47.27
Total	58.03	41.97	100	55.04	44.96	100
$\rho(\alpha, \gamma)$	−0.66	*t*-stat	−51.42	−0.87	*t*-stat	−104.04

based either on their indicator variables or fund names from CRSP.[10] Since we focus on equity funds, we require 80% of assets under management to be invested in stocks. We restrict our sample to funds that are at least 1 year old and have at least $15 million in assets under management, and we address incubation bias as in Evans (2010). Our final sample includes 3,383 U.S. actively managed domestic equity funds across a sample period from Sept. 1998 to Dec. 2018, where the Sept. 1998 start date is driven by the availability of daily fund returns from CRSP.

Table 1 reports the distribution of the market timing alpha and gamma estimates for our sample based on the standard TM and HM models in equations (1) and (2). We estimate the timing models for each fund using monthly returns across its entire time series, requiring a minimum of 12 observations for each fund. Timing gamma is negative for 58.03% and 55.04% of the funds based on TM and HM, respectively, consistent with prior evidence of perverse timing. Alpha and gamma are of opposite sign for 66.86% and 75.32% of funds based on the TM and HM measure, respectively. The most common combination is a positive alpha estimate coupled with negative gamma. Among funds with positive alpha estimates, 76.95% (TM) or 82.10% (HM) have negative timing gammas, whereas only 41.78% (TM) or 30.78% (HM) of funds with negative alphas have negative timing gammas. The correlation between alpha and gamma estimates in the cross-section of funds is −0.66 based on TM and −0.87 based on HM.

[10]Like Busse, Jiang, and Tang (2021), we exclude from our sample funds whose names contain any of the following text strings: Index, Ind, Idx, Indx, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000. We also remove funds with CRSP index fund flag equal to “D” (pure index fund) or “E” (enhanced index fund).

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Thus, the evidence shows a strong negative relation between timing alpha and gamma, consistent with previous studies.

Our second data sample consists of the trade-by-trade transaction history of 581 actively-managed mutual funds over the period from Jan. 1999 to Mar. 2012 from the Abel Noser database. The Abel Noser institutional trade database reports the date, ticker symbol, trade price, and trade direction (i.e., buy or sell) for a large sample of institutional money managers. It does not, however, disclose actual fund identities. We determine fund identities in Abel Noser by comparing the disclosed trades to changes in portofolio holding snapshots in the Thomson Reuters database and, additionally, by manual cleaning the matches based on fund names and a name list from Abel Noser as in Agarwal, Tang, and Yang (2012)) and Busse, Chordia, Jiang, and Tang (2021)).[11] To get fund characteristics, we further match the funds in the merged Abel Noser-Thomson Reuters database to the CRSP mutual fund database using the MFLINKS table available on WRDS.

As Busse et al. (2021) report, the Abel Noser sample skews toward larger funds compared to mutual fund samples sourced from CRSP. We confirm this in Table B.1 of the Supplementary Material, where we compare fund characteristics and descriptive statistics of fund market timing measures for the Abel Noser and CRSP samples. Aside from the higher TNA, however, the distribution of other fund characteristics in Abel Noser is similar to that of funds in the CRSP sample. Note also that Abel Noser data are used widely in the academic literature (see Hu, Jo, Wang, and Xie (2018)) for a comprehensive list). Nonetheless, since the sample size and sample period are smaller for Abel Noser than for CRSP, we later show that our inference does not change when we repeat our main analyses based on the subset of CRSP funds that overlaps with the Abel Noser fund sample and sample period.

Table 2 reports fund and trade characteristics for the 30,367 fund-month observations in the Abel Noser sample. On average, fund monthly net flows amount to 1.08% of fund total net assets. Each fund buys (sells) \$187.39 million (\$193.08 million) each month, on average, or 13.5% (13.1%) of its assets under management. The fact that aggregate fund trading activity as a percentage of total net assets greatly exceeds the net flow percentage suggests that sample funds trade much more than what is required to address investor cash flows.

IV. Empirical Analysis

A. Feedback Trading Evidence

To see whether the artificial timing effect illustrated in Section II is borne out in actual mutual fund data, we begin our empirical analysis by examining whether evidence of feedback trading exists within our fund sample. In line with the earlier examples, we analyze the relation between past market returns and subsequent fund beta, and we do so based on an estimation period for fund beta that is short relative

[11]See Agarwal et al. (2012) and Busse et al. (2021) for more details on the procedure used to match mutual funds in the Abel Noser data to the Thomson Reuters S12 holdings database. We thank Baozhong Yang for sharing part of the Abel Noser-Thomson Reuters link table.

TABLE 2

Summary Statistics of Fund Characteristics and Trades

Table 2 reports descriptive statistics of fund and trade characteristics at the fund-month level. Fund characteristics include fund total net assets (TNA), total net assets of fund family, fund age, investor net flow, expense ratio, turnover ratio, net return, and fund buy and sell trade volume (in dollars and percentage). The sample consists of 581 actively-managed funds across a Jan. 1999 to Mar. 2012 sample period.

Variable	Mean	Std. Dev.	p5	p25	p50	p75	p95
TOTAL_NET_ASSET ($M)	2,961.63	7,709.80	29.30	134.50	478.80	1,851.60	16,364.20
FAMILY_TNA ($B)	517.09	512.72	1.97	23.06	497.50	912.78	1,371.43
AGE (#year)	15.43	12.80	2.33	6.83	12.75	19.75	41.42
FLOW(t)/TNA($t-1$) (%)	1.08	36.01	−5.20	−1.57	−0.39	1.18	9.59
EXPENSE_RATIO (%)	1.17	0.46	0.39	0.88	1.14	1.47	1.99
TURNOVER_RATIO (%)	98.47	71.57	19.00	50.00	81.00	127.00	240.00
RETURN (%)	0.50	5.80	−9.39	−2.49	0.98	3.93	8.81
BUY_VOLUME ($M)	187.39	500.34	0.75	7.68	35.33	143.22	877.25
SELL_VOLUME ($M)	193.08	546.90	0.69	7.36	34.05	142.40	910.42
BUY(t)/TNA($t-1$) (%)	13.45	21.46	0.36	2.96	6.67	13.56	53.38
SELL(t)/TNA($t-1$) (%)	13.14	21.24	0.30	2.98	6.72	13.24	49.23

to the estimation periods typically analyzed in the mutual fund market timing literature. Most market timing studies use monthly fund returns and estimate market timing regression models (equations (1) and (2)) across a fund's entire time series of returns or based on a rolling estimation period of at least 36 months. We analyze three different time frames over which to define market returns and fund beta. The shortest estimation period requires sufficient calendar length so that we can estimate fund betas based on daily fund returns (from CRSP), and we set this period to be one-half month, comprising ten or eleven daily returns, on average. In addition to the half-month estimation interval, we also utilize estimation intervals of 1 month and one quarter.

Thus, we first examine whether fund betas during one half of a month are significantly related to market returns during the prior half-month, that is, whether funds respond to the market return with a lag. We compute the mean excess daily market return, $R^M_{t,1}$, from the 1st through the 15th and fund beta, $\beta^i_{t,2}$, based on OLS from the 16th through the 31st.[12] Similarly, we relate the first half of month fund beta to the last half of the prior month market return. To test whether fund managers alter fund beta conditional on the prior realized market return, we regress beta during the latter half month, $\beta^i_{t,2}$, on the mean daily market return during the earlier half month, $R^M_{t,1}$, that is,

$$\beta^i_{t,2} = \alpha^i + \delta^i R^M_{t,1} + \epsilon^i_{t,2}, \tag{5}$$

or on an indicator variable that equals 1 when the cumulative market return during the first half month is positive, $I_{R^M_{t,1}>0}$,

[12]Our results are robust to alternative beta estimation procedures that are less susceptible to noise given the short, half month measurement interval. For instance, we follow Bali and Engle (2010) and use daily returns over the past 252 trading days to estimate time-varying daily betas for each fund based on the dynamic conditional correlation (DCC) model (Engle (2002)). We get betas for each fund in each half month by taking the average of the daily DCC betas during the first and second halves of the month. We report the results of this alternative analysis in Table A.1 of the Supplementary Material.

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$$\beta^i_{t,2} = \alpha^i + \delta^i I_{R^M_{t,1}>0} + \epsilon^i_{t,2}, \tag{6}$$

δ^i provides an indication of the fund's feedback trading: $\delta^i > 0$ indicates the fund increases (decreases) its beta conditional on positive (negative) prior market returns, and is thus consistent with positive feedback trading, whereas the converse, $\delta^i < 0$, is consistent with negative feedback trading. Equation (5) captures timing analogous to the TM model in equation (1), and equation (6) captures timing analogous to the HM model in equation (2). We use two approaches to estimate regressions (5) and (6). In our first approach, we estimate (5) and (6) for each fund via OLS using its entire time series of returns. We then compute the cross-sectional mean timing measure, weighting the individual timing measures by the inverse of their standard errors to reduce the impact of imprecise estimates. Second, we estimate (5) and (6) via panel regressions with fund fixed effects using clustered standard errors at the fund level. We repeat these analyses based on the alternative one-month and one-quarter estimation intervals, computing $R^M_{t,1}$ and $\beta^i_{t,1}$ across 1 month or 1 quarter and $\beta^i_{t,2}$ across the subsequent 1 month or 1 quarter.

Table 3 presents the results of the initial feedback trading analysis. Panel A reports mean regression coefficients corresponding to equations (5) and (6), and Panel B reports the number of funds that show a significantly positive feedback trading coefficient and the number of funds that show a significantly negative feedback trading coefficient. The results based on all three measurement intervals and for all specifications indicate that fund managers, on average, show higher market exposure after the market performs well, and conversely, that is, they behave as positive feedback traders relative to market returns during the prior half month to 1 quarter.[13] Moreover, the statistical significance of the coefficients on the market variables is noteworthy, as the *t*-stats range from 15.06 to 35.94. In all specifications, the statistical significance of the coefficients on the market variables decreases as the measurement interval increases, consistent with fund managers showing greater sensitivity to more recent market returns.[14]

The results in Panel B are also consistent with positive feedback trading, with the percentage of funds showing statistical significance much greater than expected based on the null hypothesis regardless of the test level. By contrast, there is little evidence of negative feedback trading except based on the one-half-month measurement interval and in the extreme tail of the *t*-statistic distribution. Also, note that the strong evidence of positive feedback trading in Table 3 is not inconsistent with the negative mean market timing evidence in Table 1 because feedback trading is not the only fund feature that could affect market timing estimates.[15] For example,

[13]Investing based on time series momentum (Moskowitz, Ooi, and Pedersen (2012)) is one example of a positive feedback strategy that mutual fund managers might pursue, where fund managers increase the risk level of their portfolio after the market outperforms. Note, however, that the existence of significant time series momentum remains an open question (see Huang, Li, Wang, and Zhou (2020)).

[14]In Table B.2 of the Supplementary Material, we show that fund-level feedback trading strongly persists across calendar quarters.

[15]We repeat the Table 3 analysis based on the subset of CRSP funds that overlaps with the Abel Noser fund sample and sample period, and we report these results in Table B.3 of the Supplementary Material. The results from this reduced sample produce the same inference as the results in Table 3.

TABLE 3

Relation Between Fund Beta and Past Market Return

Table 3 examines the relation between fund beta and the lagged market return. Panel A reports mean regression coefficients based on Treynor and Mazuy (1966) in Panel A1 and based on Henriksson and Merton (1981) in Panel A2. We base the OLS columns on timing measures estimated from each fund's time series of returns. The OLS columns reflect a weighted average calculated across all funds with weights given by the inverse of the standard errors of the estimates of the individual timing measures. The panel regression columns reflect the average timing measure of all funds computed via a panel regression with fund-fixed effects using clustered standard errors at the fund level. Standard errors are adjusted for heteroskedasticity. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Panel B reports the fraction of funds that respond positively or negatively to previous market returns at different significant levels (1%, 5%, and 10%). The sample includes 3,383 actively-managed funds across a 1998–2018 sample period.

Panel A. Regression Coefficients

	OLS			Panel Regressions		
	½ Month	1 Month	1 Quarter	½ Month	1 Month	1 Quarter
Panel A1. TM						
$R^M_{t,1}$	2.705***	4.106***	5.924***	4.072***	6.193***	8.353***
	(23.56)	(22.50)	(15.06)	(32.97)	(30.25)	(17.64)
Constant	0.960***	0.960***	0.963***	0.973***	0.973***	0.970***
	(308)	(311)	(322)	(31,217)	(19,584)	(7,926)
Panel A2. HM						
$I_{R^M_{t,1}>0}$	0.023***	0.019***	0.024***	0.037***	0.031***	0.036***
	(26.45)	(23.64)	(19.35)	(35.94)	(31.61)	(22.60)
Constant	0.947***	0.948***	0.947***	0.952***	0.955***	0.947***
	(315)	(308)	(296)	(1,545)	(1,527)	(846)

Panel B. Significant Feedback Trading Estimates

	Positive Feedback			Negative Feedback		
	½ Month	1 Month	1 Quarter	½ Month	1 Month	1 Quarter
Panel B1. TM						
0.5%	8.93	4.76	3.02	1.03	0.68	0.70
1%	12.65	7.42	4.31	1.66	1.06	1.19
5%	25.24	19.01	12.53	4.11	3.04	4.28
10%	33.08	28.79	20.95	6.80	5.65	7.79
Panel B2. HM						
0.5%	15.70	5.53	5.77	1.66	0.50	0.96
1%	19.27	9.02	7.89	2.22	0.83	1.76
5%	31.42	21.22	19.92	5.47	3.37	5.40
10%	39.34	31.33	30.13	8.57	6.06	9.48

Ferson and Schadt (1996), Ferson and Warther (1996), and Edelen (1999) argue that the effects of investor cash flows on fund betas lead to negative market timing estimates. Moreover, when we form a subsample of zero-feedback trading funds by removing funds with significant positive or negative feedback trading at the 10% level, the zero-feedback trading funds show TM and HM timing gammas that average −0.342 and −0.047, respectively, which are smaller (i.e., more negative) than the corresponding gamma averages across the full sample (i.e., −0.266 and −0.034 across 3,383 funds). This result is consistent with the expectation that positive average feedback trading positively impacts market timing estimates.

B. Artificial Timing and the Alpha–Gamma Relationship

As discussed above, positive-feedback trading – increasing (decreasing) market exposure after positive (negative) market returns – contributes to spurious evidence of market timing in an analysis based on measurement intervals that are long relative to the frequency with which fund managers alter fund beta. In standard timing models such as equations (1) and (2), the return associated with spurious timing, given by $\gamma_i(R_m - r_f)^2$ for TM and $\gamma_i \max(R_m - r_f, 0)$ for HM, is offset via a reduction in the contemporaneous timing model alpha. Similarly, a negative-feedback trading manager decreases (increases) market exposure after positive (negative) market returns, and this behavior contributes to spurious evidence of perverse market timing that is offset via an increase in its contemporaneous alpha estimate. Thus, both positive and negative feedback trading would be expected to contribute to a negative cross-sectional relation between the return associated with the timing model gamma coefficient and the contemporaneous timing model alpha.

We analyze the extent to which feedback trading affects the estimates associated with standard market timing models as a function of a fund's tendency to alter its beta based on past market returns. We emphasize one-half month estimation intervals in this analysis, although the results are qualitatively similar based on 1-month or 1-quarter estimation intervals. We first sort funds into quintiles based on the time series correlation between fund beta during the second half of a month and the market return during the previous half of a month, that is, $\rho\left(\beta_{t,2}, R^M_{t,1}\right)$. We then compute for each quintile several statistics, including the mean of the return contribution associated with the timing model gamma coefficient, the mean of the timing model alpha, and the covariance between these two timing model performance estimates.

We report the results of this analysis in Panel A of Table 4 showing the results associated with the TM model, and Panel B showing the results associated with the HM model. In Panel A, the TM results indicate a strong positive correspondence between the correlation between fund beta during the second half of a month and the

TABLE 4

Timing Alpha–Gamma Relation

Table 4 reports statistics for funds sorted into quintiles based on the correlation between fund market beta estimated over a half-month interval and the market return from the prior half-month. Panel A reports results based on Treynor and Mazuy (1966), and Panel B reports results based on Henriksson and Merton (1981). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample consists of 3,383 actively-managed funds across a 1998–2018 sample period.

Panel A. TM

Portfolio	$\rho\left(\beta_{t,2}, R^M_{t,1}\right)$	γr_m^2	α	$\text{cov}(\alpha, \gamma r_m^2)$
1	−0.144	−0.146	0.043	−0.268
2	−0.024	−0.075	0.042	−0.126
3	0.029	−0.044	0.020	−0.144
4	0.093	−0.001	−0.004	−0.133
5	0.220	0.021	−0.109	−0.242
Diff. (5−1)		0.166***	−0.151***	
t		(6.44)	(−3.95)	

Panel B. HM

Portfolio	$\rho\left(\beta_{t,2}, R^M_{t,1}\right)$	$\gamma \max(r_m, 0)$	α	$\text{cov}(\alpha, \gamma \max(r_m, 0))$
1	−0.144	−0.251	0.134	−1.174
2	−0.024	−0.093	0.059	−0.463
3	0.029	−0.034	0.015	−0.592
4	0.093	0.030	−0.033	−0.599
5	0.220	0.032	−0.127	−0.842
Diff. (5−1)		0.283***	−0.260***	
t		(4.68)	(−4.55)	

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market return during the prior half of month and the return contribution associated with the timing model gamma coefficient, as $\gamma_i r_m^2$ increases monotonically across the $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintiles. The top $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintile shows a positive timing model gamma return contribution (i.e., positive artificial timing), whereas the bottom $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintile shows a negative timing model gamma return contribution (i.e., perverse artificial timing). Moreover, the difference in the timing model gamma return contribution between the top and bottom $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintiles is strongly statistically significant (t-stat = 6.44). Also evident is a strong inverse relation between the correlation between fund beta during the second half of the month and the market return during the first half of the month and the timing model alpha, with the difference in the timing model alpha between the top and bottom $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintiles strongly statistically significant (t-stat = −3.95). The results confirm that positive feedback trading (as reflected in the quintile 5 funds) generates positive artificial timing that is offset by negative timing model alpha and that negative feedback trading (as reflected in the quintile 1 funds) generates perverse artificial timing that is offset by a positive timing model alpha. Lastly, $\text{cov}\left(\alpha, \gamma r_m^2\right)$ is negative and greatest in the extreme quintiles.

The HM results in Panel B of Table 4 provide similar inference to the TM results in Panel A: a significantly strong positive relation between $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ and $\gamma_i \max(r_m, 0)$, a significantly strong negative relation between $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ and the timing model alpha, and relatively large negative $\text{cov}(\alpha, \gamma \max(r_m, 0))$ in the extreme $\rho\left(\beta_{t,2}, R_{t,1}^M\right)$ quintiles.

Table 4 examines the cross-sectional correspondence between feedback trading and market timing estimates; we also analyze their time series relation. For each fund, for each nonoverlapping 2-year interval, we estimate the standard market timing gamma (γ_i in equation (1) or (2)) once based on 24 monthly returns and the feedback trading estimate (δ^i in equation (5) or (6)) based on a half-month measurement interval (i.e., the second-half-of-month beta and the first-half-of-month market return). For example, a 20-year sample period produces a time series of ten estimates of each. We then compute value-weighted average estimates across funds period by period and the time series correlation of these two estimates.

Based on the TM market timing model (equations (1) and (5)), the time series correlation is 0.49, and based on the HM market timing model (equations (2) and (6)), the time series correlation is 0.30. The results thus show that a strong correspondence exists across time between the way funds respond to past market returns and their standard market timing estimates.

C. Fund Stock Trades, Feedback Trading, and Market Timing

Based on daily fund returns, our prior findings in Table 3 indicate that funds buy (sell) relatively high (low) beta stocks conditional on positive past market return. We next use fund trade-level data to examine directly the relation between market returns and the systematic risk of the stocks that funds trade.

We first calculate the betas of fund trades as follows: We estimate the beta of an individual stock j based on a regression of monthly excess returns (in excess of the risk-free rate r) on monthly excess market returns and other risk factors during the 36-month time period prior to the trade, requiring a minimum of 12 observations, that is,

$$(7)\quad R_{j,t} - r_t = \alpha_{j,t} + \beta_{j,t}^{M}(R_t^M - r_t) + \beta_{j,t}^{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{j,t}^{\mathrm{HML}}\mathrm{HML}_t + \beta_{j,t}^{\mathrm{UMD}}\mathrm{UMD}_t + \epsilon_{j,t},$$

where we take the size (SMB), book-to-market (HML), and momentum (UMD) factors from Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Following Agarwal et al. (2012), for each fund, we separate its traded stocks into two groups each day based on whether the stock was bought or sold, and we then compute the trade dollar-weighted average buy and sell beta as

$$(8)\qquad \beta_d^{i,B} = \sum_{j=1}^{N} \frac{B_{j,d}^i}{\sum_{k=1}^{N} B_{k,d}^i}\beta_{j,d},\ \beta_d^{i,S} = \sum_{j=1}^{N} \frac{S_{j,d}^i}{\sum_{k=1}^{N} S_{k,d}^i}\beta_{j,d},$$

where $B_{j,d}^i$ ($S_{j,d}^i$) is the dollar value of stock j bought (sold) by mutual fund i on day d, and $\beta_{j,d}$ is the beta of stock j on day d, estimated as in equation (7). For instance, a fund that trades according to a positive feedback trading strategy would buy high-beta stocks and sell low-beta stocks after positive market returns. We combine the buy and sell betas for fund i on day d from equation (8) into an estimate of the fund's trade beta as

$$(9)\qquad \beta_d^{i,\mathrm{trade}} = \frac{B_d^i}{B_d^i + |S_d^i|}\beta_d^{i,B} - \frac{|S_d^i|}{B_d^i + |S_d^i|}\beta_d^{i,S},$$

where

$$(10)\qquad \beta_d^i = \sum_{j=1}^{N} B_{j,d}^i,\ S_d^i = \sum_{j=1}^{N} S_{j,d}^i.$$

$\beta_d^{i,\mathrm{trade}} > 0$ indicates that the fund's trades, on net, lead to an increase in fund beta, and conversely for $\beta_d^{i,\mathrm{trade}} < 0$.[16] As an example of how the trade beta in equation (9) differs from simply taking the difference between the mean buy beta and the mean sell beta, suppose a fund manager buys high-beta stocks and sells low-beta stocks prior to a period of positive market returns. Based on the difference between his mean buy beta and mean sell beta, the manager would appear to be a good market timer. However, our inference regarding the manager's ability to time the market would change if he had purchased \$100 of the high-beta stocks while selling \$1,000 of the low-beta stocks, since he reduced his net market exposure. The trade beta in equation (9) captures the impact of the dollar amount of the manager's transactions.

[16]If the fund only buys stocks on day d, then the fund trade beta is equal to the beta of buy trades. If the fund only sells stocks on day d, then the fund trade beta is $-\beta_d^{i,S}$. We treat the beta of fund trades as missing if the institution did not trade on a particular day.

We provide summary statistics for the fund trade beta estimates in Table B.4 of the Supplementary Material. Based on these trade beta estimates, we examine whether funds adjust their portfolio betas conditional on past, contemporaneous, or future market returns. We examine the relation via cross-sectional regressions. Whereas some prior studies use fund portfolio holdings to test market timing (e.g., Jiang et al. (2007)), we go one step further and use actual fund trades to more directly test fund managers' ability to time the market.

In our regression analysis, we explicitly examine the relations between fund beta and market returns reflected in the TM and HM market timing measures in equations (1) and (2). For TM, we estimate

$$\beta_d^{i,\text{trade}} = \alpha^i + \gamma^i R_t^M + \epsilon_d^i, \tag{11}$$

where $\beta_d^{i,\text{trade}}$ is the beta of all of fund i's trades on day d (as defined by equation (9)), and R_t^M is the excess market return during period t, where t reflects alternative periods relative to trade day d, ranging from 10 trading days prior to day d to 10 trading days after day d. For each fund, we estimate regression (11) over the fund's entire sample period for each of the alternative t period definitions. A positive γ^i is consistent with the fund increasing (decreasing) the beta of its portfolio via stock trades when R_t^M is positive (negative). Positive γ^i would be consistent with positive artificial (genuine) timing in mutual funds when t reflects a period prior to (after) day d. Similarly, for HM, we estimate

$$\beta_d^{i,\text{trade}} = \alpha^i + \gamma^i I_{R_t^M>0} + \epsilon_d^i, \tag{12}$$

where $I_{R_t^M>0}$ is an indicator variable representing a positive market return during period t. In addition to estimating equations (11) and (12) for fund trades (i.e., equation (9)), we also run the regressions separately for buy trades and for sell trades (i.e., equation (8)).

As an alternative to equations (11) and (12) regression methodology, we estimate the following TM and HM equations via panel regressions with fund-fixed effects using clustered standard errors at the fund level:

$$\beta_d^{i,\text{trade}} = \alpha + \lambda^i + \gamma R_t^M + \epsilon_d^i, \tag{13}$$

$$\beta_d^{i,\text{trade}} = \alpha + \lambda^i + \gamma I_{R_t^M>0} + \epsilon_d^i. \tag{14}$$

The panel methodology determines the average feedback trading coefficient (γ) across all mutual funds and allows for robust standard errors.

Table 5 shows the estimation results. Panel A provides summary statistics of the feedback trading coefficients, where we use equations (11) and (12) to estimate the relation between trade beta and the prior day's market return. The mean and median of all of the coefficients are positive, consistent with positive feedback trading on average across the fund sample.

Panel B of Table 5 reports equations (11) and (12) regression results that span the full range of time periods over which the market return is measured (i.e., from 10 trading days before fund trade day d to 10 trading days after). We report the mean of the feedback trading measures cross-sectionally, where we weight each estimate by the inverse of its standard error to mitigate the influence of imprecise estimates. All of the coefficient estimates on past market returns based on the fund trade variables (column 3 in the table for TM and column 6 for HM) are significantly positive at the 5% level or higher. The evidence thus strongly suggests that funds significantly respond to *past* market returns by actively increasing the beta of their portfolio after relatively good market returns and by actively reducing the beta of their portfolio after relatively poor market returns. That is, funds behave as positive feedback traders with respect to the market. The results also suggest that mutual

TABLE 5

Fund Trade Beta Versus Market Return

Table 5 reports results that assess the relation between the value-weighted fund trade beta (aggregated daily) and past, contemporaneous, or future market return based on regressions (11)–(14). Panel A provides summary statistics for the feedback trading measure ($\hat{\gamma}$) based on Treynor and Mazuy (1966) and Henriksson and Merton (1981). We estimate each fund's feedback trading via equations (11) and (12) using the trade beta from day t and the market return from day $t-1$. $\hat{\gamma}^{\text{adj}}$ reflects normalizing each feedback trading estimate by dividing by its standard error. For each fund, we estimate gamma over the entire sample period. In Panel B, we calculate a weighted average of the gamma measures across all funds, with weights given by the inverse of the standard errors of the estimates of the individual timing measures. In Panel C, the average timing measure across all funds is computed via a panel regression with fund fixed effects using clustered standard errors at the fund level. *t*-statistics are reported in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. The sample consists of 581 actively-managed funds across a Jan. 1999 to Mar. 2012 sample period.

Panel A. Summary Statistics of Feedback Trading Measures

Variable	Mean	Std. Dev.	p5	p25	p50	p75	p95
$\hat{\gamma}_{\text{TM}}$	1.062	13.90	−18.46	−2.631	1.235	5.233	17.86
$\hat{\gamma}_{\text{HM}}$	0.032	0.216	−0.271	−0.0563	0.0361	0.123	0.328
$\hat{\gamma}_{\text{TM}}^{\text{adj}}$	0.443	2.046	−2.915	−0.680	0.408	1.393	3.640
$\hat{\gamma}_{\text{HM}}^{\text{adj}}$	0.480	1.783	−2.365	−0.613	0.438	1.468	3.443

Panel B. Regression Based on Inverse Standard-Error Weights

	TM			HM		
	Beta Buy	Beta Sell	Beta Trade	Beta Buy	Beta Sell	Beta Trade
Return	1	2	3	4	5	6
$R^M_{d-10,d-1}$	0.065	0.032	0.274**	0.420	0.461	1.287*
	(0.90)	(0.48)	(2.46)	(1.03)	(1.15)	(1.89)
$R^M_{d-5,d-1}$	0.181**	−0.055	0.497***	0.909**	−0.427	2.331***
	(2.05)	(−0.65)	(3.30)	(2.51)	(−1.22)	(3.75)
$R^M_{d-3,d-1}$	0.233**	−0.121	0.622***	0.856**	−0.507	2.557***
	(2.09)	(−1.21	(3.57)	(2.43)	(−1.41)	(4.23)
$R^M_{d-2,d-1}$	0.293**	−0.145	0.871***	0.771**	−0.589*	3.554***
	(2.52)	(−1.28	(4.28)	(2.34)	(−1.66)	(5.87)
R^M_{d-1}	0.402***	−0.199	1.256***	0.795**	−0.118	3.538***
	(2.78)	(−1.31)	(4.73)	(2.39)	(−0.36)	(6.54)
R^M_{d}	0.278**	−0.292**	−1.422***	0.342	−0.695**	−3.827***
	(2.18)	(−1.99)	(−4.46)	(1.21)	(−2.05)	(−5.87)
R^M_{d+1}	−0.078	−0.018	−0.023	−0.577**	−0.190	−0.218
	(−0.66)	(−0.15)	(−0.14)	(−2.03)	(−0.73)	(−0.58)
$R^M_{d+1,d+2}$	−0.079	−0.006	0.136	−0.216	−0.008	0.253
	(−0.81)	(−0.05)	(1.05)	(−0.65)	(−0.02)	(0.57)
$R^M_{d+1,d+3}$	−0.121	−0.024	0.092	−0.418	−0.344	0.423
	(−1.39)	(−0.27)	(0.78)	(−1.26)	(−0.94)	(0.99)
$R^M_{d+1,d+5}$	−0.116	−0.076	0.047	−0.432	−0.355	−0.229
	(−1.59)	(−1.00)	(0.45)	(−1.23)	(−1.01)	(−0.48)
$R^M_{d+1,d+10}$	−0.032	−0.044	0.007	−0.144	−0.392	0.005
	(−0.44)	(−0.50)	(0.08)	(−0.36)	(−1.04)	(0.01)

(continued on next page)

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TABLE 5 (continued)

Fund Trade Beta Versus Market Return

Panel C. Panel Regression with Fund Fixed Effects

	TM			HM		
	Beta Buy	Beta Sell	Beta Trade	Beta Buy	Beta Sell	Beta Trade
Return	1	2	3	4	5	6
$R^M_{d-10,d-1}$	0.132***	0.023	0.323***	0.483	0.479	1.249**
	(2.81)	(0.60)	(3.57)	(1.41)	(1.60)	(2.04)
$R^M_{d-5,d-1}$	0.209***	−0.071	0.494***	0.882***	−0.306	1.991***
	(4.09)	(−1.47)	(4.20)	(3.16)	(−1.07)	(3.22)
$R^M_{d-3,d-1}$	0.264***	−0.116**	0.587***	0.944***	−0.493**	2.565***
	(4.54)	(−2.04)	(3.96)	(3.47)	(−1.97)	(3.87)
$R^M_{d-2,d-1}$	0.299***	−0.127**	0.864***	0.870***	−0.531**	3.368***
	(4.69)	(−2.08)	(5.19)	(3.22)	(−2.00)	(5.26)
R^M_{d-1}	0.420***	−0.176**	1.250***	0.854***	−0.255	3.344***
	(5.67)	(−2.39)	(5.54)	(3.67)	(−1.19)	(6.04)
R^M_{d}	0.342***	−0.312***	−1.366***	0.670***	−0.690***	−4.122***
	(4.31)	(−4.27)	(−4.22)	(3.15)	(−3.20)	(−5.49)
R^M_{d+1}	−0.071	−0.039	0.080	−0.657***	−0.247	−0.207
	(−1.27)	(−0.65)	(0.94)	(−3.46)	(−1.31)	(−0.80)
$R^M_{d+1,d+2}$	−0.075	−0.007	0.130*	−0.382*	−0.042	0.010
	(−1.44)	(−0.13)	(1.78)	(−1.78)	(−0.18)	(0.04)
$R^M_{d+1,d+3}$	−0.092*	−0.000	0.093	−0.429*	−0.099	0.176
	(−1.88)	(−0.00)	(1.31)	(−1.93)	(−0.41)	(0.62)
$R^M_{d+1,d+5}$	−0.098**	−0.026	0.010	−0.354	−0.063	−0.589*
	(−2.36)	(−0.65)	(0.16)	(−1.52)	(−0.26)	(−1.94)
$R^M_{d+1,d+10}$	−0.055	−0.008	−0.036	−0.259	−0.226	−0.455
	(−1.55)	(−0.24)	(−0.67)	(−0.90)	(−0.81)	(−1.19)

funds display less positive feedback trading with respect to their sales than with their purchases, as the positive coefficient on the trade variable is driven by positive coefficients on buys rather than negative coefficients on sells. Panel C reports the results associated with the panel regressions with fund-fixed effects in equations (13) and (14). The panel regression results are qualitatively similar to the Panel B results, showing strong evidence that funds behave as positive feedback traders based on both the TM and HM approaches.[17]

The trade beta results also show that funds trade opposite to the same-day market return, that is, they buy on down-market days and/or sell on up-market days. One possible reason why funds trade opposite to the same-day market return is that down- (up-) market days provide favorable entry (exit) prices for stocks that funds had been looking to buy (sell). That is, the same-day effects could be driven by funds opportunistically responding to temporary pockets of stock liquidity.[18]

Lastly, we examine the relation between the betas of stocks traded by funds and *future* market returns. It is these results that indicate whether the fund sample

[17]In untabulated results, we find that evidence of feedback trading is not solely driven by the prior-day effect. For instance, using fund trade as the regressand, the coefficient estimates on the past market return from day −5 to day −2 are statistically significant.

[18]We do not focus on the relation between fund betas and the contemporaneous daily market return because the intraday time stamps in Abel Noser are not reliable (see, e.g., Choi, Park, Pearson, and Sandy (2017), Hu et al. (2018)), such that we cannot discern whether the contemporaneous market return is in the information set when fund managers trade.

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shows evidence of genuine short-horizon market timing ability, that is, whether fund managers take appropriate action *before* the market moves. By contrast to the results based on past market returns, no significant relation exists, by and large, between the betas of stocks that funds trade and market returns over the following 1, 2, 3, 5, or 10 days, consistent with no genuine short-horizon market timing ability among mutual funds.[19]

As an alternative to the regression analyses above, we also analyze the relation between trade betas and market returns via univariate sorts where we assign subsample periods to quintiles based on excess market return. The results, which we report in Table B.5 of the Supplementary Material, provide similar inference to the regression results in Table 5.

Overall, our results provide direct evidence regarding the "artificial timing" mechanism that leads to the strong negative cross-sectional correlation between timing model alpha and gamma documented extensively in the prior literature. Moreover, based on directly examining the relation between the betas of stocks that funds transact and future market returns, we find no evidence of genuine short-horizon market timing ability, on average, among mutual funds.

D. Why Do Funds Feedback Trade?

Given the evidence of feedback trading in Tables 3 and 5, it is important to consider reasons why funds feedback trade. We explore several possibilities. First, we examine how strategic investment behavior not explicitly focused on feedback trading can lead to a significant relation between the lag return of the stock market and mutual fund beta. In particular, Grinblatt et al. (1995) and Carhart (1997) show that funds behave as momentum investors, buying stocks with relatively strong performance and exiting those that are relatively weak. Since we would expect winning stocks to show relatively high betas after an increasing market, momentum trading could contribute to the significant relation between past market performance and the beta of stock purchases. We also explore whether evidence of feedback trading relates to the disposition effect (selling winners and keeping losers; Shefrin and Statman (1985)), though trades aligned with the disposition effect would be expected to generate evidence of negative feedback trading. Beyond showing whether momentum trading and the disposition effect lead to evidence of feedback trading, we examine whether significant feedback trading is apparent after controlling for these effects.

Second, following the long literature that explores the relation between changes in fund risk and past performance (e.g., Brown et al. (1996), Chevalier and Ellison (1997)), we examine whether a fund's feedback trading relates to its recent performance.[20] The idea is that, after performing poorly, a fund could be sensitive to the

[19]We repeat the Table 5 analysis from 1999 to 2012 (i.e., the Abel Noser sample period) and find qualitatively similar results to the full sample period results.

[20]Additional related papers include Koski and Pontiff (1999), Busse (2001), Basak, Pavlova, and Shapiro (2007), Kempf and Ruenzi (2008), Chen and Pennacchi (2009), Kempf, Ruenzi, and Thiele (2009), Elton, Gruber, Blake, Krasny, and Ozelge (2010), Huang, Sialm, and Zhang (2011), Basak and Makarov (2012), Schwarz (2012), Lee, Trzcinka, and Venkatesan (2019), and Ma and Tang (2019).

market return and change its market exposure to try to make up its performance deficit or prevent itself from falling further behind.

Third, we estimate whether investor flows correlate with lag feedback trading. If investors value feedback trading, possibly because these strategies help funds manage risk and time volatility (e.g., Busse (1999)), then a significant positive cross-sectional relation should exist between flows and lag fund feedback trading estimates. This positive relation would provide fund managers with an incentive to feedback trade since a fund's fees positively relate to its assets under management. A final possibility relates to Edelen and Warner's (2001) finding that aggregate daily fund investor flows correlate positively with the lag market return. Although we are unable to explore higher frequency effects related to daily fund flows, we examine the relation between flows and feedback trading at a lower, monthly frequency. Evidence that feedback trading relates to lag fund flows might reflect funds investing new flows after strong stock market returns.[21]

1. Momentum Trading and the Disposition Effect

To explore whether our prior findings are driven by momentum investing, we examine the exposure of a fund's betas to previous market returns after controlling for the traded stocks' past returns. More precisely, we estimate the following TM and HM equations via panel regressions,

$$\beta_d^{i,\text{trade}} = \alpha + \lambda^i + \gamma R_{d-1}^M + \theta \text{PASTRET}_d^{i,\text{trade}} + \epsilon_d^i, \tag{15}$$

$$\beta_d^{i,\text{trade}} = \alpha + \lambda^i + \gamma I_{R_{d-1}^M > 0} + \theta \text{PASTRET}_d^{i,\text{trade}} + \epsilon_d^i, \tag{16}$$

where $\beta_d^{i,\text{trade}}$ is the beta of all of fund i's trades on day d (as defined by equation (9)), $\text{PASTRET}_d^{i,\text{trade}}$ is the value-weighted average of the prior 6-month returns of the stocks that fund i trades on day d (i.e., $t-2$ to $t-7$, with t given by the month associated with day d), and we examine the trade beta as a function of the prior 1-day market return, R_{d-1}^M and $I_{R_{d-1}^M > 0}$. In addition to estimating equations (15) and (16) based on fund trade betas, we estimate the equations separately based on the betas of fund purchases and sales (i.e., equation (8)).

Table 6 shows the regressions (15) and (16) results. Consistent with funds trading on stock momentum, the coefficients on the prior 6-month stock returns indicate that funds buy (sell) stocks with relatively positive (negative) past 6-month returns. Nonetheless, even after controlling for the tendency for funds to trade on price momentum, trade beta remains strongly significantly positively related to prior market returns for both the TM and HM specifications, consistent with funds exhibiting positive feedback trading behavior relative to the aggregate stock market. Like our earlier evidence, the effect is strongest for buy transactions.

We also analyze whether evidence of feedback trading is solely attributable to the disposition effect (selling winners and keeping losers; Shefrin and Statman

[21]Besides the potential reasons discussed above, positive feedback trading could also relate to fund managers' behavioral biases, such as recency bias, loss aversion, and fear of missing out. Agency issues such as insufficient investor monitoring could also contribute to the presence of feedback trading.

TABLE 6

Feedback Trading and Momentum

Table 6 reports results that estimate fund feedback trading after controlling for momentum trading as in equations (15) and (16). Momentum is the value-weighted prior return of the stocks funds buy, sell, or trade. Columns 1–3 are based on Treynor and Mazuy (1966), and columns 4–6 are based on Henriksson and Merton (1981). We compute the average timing measure of all funds via a panel regression with fund fixed effects using clustered standard errors at the fund level. *t*-statistics are reported in parentheses. Coefficients marked with ***,**, and * are significant at the 1%, 5%, and 10% levels, respectively. The sample consists of 581 actively-managed funds across a Jan. 4, 1999, to Mar. 30, 2012 sample period.

	TM			HM		
	Buy Beta	Sell Beta	Trade Beta	Buy Beta	Sell Beta	Trade Beta
	1	2	3	4	5	6
R^M_{d-1}	0.4226***	−0.1764**	1.1261***			
	(5.69)	(−2.39)	(5.29)			
$I_{R^M_{d-1}>0}$				0.0086***	−0.0025	0.0298***
				(3.69)	(−1.15)	(5.80)
$\text{PASTRET}_d^{i,\text{buy}}$	0.0273**			0.0273**		
	(2.21)			(2.21)		
$\text{PASTRET}_d^{i,\text{sell}}$		0.0244***			0.0245***	
		(2.76)			(2.76)	
$\text{PASTRET}_d^{i,\text{trade}}$			0.5078***			0.5077***
			(18.08)			(18.08)
No. of obs.	387,974	371,897	454,034	387,974	371,897	454,034
R^2	0.000	0.000	0.034	0.000	0.000	0.034
No. of funds	579	581	581	579	581	581

(1985)). We calculate capital gains overhang (CGO) following Grinblatt and Han (2005), and our month-end CGO is the capital gains overhang of the last week of the month. Our results show that trade beta remains strongly significantly positively related to the prior market return after controlling for the disposition effect (see Table B.6 of the Supplementary Material).

2. Feedback Trading and Past Fund Performance

The strong relation between mutual fund performance and subsequent investor flows (e.g., Ippolito (1992), Sirri and Tufano (1998)) motivates numerous prior analyses of mutual fund strategic risk-taking behavior in the context of fund tournaments (e.g., Brown et al. (1996), among many others), which examine the relation between changes in fund risk and past fund performance. Since market returns directly impact fund returns, we examine whether feedback trading relates to past fund performance. Each month, we sort funds into deciles based on feedback trading (i.e., $\widehat{\gamma}$ or $\widehat{\gamma}^{\text{adj}}$ from equations (11) and (12) using the prior 3-month trade data from $t-2$ to t). For each decile, we compute the average fund performance during the 1-, 3-, or 6-month period that precedes the time frame used to estimate feedback trading, that is, during month $t-3$, from $t-5$ to $t-3$, or from $t-8$ to $t-3$. We estimate fund performance based on the Carhart 4-factor model with daily returns. Table 7 reports the past 4-factor alpha (weighted by fund TNA) of the feedback trading deciles. Panel A reflects sorts based on the TM feedback trading specification (i.e., equation (11)), and Panel B is based on HM (equation (12)).

Overall, Table 7 results show an inverse relation between past fund performance and feedback trading. For instance, based on the unadjusted feedback trading measure, all 4-factor alpha differences between the decile 10 and decile 1 portfolios are significantly negative at the 5% level. Results based on the adjusted

TABLE 7

Feedback Trading and Past Performance

In Table 7, we sort funds into deciles by feedback trading and examine the past performance of each decile. For each fund, each month t, we estimate the feedback trading measure ($\hat{\gamma}$) via equations (11) and (12) using the prior 3-month trade data ($t-2$ to t). $\hat{\gamma}^{adj}$ reflects normalized feedback trading estimates (by dividing by its standard error). Panel A reports TNA-weighted performance of the deciles based on the Treynor and Mazuy (1966) measure. Panel B is based on the Henriksson and Merton (1981) measure. Fund performance is estimated based on the Carhart 4-factor model with daily returns over the past 1 month ($t-3$), 3 months ($t-5$ to $t-3$), or 6 months ($t-8$ to $t-3$). Alpha is in percentage. We base the t-statistics of the Alpha_{3m} (Alpha_{6m}) differences (in parentheses) on Newey and West's correction for time-series correlation with 3 (6) lags. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The sample consists of 581 actively managed funds across a Jan. 1999 to Sept. 2011 sample period.

$\hat{\gamma}$	Alpha_{1m}	Alpha_{3m}	Alpha_{6m}	$\hat{\gamma}^{adj}$	Alpha_{1m}	Alpha_{3m}	Alpha_{6m}
Panel A. TM							
1 (Low)	0.784	0.585	0.772	1 (Low)	0.702	0.381	0.624
2	0.603	0.386	0.558	2	0.929	0.215	0.492
3	0.322	0.329	0.384	3	−0.439	0.128	0.129
4	0.441	0.140	0.186	4	0.276	0.018	0.063
5	0.511	0.428	0.405	5	−0.127	0.252	0.376
6	0.749	0.425	0.254	6	0.992	0.652	0.374
7	−0.193	−0.070	−0.044	7	−0.099	−0.162	−0.144
8	0.368	−0.166	−0.242	8	0.700	0.152	−0.050
9	0.359	−0.099	−0.088	9	0.184	−0.010	−0.172
10 (High)	−1.226	−0.618	−0.629	10 (High)	0.002	−0.241	−0.164
Diff. (10−1)	−2.010***	−1.203***	−1.401***	High-Low	−0.700	−0.622*	−0.788**
t-stat.	(−2.72)	(−2.71)	(−3.75)	t-stat.	(−1.14)	(−1.78)	(−2.44)
Panel B. HM							
1 (Low)	0.568	0.442	0.324	1 (Low)	−0.115	0.210	0.453
2	0.691	0.533	0.517	2	1.079	0.410	0.774
3	0.308	0.064	0.510	3	0.321	0.039	0.182
4	0.148	0.220	0.171	4	0.003	0.205	0.138
5	0.522	0.214	0.235	5	0.532	0.286	0.290
6	−0.219	0.203	0.173	6	0.183	0.219	0.135
7	0.114	0.052	−0.045	7	−0.261	−0.115	−0.049
8	0.339	−0.034	−0.056	8	0.950	0.135	0.025
9	0.627	−0.137	−0.114	9	0.100	−0.085	−0.151
10 (High)	−1.326	−0.488	−0.449	10 (High)	−0.606	−0.352	−0.322
Diff. (10−1)	−1.894**	−0.930**	−0.773**	High-Low	−0.491	−0.562	−0.775**
t-stat.	(−2.11)	(−1.99)	(−2.57)	t-stat.	(−0.66)	(−1.57)	(−2.23)

feedback trading measure are weaker, though half of the decile 10 – decile 1 4-factor alpha differences are statistically significant. The results indicate that poorly-performing funds tend to increase (decrease) their beta following relatively good (poor) market returns, whereas top-performing funds do the opposite. The interpretation is that poorly performing funds change their market exposure in an effort to make up their performance deficit, whereas top performers try to lock in their favorable ranking.

3. Investor Flows

If mutual fund investors value feedback trading for various reasons, we should find investor flows to significantly relate to estimates of feedback trading. Moreover, a positive relation between investor flows and feedback trading would give funds an incentive to feedback trade, insofar as a fund's fees positively relate to its assets under management. We examine how fund investors respond to feedback trading by regressing investor monthly net flows on prior feedback trading measures. We estimate feedback trading via equations (11) and (12), where we regress trade beta on the past half-month market return across the past 3 months of trade data. We test the relation using pooled OLS regressions, panel regressions with fixed effects (using clustered standard errors at the fund level), and Fama–Macbeth regressions. Previous literature shows a strong flow-performance relation (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)), especially when measuring performance with CAPM alpha (Barber, Huang, and Odean (2016)), Berk and van Binsbergen (2016)). Consequently, we use CAPM alpha as a control variable. In some specifications, we include additional fund-level control variables, including the log of total net assets, expense ratio, turnover ratio, net flow, log of fund age, and log of family TNA, all measured at the end of the prior month.

Table 8 shows the regression results. Panel A shows results based on regressions that only include CAPM alpha as a control variable; Panel B shows results based on the full set of control variables. Across the various specifications in Table 8, the relation between feedback trading and investor flows is positive overall, but somewhat sensitive to the specification. In Panel A, the coefficient on the feedback trading measure is significantly positive, with particularly strong results for the TM timing model. The Panel B results show that after including a full set of control variables, the relation between feedback trading and investor flows weakens, especially in columns 3 and 6.

Although we cannot say for certain why investors value feedback trading, the evidence of a positive flow effect may come from the fact that positive feedback trading helps hedge downside risk during extended market drawdowns. For instance, even though the autocorrelation of monthly market returns is insignificant on average across our sample period, bear markets are often characterized by a drawdown in the stock market that lasts several months. For example, during the 2008–2009 financial crisis, Lehman Brothers declared bankruptcy on Sept. 15, 2008, but the stock market bottomed out several months later on Mar. 9, 2009. By reducing market exposure relatively early during an extended drawdown, positive feedback trading positively impacts fund total returns relative to maintaining constant market exposure. Figure 1 illustrates this feature by plotting the cumulative return and alpha difference between the top and bottom deciles of funds sorted based on lag feedback trading. The figure shows economically meaningful performance advantages for feedback trading funds during extended drawdowns reflected by the upward slope in the performance difference plots during the 2001 and 2008–2009 recessions.[22]

Lastly, we reverse the dependency between feedback trading and investor flows and examine whether feedback trading relates to lag investor flows. The idea is that funds trade in response to flows, and flows relate to lag market returns (Edelen and Warner (2001)). Therefore, we regress feedback trading estimates on prior month investor net flows, using the same set of variables that we use in the Table 8 analysis. We test the relation using pooled OLS regressions, panel regressions with fixed effects (using clustered standard errors at the fund level), and Fama–Macbeth regressions. We present the results in Table B.7 of the Supplementary Material. Regardless of the specification, the results show no significant

[22]A related reason why funds might positively feedback trade is if these strategies explicitly help funds time volatility (Busse (1999), Ferson and Mo (2016)). In untabulated results, we find a positive, but insignificant relation between feedback trading and volatility timing.

TABLE 8

Feedback Trading and Investor Flows

Table 8 reports the results of our analysis of the flow response to the feedback trading measures. We regress monthly net fund flows on prior feedback trading measures while controlling for the CAPM alpha or other mutual fund characteristics. For each fund, each month, we estimate the feedback trading measure ($\hat{\gamma}$) via equations (11) and (12) based on Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively, and CAPM alpha using the prior 3-month trade data. The feedback trading measure is based on the regression of trade beta on the past half-month market return. $\hat{\gamma}^{\text{adj}}$ reflects normalizing each feedback trading estimate by dividing by its standard error. Columns 1 and 4 report pooled OLS regression results. Columns 2 and 5 are based on panel regressions with fund-fixed effects using clustered standard errors at the fund level. In columns 3 and 6, we estimate cross-sectional regressions each month and report the time-series average of the monthly coefficients. We base the *t*-statistics in parentheses on Newey and West's (1986) correction for time-series correlation with 3 lags. The coefficients are scaled by 100 for ease of reading. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. The sample consists of 581 actively managed funds across a Jan. 1999 to Sept. 2011 sample period.

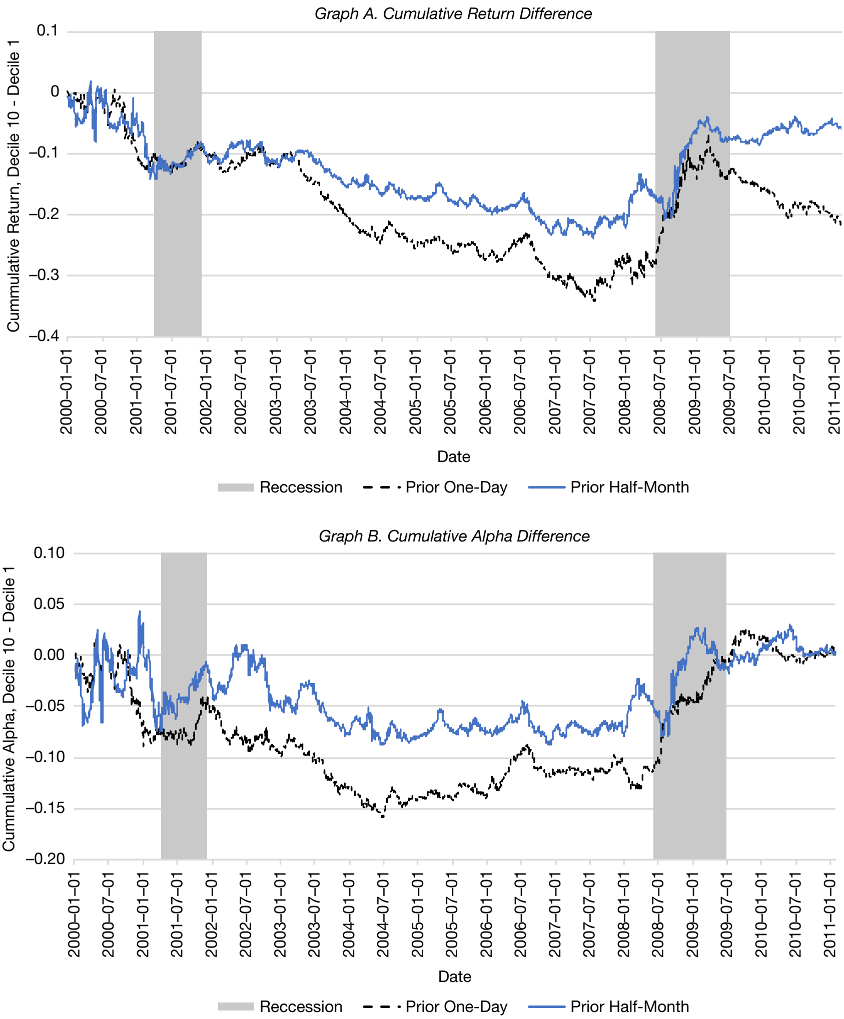
	TM			HM		
	1	2	3	4	5	6
Panel A. Specifications Controlling for CAPM Alpha						
$\hat{\gamma}^{\text{adj}}$	0.077***	0.053**	0.061***	0.031*	0.025*	0.064***
	(4.55)	(2.48)	(2.76)	(1.65)	(1.69)	(2.95)
α(%)	0.120***	0.115***	0.162***	0.120***	0.115***	0.162***
	(27.01)	(15.98)	(12.45)	(26.74)	(15.94)	(12.35)
Constant	0.197***	0.200***	0.197**	0.203***	0.205***	0.193**
	(8.24)	(57.89)	(2.38)	(8.43)	(67.32)	(2.35)
No. of obs.	28,098	28,098	28,098	28,096	28,096	28,096
R^2	0.054	0.055	0.085	0.054	0.055	0.084
Panel B. Specifications with Full Set of Control Variables						
$\hat{\gamma}^{\text{adj}}$	0.051***	0.042**	0.019	0.022*	0.020**	0.014
	(3.26)	(2.08)	(1.31)	(1.88)	(1.98)	(1.02)
α(%)	0.076***	0.078***	0.099***	0.075***	0.077***	0.097***
	(16.16)	(13.95)	(10.92)	(15.85)	(13.81)	(10.63)
log(TNA)	−0.026	−0.373***	−0.044	−0.026	−0.376***	−0.044
	(−1.39)	(−3.35)	(−1.56)	(−1.42)	(−3.37)	(−1.56)
log(AGE)	−0.693***	−1.626***	−0.526***	−0.695***	−1.622***	−0.520***
	(−18.49)	(−6.98)	(−7.48)	(−18.45)	(−6.99)	(−7.50)
log(FAMILY_TNA)	0.038***	0.028	0.044***	0.040***	0.024	0.043***
	(3.34)	(0.30)	(3.12)	(3.42)	(0.26)	(3.11)
EXPENSE_RATIO	−0.214***	−0.334	−0.150	−0.208***	−0.273	−0.150
	(−3.90)	(−0.78)	(−1.55)	(−3.76)	(−0.63)	(−1.56)
TURNOVER_RATIO	−0.001**	−0.001	−0.001	−0.001**	−0.001	−0.001
	(−2.24)	(−1.42)	(−1.48)	(−2.20)	(−1.36)	(−1.59)
LAGGED_FUND_FLOW	0.201***	0.157***	0.270***	0.202***	0.159***	0.273***
	(15.10)	(9.79)	(17.34)	(15.00)	(9.70)	(16.94)
Constant	1.823***	6.684***	1.360***	1.813***	6.670***	1.343***
	(9.36)	(4.33)	(4.68)	(9.26)	(4.32)	(4.61)
No. of obs.	27,630	27,630	27,630	27,364	27,364	27,364
R^2	0.175	0.140	0.283	0.176	0.141	0.285

correspondence between feedback trading and lag investor flows. We acknowledge, however, that a higher-frequency relation could exist between flows on day t and fund feedback trading on day $t+1$. For instance, Edelen and Warner (2001) show that aggregate fund flows positively relate to the prior-day market return. As such, it seems plausible that fund trading indirectly responds to the lag market return via the fund's response to daily investor flows. Regardless, it seems unlikely that a daily relation between lag flows and fund trades would explain the significant relation between fund betas and lag market returns measured over longer intervals extending out to a quarter, as reflected in Table 3.

FIGURE 1

Performance Difference: Top Versus Bottom Feedback Trading Deciles (2000–2011)

Figure 1 shows the cumulative return difference (Graph A) and the cumulative alpha difference (Graph B) between the top and bottom decile of funds sorted based on feedback trading. We first compute feedback trading based on the equation (11) regression of trade beta on the past 10-day (blue/solid line) or past 1-day (black/dashed line) market return during the prior 3 months. We sort funds into deciles based on the trading measure $\hat{\gamma}^{\text{adj}}$ ($\hat{\gamma}^{\text{adj}} = \hat{\gamma}/\text{SE}(\hat{\gamma})$) and track the future performance of the top and bottom deciles over the next half month. The sample consists of 581 actively-managed funds.



E. Performance Implications

Our results indicate that funds alter the beta of their portfolios in response to past market returns and that changes in fund beta do not correlate with future market returns. This feedback trading behavior leads to artificial market timing, but not genuine market timing. Consequently, we would not expect favorable performance implications to be associated with funds that actively alter their betas in this manner. Moreover, given that altering beta necessitates trading, we might even expect negative performance implications to feedback trading since trading generates transaction costs. In this section, we thus analyze the performance implications of feedback trading. We first examine the relation between feedback trading and transaction costs, and we then analyze the relation between feedback trading and overall fund performance.

1. Transaction Costs

We first compute TM-based and HM-based feedback trading measures, $\widehat{\gamma}^i$, for each fund over its entire sample period with equations (11) and (12), and then normalize each estimate by dividing by its standard error.[23] Next, following Busse et al. (2021), we use Abel Noser transaction-level data to estimate trading costs based on the difference between the trade execution price and a benchmark price:

$$\text{(17)} \qquad \text{TRADECOST} = D \times \frac{\text{PRICE} - \text{BENCHMARKPRICE}}{\text{BENCHMARKPRICE}},$$

where PRICE is the execution price of a trade, and D denotes the trade direction (1 for a buy and -1 for a sell). For BENCHMARKPRICE, we use pre-ticket stock prices, including i) the price at the time the fund places the order ticket (e.g., Anand, Irvine, Puckett, and Venkataraman (2012))), ii) the opening price on the day the first share in the order ticket trades (e.g., Anand et al. (2013)), Frazzini, Israel, and Moskowitz (2015))), and iii) the closing price the day before the first share in the order ticket trades (e.g., Keim and Madhavan (1997), Frazzini et al. (2015)). The transaction cost estimates capture implicit trading costs, including price impact and costs related to the bid–ask spread. To obtain fund-level transaction costs for a given fund-month, we multiply the ticket-level cost measures in equation (17) by the dollar value of each ticket and then sum over all of the fund's tickets in the month. We then divide by the average TNA of the previous month-ends.

We analyze the relation between feedback trading and transaction costs via two approaches. First, we sort funds into quintiles based on their feedback trading estimate ($\widehat{\gamma}$) or adjusted estimate ($\widehat{\gamma}^{\text{adj}}$) from equations (11) and (12). Quintile 1 (5) contains funds with the lowest (highest) estimate of feedback trading. We then compute the mean transaction cost estimate (i.e., execution shortfall, prior-day close cost, and open price cost) for each quintile. We present the quintile results in Panel A of Table 9.

We also examine the relation between feedback trading and transaction costs via monthly cross-sectional regressions as follows:

$$\text{(18)} \qquad \text{TRADECOST}_t^i = a + b_1 \text{FEEDBACKTRADING}^i + b_2 Z_{t-1}^i + \zeta_t^i,$$

where TRADECOST_t^i is the fund-level implicit cost for fund i in month t, and FEEDBACKTRADING^i represents fund feedback trading estimated via $\widehat{\gamma}$ or $\widehat{\gamma}^{\text{adj}}$ in equation (11) or (12). Z_{t-1}^i is a set of fund-level control variables at the end of the prior month, including log of total net assets, expense ratio, turnover ratio, net flow,

[23] We repeat the analysis in this section based on time-varying feedback trading measures, where we estimate equations (11) and (12) for each fund each month. The results, which we report in Table B.8 of the Supplementary Material, are qualitatively similar to the results reported here.

log of fund age, log of family TNA, and fund net return. We base the *t*-statistics on Newey and West's (1986) correction for time-series correlation with 12 lags. We report the cross-sectional regression results in Panel B of Table 9 based on the three alternative transaction cost estimates (execution shortfall, prior-day close cost, and open price cost).

Both the quintile results in Panel A of Table 9 and the cross-sectional results in Panel B of Table 9 indicate a statistically strong positive relation between fund feedback trading and implicit fund-level trading costs. In Panel A, all 12 quintile 5–quintile 1 differences are statistically significant at the 1% level. Based on execution

TABLE 9

Feedback Trading and Transaction Costs

Panel A of Table 9 reports the execution shortfall, prior-day close cost, and open price cost on portfolios of mutual funds sorted on their feedback trading measure. We estimate each fund's feedback trading measure ($\hat{\gamma}$) on equations (11) and (12) based on Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively. $\hat{\gamma}^{adj}$ reflects normalizing each feedback trading estimate by dividing by its standard error. At the beginning of each month from Jan. 1999 to Sept. 2011, we form quintile portfolios of mutual funds based on their feedback trading measure. Quintile 1 contains fund with the lowest feedback trading, and Quintile 5 contains funds with the highest feedback trading. Transaction cost estimates are monthly measures expressed as a percentage of fund TNA. Panel B reports cross-sectional coefficient estimates from regressions of fund-level transaction costs on fund feedback trading estimates based on fund trades and fund-level variables as in equation (18). We estimate cross-sectional regressions each month and report the time-series average of the monthly coefficients. The coefficients are scaled by 100 for ease of reading. *t*-statistics (in parentheses) are based on Newey and West's (1986) correction for time-series correlation with 12 lags to account for persistence in trading cost estimates. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. The sample consists of 581 actively-managed funds across a Jan. 1999 to Sept. 2011 sample period.

Panel A. Quintile Sorts

	Execution Shortfall	Prior-Day Close Cost	Open Price Cost
Panel A1. Sorted on $\hat{\gamma}_{TM}$			
1 (Low $\hat{\gamma}_{TM}$)	0.025	−0.020	−0.002
2	0.041	0.040	0.040
3	0.039	0.076	0.059
4	0.037	0.097	0.069
5 (High $\hat{\gamma}_{TM}$)	0.053	0.132	0.097
Diff. (5−1)	0.028***	0.152***	0.099***
t-stat.	(3.62)	(6.32)	(6.66)
Panel A2. Sorted on $\hat{\gamma}_{TM}^{adj}$			
1 (Low $\hat{\gamma}_{TM}^{adj}$)	0.021	−0.030	−0.008
2	0.040	0.044	0.041
3	0.036	0.065	0.051
4	0.049	0.109	0.083
5 (High $\hat{\gamma}_{TM}^{adj}$)	0.044	0.129	0.092
Diff. (5−1)	0.023***	0.159***	0.100***
t-stat.	(4.75)	(6.66)	(7.09)
Panel A3. Sorted on $\hat{\gamma}_{HM}$			
1 (Low $\hat{\gamma}_{HM}$)	0.025	−0.013	0.001
2	0.026	0.034	0.031
3	0.045	0.072	0.061
4	0.043	0.083	0.065
5 (High $\hat{\gamma}_{HM}$)	0.054	0.147	0.105
Diff. (5−1)	0.029***	0.160***	0.104***
t-stat.	(4.03)	(6.13)	(6.51)
Panel A4. Sorted on $\hat{\gamma}_{HM}^{adj}$			
1 (Low $\hat{\gamma}_{HM}^{adj}$)	0.024	−0.015	0.000
2	0.027	0.042	0.035
3	0.039	0.059	0.050
4	0.048	0.088	0.073
5 (High $\hat{\gamma}_{HM}^{adj}$)	0.052	0.143	0.100
Diff. (5−1)	0.028***	0.158***	0.100***
t-stat.	(7.56)	(7.08)	(8.20)

(continued on next page)

TABLE 9 (continued)
Feedback Trading and Transaction Costs

Panel B. Cross-Sectional Regressions

	Execution Shortfall		Prior-Day Close Cost		Open Price Cost	
	1	2	3	4	5	6
Panel B1. TM						
$\hat{\gamma}$	0.0021*** (4.33)		0.0095*** (6.03)		0.0061*** (6.20)	
$\hat{\gamma}^{adj}$		0.0033*** (6.88)		0.0180*** (7.33)		0.0113*** (7.91)
Constant	0.1280*** (6.06)	0.1309*** (6.22)	0.1662*** (3.73)	0.1967*** (4.71)	0.1632*** (5.61)	0.1811*** (6.65)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	24,053	24,053	24,378	24,378	24,387	24,387
R^2	0.125	0.121	0.133	0.131	0.142	0.139
# months	153	153	153	153	153	153
Panel B2. HM						
$\hat{\gamma}$	0.0940*** (5.89)		0.3756*** (6.63)		0.2456*** (7.00)	
$\hat{\gamma}^{adj}$		0.0044*** (9.47)		0.0193*** (7.14)		0.0124*** (8.23)
Constant	0.1303*** (6.07)	0.1323*** (6.24)	0.1676*** (3.53)	0.1884*** (4.48)	0.1643*** (5.28)	0.1774*** (6.48)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	24,048	24,048	24,373	24,373	24,382	24,382
R^2	0.125	0.122	0.130	0.129	0.140	0.138
# months	153	153	153	153	153	153

shortfall, the results suggest that high feedback trading funds show transaction costs that are between 0.023% and 0.029% higher per month (approximately 0.3% higher per year) than low feedback trading funds. Transaction cost differences between the high and low quintiles are larger based on prior-day close and open price transaction cost estimates, though some of these differences are likely mechanically driven. For instance, since stock prices are positively correlated with the market, high (low) feedback trading funds buy on average after stock price increases (decreases), resulting in high (low) prior-day close and open price transaction cost estimates.

In Panel B of Table 9, the coefficient on the feedback trading variable is statistically significant at the 1% level across all specifications. As feedback trading directly leads to evidence of artificial timing, this evidence supports a conjecture on artificial timing and transaction costs by Pfleiderer and Bhattacharya (1983). Since trading costs are positively correlated with trading activity on average, the results suggest that funds actively trade based on past market returns, and their feedback trading leads to relatively high aggregate transaction costs. The coefficient estimates on the control variables (reported in Table B.9 of the Supplementary Material) indicate that larger funds, funds from larger fund families, and funds with lower turnover have lower transaction costs as a percentage of fund TNA, which is consistent with Busse et al. (2021).

2. Fund Performance

Since transaction costs directly impact fund returns, the positive relation between feedback trading and transaction costs should negatively impact the relation between feedback trading and fund performance. To examine the relation between feedback trading and fund performance, we form quintile portfolios of mutual funds based on feedback trading estimates from equations (11) and (12). Quintile 1 contains funds with the lowest estimates of feedback trading, and quintile 5 contains funds with the highest estimates of feedback trading. For each quintile, based on the full-time series of equal-weighted fund returns, we compute the i) excess return, ii) Carhart (1997) 4-factor alpha, and iii) 5-factor alpha, based on augmenting the 4-factor model with a liquidity factor (Pástor and Stambaugh (2003)), as well as the difference in return and risk-adjusted return between the highest and lowest quintiles.

Table 10 reports the results, with Panels A and B based on using the TM approach to estimate feedback trading and Panels C and D based on HM. The table indicates a strong negative relation between the extent to which a fund feedback

TABLE 10

Performance of Mutual Funds Sorted on Feedback Trading

Table 10 reports the excess return, Fama–French 3-factor alpha, Carhart 4-factor alpha, and 5-factor alpha (i.e., Carhart 4 factors plus the liquidity factor of Pástor and Stambaugh (2003)) on portfolios of mutual funds sorted on the feedback trading measure. At the beginning of each month from Jan. 1999 to Sept. 2011, we form decile portfolios of mutual funds based on their feedback trading measure. We estimate each fund's feedback trading measure ($\hat{\gamma}$) with equations (11) and (12) based on Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively. $\hat{\gamma}^{adj}$ reflects normalizing each feedback trading estimate by dividing by its standard error. Quintile 1 contains fund with the lowest feedback trading, and Quintile 5 contains funds with the highest feedback trading. The return and alphas are in monthly percentage. In parentheses are *t*-statistics. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Excess Return	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A. Sorted on $\hat{\gamma}_{TM}$				
1 (Low $\hat{\gamma}_{TM}$)	0.435	0.205	0.212	0.165
2	0.212	0.098	0.103	0.073
3	0.221	0.085	0.085	0.046
4	0.188	0.034	0.032	−0.003
5 (High $\hat{\gamma}_{TM}$)	0.134	−0.023	−0.039	−0.063
Diff. (5−1)	−0.301**	−0.228***	−0.251***	−0.228***
t-stat.	(−2.44)	(−2.62)	(−3.44)	(−3.08)
Panel B. Sorted on $\hat{\gamma}^{adj}_{TM}$				
1 (Low $\hat{\gamma}^{adj}_{TM}$)	0.419	0.209	0.215	0.175
2	0.235	0.105	0.111	0.071
3	0.191	0.041	0.045	0.002
4	0.240	0.062	0.057	0.025
5 (High $\hat{\gamma}^{adj}_{TM}$)	0.106	−0.018	−0.034	−0.055
Diff. (5−1)	−0.313***	−0.227***	−0.249***	−0.230***
t-stat.	(−2.67)	(−2.59)	(−3.30)	(−2.99)
Panel C. Sorted on $\hat{\gamma}_{HM}$				
1 (Low $\hat{\gamma}_{HM}$)	0.404	0.197	0.205	0.164
2	0.255	0.124	0.130	0.094
3	0.261	0.105	0.105	0.072
4	0.172	0.040	0.037	−0.011
5 (High $\hat{\gamma}_{HM}$)	0.101	−0.066	−0.083	−0.100
Diff. (5−1)	−0.303***	−0.263***	−0.288***	−0.264***
t-stat.	(−2.65)	(−3.01)	(−3.99)	(−3.59)
Panel D. Sorted on $\hat{\gamma}^{adj}_{HM}$				
1 (Low $\hat{\gamma}^{adj}_{HM}$)	0.389	0.190	0.197	0.160
2	0.253	0.113	0.123	0.074
3	0.203	0.033	0.034	−0.012
4	0.209	0.054	0.043	0.022
5 (High $\hat{\gamma}^{adj}_{HM}$)	0.137	0.011	−0.002	−0.026
Diff. (5−1)	−0.252**	−0.179**	−0.199***	−0.186***
t-stat.	(−2.49)	(−2.31)	(−3.00)	(−2.74)

trades with respect to the market and fund performance, regardless of the performance measure and regardless of whether we measure feedback trading via the TM or HM approach. In all the panels, the return and risk-adjusted return difference are statistically significant at the 1% or 5% level. Note, however, that the performance differences shown in Table 10 stem not only from transaction costs differences between high and low feedback trading, but also from the strong inverse relation between past fund performance and feedback trading (as reflected in Table 7). That is, some of the poor past performance associated with high feedback trading persists to the period when funds feedback trade, since poor mutual fund performance persists (e.g., Carhart (1997)). Moreover, for positive feedback traders, our finding of higher transaction costs and lower performance associated with feedback trading provides an additional explanation for the negative cross-sectional relation between timing model estimated alpha and gamma.[24]

V. Conclusion

Since there is little evidence to suggest that the aggregate stock market is predictable, it is not surprising that evidence of mutual fund timing ability is elusive. It is surprising, however, that prior studies find that skillful market timers are poor stock pickers and vice versa. We shed light on this puzzle by showing that the inverse relation between estimates of timing ability and stock selection can be explained as an artifact of the empirical approach used to estimate timing ability. In particular, a substantial mismatch exists between the intra-daily frequency with which a fund manager actively manages his fund and the long estimation intervals typically used in mutual fund research. Further, a fund can change its risk exposure during an estimation interval based on the market returns during the same estimation interval.

We show that mutual fund portfolio betas relate significantly to *past* movements in the aggregate stock market: funds increase risk after strong market returns, and vice versa. Although momentum trading contributes to evidence of positive feedback trading, positive feedback trading significantly exists after controlling for momentum trading and the disposition effect. We also find that a fund's feedback trading relates to its past performance, with poorly performing funds showing significantly greater positive feedback trading than top performers.

When monthly fund returns are analyzed via standard market timing regression models, the higher-frequency positive feedback trading of fund managers leads to erroneous market timing inference, including evidence of "artificial" timing. Artificial timing has no positive performance implications because changes in fund beta are not correlated with future stock market returns. Moreover, since fund managers generate transaction costs when they trade based on past market returns, feedback trading negatively impacts fund performance. By contrast to our strong evidence of artificial timing, we find no evidence that funds show genuine short-

[24]The negative relation between feedback trading and performance is robust to analyzing via cross-sectional regressions with control variables, time-varying artificial timing measures, and alternative performance measures including Cremers, Petajisto, and Zitzewitz's (2012) CPZ 4- and 7-factor alpha measures. Please see Tables B.10–B.12 of the Supplementary Material.

horizon market timing ability based on the relation between fund trade betas and future market returns.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001363.

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