Monetary Policy and Mutual Funds: Reaching for Yield in Response to Low Rates

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Abstract

This paper studies the effect of monetary policy and flow-performance incentives on risk taking for the class of Active Equity Mutual Funds. First, we document that the past decade provided several conditions that encouraged these funds to "reach for yield," with low interest rates encouraging large outflows from Money Market Funds (MMFs). Leveraging previous studies on similar reaching for yield by MMFs, we analyze fund returns and risk taking during and around the recent financial crisis. We observe that low interest rate periods tend to be associated with both higher measures of performance and excessive risk taking. Further, we utilize discrete Fed announcements providing forward guidance about interest rates and asset purchases to inform event studies analyzing these factors. Our results are broadly consistent with these funds reaching for yield, and provide evidence of a strong interaction between unconventional low-rate policy and mutual fund behavior.

1 Introduction

In the aftermath of the financial crisis, the Federal Reserve explored several unconventionary policies in order to encourage economic growth, including an unprecedented decision to lower short-term nominal interest rates to zero. This initial action was followed with a sequence of announcements providing forward guidance that the short-term rate would stay at these levels for an extended period.

Although these policies have since been widely commended for reviving sluggish economic growth and boosting employment in the U.S., several studies have also documented that these policies may have induced perverse incentives in the asset management industry. Recently, Di Maggio and Kacperczyk (2014) found that, in response to zero lower bound policies, Money Market Funds (MMFs)–which, by regulation, are obliged to invest in safe short-term assets–invested in riskier asset classes. Further, Chodorow-Reich (2014) show that MMFs, under pressure to waive fees in a low rate environment, reached for yield in order to offset these cost.

There are many reasons to expect an interaction between MMFs and Active Equity Mutual Funds (AEMFs). MMFs' reaching for yield and contemporaneous outflows from MMFs strongly point to investors' desire for higher returns. To the extent that AEMFs represent an asset class with higher expected return, there exists a strong complementarity between these asset classes; thus, the monetary policy shock ought to have significant implications for the risk-taking behavior of mutual funds as well. Specifically, asset managers may actively take on more risks to maximize expected returns to attract money ready to leave money funds.

In this paper, we examine implications of the zero interest rate policy for the behavior of active management industry. Historically, mutual funds show relatively little variation in fees (Berk and Green, 2004), and in turn, maximizing fund manager profits is well approximated by maximizing assets under management. Since assets also exhibit some persistence (Gruber, 1996), then MMF outflows present strong opportunities for future profits. Thus, a fund manager has a distinct incentive to attract this new money.

The traditional definition of "reaching for yield" refers to a classic principal-agent conflict in which funds increase yield by taking on more risk than their stakeholders would prefer. Incentive to attract new money and new investors could induce increased risk taking. The net benefit of increasing risk, however, is more delicate. The cost of increasing risk ought to be compared to the benefit of increased returns, for example, by studying changes in fund Sharpe Ratios or other risk-adjusted measures. One contribution of our study is that we demonstrate that in our sample the cost of higher returns offsets the benefit, and the overall effect on funds' Sharpe Ratios is statistically insignificant.

Overall, we believe AEMFs provide an ideal laboratory for studying "reach for yield" for two reasons. First, according to the Investment Company Institute report (2015), equity funds alone comprise 52 percent of total

U.S. mutual fund assets, compared to money market funds holding only 17 percent. Thus, studying the impact of low interest rate environments on the asset management industry necessitates studying equity funds. Second, equity funds are subject to much weaker constraints on risk taking than MMFs. This implies the possible excess risk taking will be more marked for equity funds, and of greater consequence.

In this paper, we assess empirically the equilibrium response of AEMFs to the low interest rate environment using data on the universe of actively managed US equity-only mutual funds between 2005 and 2014. We exploit both time-series and cross-sectional variation in the data to identify the effect of the monetary policy. Although panel regressions comprise the majority of our analysis, we confirm our results against potential endogeneity by studying a series of FOMC announcements. These decisions were plausibly exogenous with respect to equity funds' behavior; hence, they constitute a useful shock. Access to daily mutual fund returns allows us to measure effects on return and risk taking within relatively short event windows.

1.1 Summary

The main contribution of this paper is our characterization of mutual funds' increased risk in response to recent low-interest rate policy. In Section (2), we begin by characterizing the economic environment faced by mutual funds during the recent financial crisis, and provide evidence that these conditions were particularly conducive to reaching for yield. Specifically, prior studies have established that unprecedented low-rate policy squeezed Money Market Fund yields and led to significant outflows. These outflows provided a large source of potential inflows for an industry with a strongly established flow-performance relationship. Put together, these provided very strong incentives for AEMFs to compete for these flows by reaching for yield.

Section (3) serves as the bulk of the paper and presents our empirical results. Overall, our analysis provides a variety of evidence in support of reaching for yield behavior by AEMFs. First, we confirm that for the funds in our sample, past performance strongly predicts future flows. Then, we establish that low interest rates are associated with higher gross returns and higher benchmark spreads. However, we also show that these returns come at the cost of higher realized risk beyond what would be desirable for the risk-taking channel of monetary policy. Our analysis clearly characterizes the increased risk taking as *excessive*, as funds increase risk relative to their benchmarks and this risk is sufficiently large to offset most gains in risk-adjusted performance measures such as Sharpe Ratios.

Consistent with reaching for yield behavior, we also find that the cross-sectional spread of risk also increases during these low interest rate periods and find evidence that funds with stronger incentives to attract investors were more likely to reach for yield. Finally, we confirm our analysis using a series of Fed announcements and find that the surprise component on the day of announcement predicts higher return, benchmark spread, and realized volatility.

Put together, all these results provide strong support for our hypothesis. All of our regression results are reported in the Appendix, and Section (4) concludes our paper.

2 Background

In this section, we explore the overall trends in the fund industry and their interaction with government policy. We begin by reviewing the evidence for Money Market Funds (MMFs), and present some strong reasons we expect similar if not greater effects to be observed among the Active Equity Mutual Funds (AEMFs) that are the focus of this paper.

2.1 Money Market Funds

Prior to 2007, Money Market Funds enjoyed a strong reputation as a stable asset class and even a cash substitute. Since then, their storied role in the lead-up and unfolding of the recent financial crisis has weakened this reputation and brought this asset class under the scrutiny of regulators and academics alike. Indeed, this class of funds has proved to be an invaluable case study on the effects, intended or otherwise, of financial regulation and monetary policy. In particular, recent studies have demonstrated that this class of funds has exhibited "reaching for yield" behavior in response to both unprecedented low interest rate policy (Di Maggio and Kacperczyk, 2014; Chodorow-Reich, 2014), and slow regulatory response (Kacperczyk and Schnabl, 2013).

Overall, demand for MMFs has fluctuated widely since 2007. Using data on the universe of taxable MMFs collected from Compustat, we graph the 3-month moving average of monthly net fund flows in Figure (1). We note that overall fund flows have been largely negative since the financial crisis and the industry experienced large and persistent outflows during 2010. Only in recent years have these flows begun to stabilize and recover.

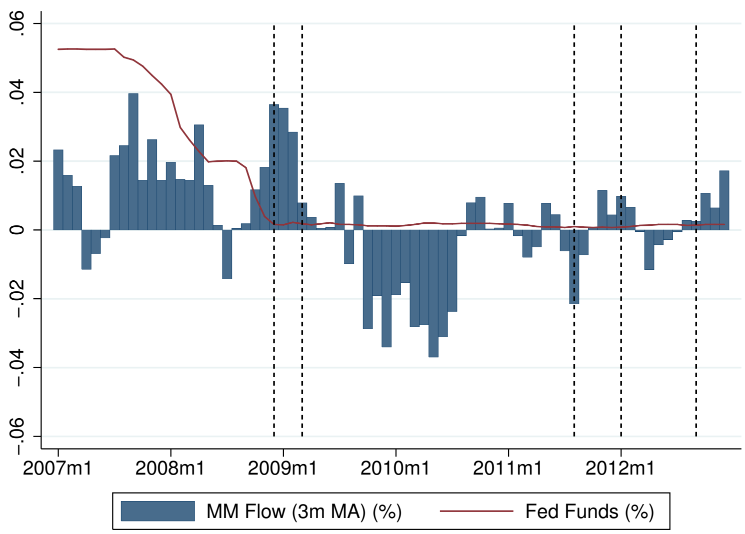

Figure 1: MMF Net Flows and Monetary Policy.

In addition, this Figure presents strong evidence that unconventionary monetary policy had a strong influence on fund flows. The solid line in this graph depicts the Fed Funds rate and the dashed vertical lines denote a selection of Fed announcements regarding unconventional monetary policy. In particular, we mark announcements of forward guidance of zero interest rate policy in the months 12/08, 3/09, 8/11, 1/12, and 9/12.

This figure presents evidence that low-interest rates and forward guidance are strongly related to fund flows. First, declining interest rates leading into 2009 coincide with a similar trend in fund flows. Second, the first pair of forward guidance announcements is followed by a significant and protracted contraction of the MMF industry. The last 3 announcements coincide with large shifts in the fund flow trends, consistent with these announcements containing some form of interest rate "surprise" for market participants.

Put together, these observations paint a picture of a MMF industry struggling to generate yields in a low interest rate environment. Studies have documented that MMFs responded to this challenge by "reaching for yield."

For example, Kacperczyk and Schnabl (2013) present evidence that MMFs responded to strong flow-performance incentives by taking on additional risk during the lead up to the financial crisis. Over this period, a growing risk premium on eligible money market instruments, unchecked by regulators, provided opportunities to expand risk. Di Maggio and Kacperczyk (2014) present evidence that these low-interest rate environments are associated with increased MMF risk and exit.

Figure (2) below illustrates this relationship leading into and during the recent financial crisis. The figure compares the 3-month moving average of monthly net flow into MMFs against two measures of MMF risk: the interquartile range (IQR) of MMF yield, and the spread between average MMF yield the 1-month Treasury rate.

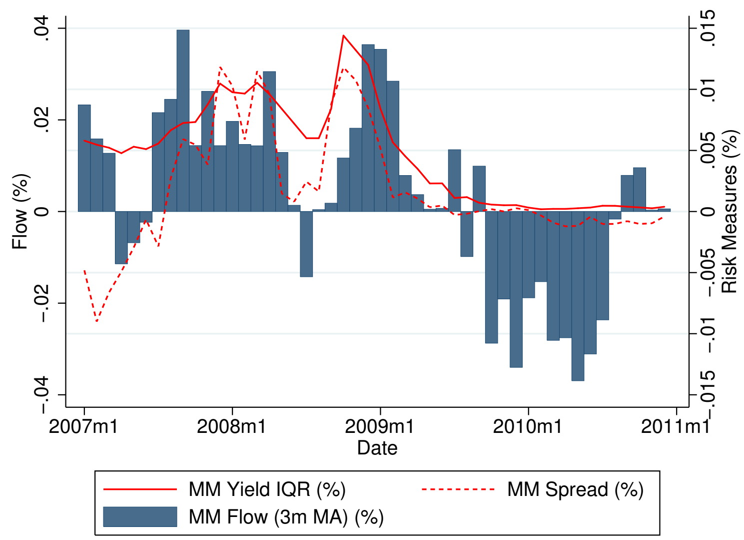

Figure 2: MMF Net Flows and Risk Measures.

In this figure we observe a strong correlation between risk taking and fund flow. This effect is most evident in 2008 when increasing risk measures directly precede higher inflow into MMFs. Funds appear to have been rewarded for “reaching for yield” with increased flows in following periods. This phenomenon is empirically confirmed in the studies mentioned in this section.

2.2 Active Equity Mutual Funds

In this paper, we study similar risk-taking behavior for Active Equity Mutual Funds. Although the nature of these two products is significantly different, several empirical observations suggest that these classes of funds were in otherwise very comparable and in fact complementary positions.

First, over the recent decade the universe of all Equity Mutual Funds (EMFs) have experienced cashflows that strongly oppose those of MMFs. Figure (3) illustrates these cashflows.

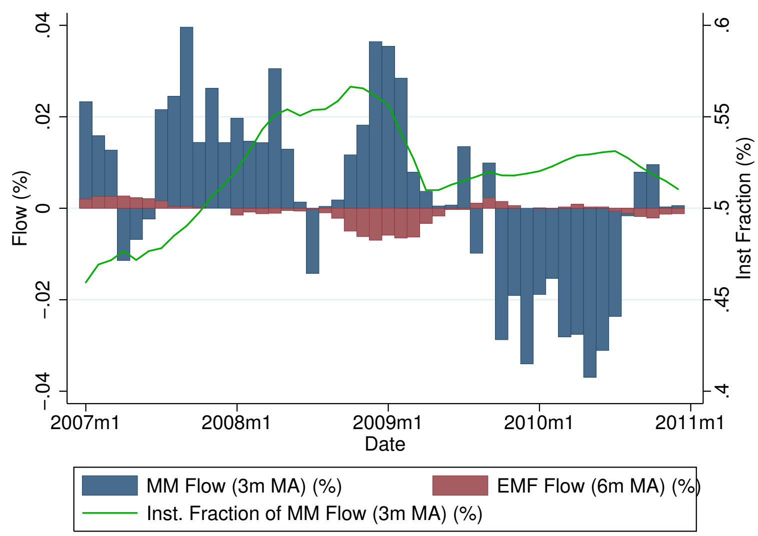

Figure 3: Net fund flows for MMFs and EMFs. The fraction of MM Flows from Institutional Funds is represented by the dashed line (plotted against the right axis). The MMF data were collected from Compustat, and the EMF data are from (ICI, 2015).

This graph shows a strong inverse relationship between net flows for MMFs and EMFs; this relationship is particularly strong during 2009 as the Fed Funds rate approached zero. This complementarity suggests that outflows from MMFs may have been diverted towards EMFs. Further, this figure includes the fraction of these MM flows attributed to institutional funds. We observe that this fraction tends to increase when MMF flows are large, which implies that institutional fund flows may be more mobile. For *Active* EMFs, these flows presented a potential opportunity to attract additional capital; and AEMFs with institutional share classes may have been faced with an even greater opportunity.

Second, despite the difference in the size of net flow fluctuations in Figure (3), AEMFs and MMFs share a similar flow-performance relationship. In fact, there is strong empirical evidence of a flow-performance relationship across all mutual funds. A number of studies have documented this link (e.g., Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), Guercio and Tkac (2002)), and it has been confirmed in a number of settings including the pension fund industry (Guercio and Tkac, 2002), and across countries (Ferreira et al., 2012). In this study, we also confirm this relationship for the subset of AEMFs.

Lastly, overall net flows for actively managed funds reflect an industry that was similarly struggling during the financial crisis. Pressure from ETFs and indexed mutual funds have led to strong and consistent cashflows over the past decade. Figure (4) graphs cumulative outflows from AEMFs since 2007 from our Compustat/Morningstar dataset, and independently collected from the ICI. Both of these lines indicate strong and persistent outflows from AEMFs, and the data from the ICI corroborates our analysis.

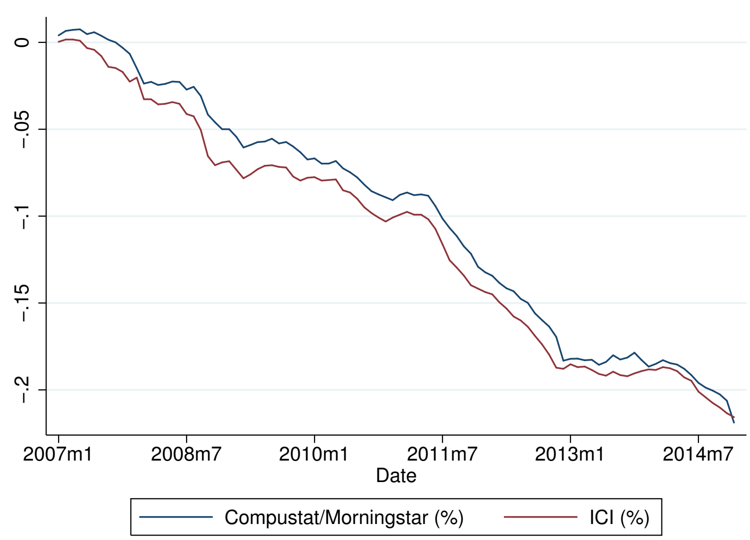

Figure 4: Cumulative Outflows from AEMFs.

Put together, these observations provide a strong motivation to study reaching for yield-type behavior among AEMFs. In the following section, we explore this risk-taking behavior and present our empirical results.

3 Empirical Results

This section presents the main results of our paper. After describing our data, we begin by confirming the relationship between fund return and fund flows–i.e., that an incentive exists for mutual funds to generate higher returns. Then, we will focus on the relationship between monetary policy and mutual fund performance–especially during periods of extremely low interest rates. We demonstrate that (1) overall fund returns exhibit a strong relationship with monetary policy, (2) return-flow sensitivity increases in low rate environments, increasing incentives for funds to reach for yield, and (3) funds indeed "reach for yield" by increasing risk in response to these incentives.

3.1 Data Description

Overall fund-level and monthly data are collected from both Morningstar and Compustat; they are combined using methods described in the Data Appendix of Pástor et al. (2015). Daily data was collected from Morningstar to generate estimates of volatility and weekly returns. Index data and interest rates were downloaded from the Federal Reserve Bank of St. Louis' FRED platform. Our data include the years 2005-2015 to restrict our analysis to behavior around the recent financial crisis.

Our selection of equity mutual funds is restricted to domestic equity mutual funds. Based on funds' investment results, Morningstar assigns these funds in nine different categories: large growth, large blend, large value, medium growth, medium blend, medium value, small growth, small blend, small value. Morningstar also assigns these categories a Russell benchmark, which we use to normalize risk and return for these funds.

From our data preparation, a few points are worth noting.

All of our analysis in this paper is performed at the fund-level–we collect return data at the share-class level and aggregate by weighing the returns with share-level assets.

Following Pástor et al. (2015), we identify AEMFs as EMFs that are not indexed. Specifically, we denote AEMFs as funds which are neither (1) indicated by Compustat or Morningstar as index funds, nor (2) have names that contain the word "index." The consistency between our calculations and those by ICI in Figure (4) indicates that, although our dataset may exclude some funds, the overall behavior is similar.

3.2 Mutual Fund Incentives

We begin our study by confirming the flow-performance relationship for the AEMFs in our dataset.

Following Chevalier and Ellison (1997) and Sirri and Tufano (1998), we define fund flow as the growth in total assets adjusted for fund performance during the period. Defining r_t^i as mutual fund i's annualized return in month t and A_t^i as total fund assets measured at the end of month t, the flow for this period is defined as:[1]

$$f_t^i = \frac{A_t^i - A_{t-1}^i(1 + r_t^i)}{A_{t-1}^i} \tag{1}$$

Then, our model specification is given by:

$$f_{t+1}^i = a_0 + a_1 x_t^i + a_2 \times X_t^i + e_t^i \tag{2}$$

Here, x_t^i represents the performance variable and X_t^i contains the fund and time specific control variables. Our control variables include a fund's expense ratio, the log of total fund assets, a fund's age, and the standard deviation of fund flows during that period. Since our focus is on the effect of monetary policy in this environment, we also include the Fed Funds rate as a control variable in this regression.

To control for time independent fund-level heterogeneity we include fixed effects at the fund level. Further, to alleviate concerns that interest rates proxy for overall market conditions, we include time fixed effects by year. Standard errors are clustered by Morningstar category and year, allowing for serial correlation within years and cross-sectional correlation across funds in the same category. This clustering provided more conservative standard errors than clustering only by category, mitigating potential cluster bias. To ensure extreme observations are not driving our results, we winsorize flows,

[1]Though this definition assumes flows occur at the end of the period, our results are robust to other definitions. Sirri and Tufano (1998) and Ferreira et al. (2012) use the same assumption.

returns, volatility, and Sharpe Ratios at the 0.5% and 99.5% levels. All regression results are located in the Appendix.

Table (3) reports the results of our analysis for three different performance measures. The first column reports the simplest specification using annualized return r_t^i. The second column adjusts for risk by calculating the spread relative to the reported Morningstar benchmark $\Delta_t^i = r_t^i - r_t^{ib}$. Finally, the third column reports the monthly Sharpe Ratio SR_t^i using daily returns to calculate monthly realized volatility, and with the One-Month T-Bill Rate as the risk-free rate.

Across all specifications, we observe a positive and statistically significant performance effect on future fund inflows. These effects are also economically significant: for example, a one standard deviation increase in return predicts a 7.8% gross increase in annualized future inflows. Similarly, a standard deviation increase in either benchmark spread or Sharpe ratio predict increases of 2.2% and 3.0%, respectively. Combining performance measures in a single regression still yields positive and significant coefficients for both gross return r_t, and benchmark-adjusted return Δ_t^i; the coefficient for the Sharpe ratio remains significant at a 10% level.

In Guercio and Tkac (2002), the authors use annual data from an older time period (1984-1994) to estimate the flow-performance relationship; they find the coefficient on annual excess return vs. the S&P500 to be 0.87 and 0.85 for outperformers and underperformers, respectively. Using a different time period and sample of funds, we find a similar measure as our monthly estimate of 0.0831 implies an annual coefficient of around 1.00. Thus, both in magnitude and direction we find evidence consistent with past studies on the relationship between flow and fund performance.

3.3 Performance and Policy

Given mutual funds' incentive to increase performance, we turn our attention to the relationship between fund performance and monetary policy. During low interest rate periods, yields on short term instruments and related assets are compressed; Di Maggio and Kacperczyk (2014) and Chodorow-Reich (2014) establish clear linkages between monetary policy and performance by MMFs that hold these assets. The purpose of this study is to study the effect of monetary policy on a greater set of assets–namely those held by actively managed mutual funds.

We begin with a simple model that connects the Fed Funds rate to mutual fund returns. Our simplest specification is given by:

$$r_t^i = a_0 + a_1 FF_t + a_2 \times X_{t-1}^i + e_t^i \tag{3}$$

As before X_{t-1}^i contains the fund and time-specific controls. These controls, clustering of errors, and fixed effects mirror the specification from Table (3). The results from this simple model are reported in the first column of Table (4). We observe that mutual fund returns, on average, move at approximately a 14:1 ratio with the overall level of the Fed Funds rate. In the sample period, this is also economically significant as the rate exhibited a monthly standard deviation of about 2% (though this is mostly driven by the large decrease early in the sample).

Thus, we observe a significant and positive overall effect of the Fed Funds rate on mutual fund returns. This relationship strongly mirrors that described in Di Maggio and Kacperczyk (2014) between the Fed Funds rate and MMF yields. However, MMF yields are generally lower risk and their benchmark rate over this period (typically the 1-month T-Bill) does not vary much, whereas the benchmark return for these equity funds varies significantly.

Thus, we consider a specification that controls for the benchmark return r_t^{ib} in Column (2) of Table (4). Controlling for this measure, we find results that are more consistent with the overall narrative described in Section (2). In particular, when the Fed Funds rate is lower (and some MMF outflows are diverted to equity funds), fund performance is stronger. This relationship is the first piece of evidence of similar reaching for yield behavior by AEMFs: these funds actually increased their returns relative to their benchmarks during these low-interest rate periods.

Further, recent times have included periods of *exceptionally* low interest rates, as the Federal Reserve has held interest rates at or near zero. Such unconventional periods allow us to study the relationship between mutual fund returns and monetary policy in greater detail.

To this end we introduce another specification that isolates such periods. Define an indicator variable l_t that is equal to one when the interest rate is below a level $\bar{i}$ and 0 otherwise. For this study we define a low-rate period as one in which the Fed Funds rate is less than 1%, though our results were robust to lower levels as well. We specify an augmented model as follows:

$$r_t^i = a_0 + a_l l_t + a_1 FF_t + a_2 \times X_{t-1}^i + e_t^i \tag{4}$$

The results from these panel regressions are reported in the last two column of Table (4). We observe first that low Fed Funds periods are in fact associated with higher fund returns, and drive the strong negative relationship between the rate and fund returns. In fact, when we include the low-rate dummy variable the coefficient on the Fed Funds rate becomes positive and statistically insignificant. Put together, these results highlight a divergence between unconventional and conventional monetary policy.

We also repeat this analysis using the two other measures of fund performance considered in the previous subsection: Δ_t^i, SR_t^i. The results for benchmark spread are reported in Table (5) and mirror the results for unadjusted returns. Specifically, low rate periods are associated with higher benchmark spreads, and these periods generate a negative relationship between the Fed Funds rate and this performance measure.

Although the results for r_t^i and Δ_t^i are almost identical, introducing volatility in the Sharpe Ratio generates significantly different results. Four specifications are provided in Table (6). The first two columns report results without controlling for the Sharpe Ratio of the benchmark, and the last two report results with this variable included. The results are mostly mixed and insignificant. Without controlling for the benchmark, mutual fund Sharpe Ratios tend to decrease during low rate periods as we observe a positive coefficient on the Fed Funds rate in Column (1) and a negative coefficient on l_t in Column (2). However, both of these are only significant at the 10% levels.

When we control for the Sharpe Ratio of the benchmark, SR_t^{ib}, we observe that the Sharpe Ratio weakly increases when the Fed Funds rate decreases. However, when we include the low-rate dummy we find no evidence that these low-rate periods produce higher Sharpe Ratios. Put together, the results in Table (6) present evidence that these higher returns and benchmark spreads did not actually yield higher performance when measured as a Sharpe Ratio.

Thus, for mutual funds low-rate periods are associated with both higher returns and higher benchmark spreads, but not higher Sharpe Ratios. These results are consistent with the traditional definition of "reaching for yield," as this higher yield is associated with increased risk. However, for mutual funds there exist many potential sources of increased returns. Since we only observe a single time series of returns for each fund it is difficult to attribute their returns to any individual factor. In the following subsections, we will attempt to disentangle the cause of these returns by taking advantage of cross-sectional evidence and discrete announcements.

3.4 Yield and Risk

In this subsection, we take a closer look at mutual funds' risk-taking behavior. We have already established that mutual fund returns and spreads tend to increase when the Fed Funds rate is low. Now, we study how these returns may be generated.

As mentioned earlier, given our limited data we cannot determine whether mutual funds increase the riskiness of their portfolios ex-ante. We can only study the time-series of realized returns to determine risk ex-post. We begin our analysis with such a specification, measuring risk in the traditional sense as the monthly standard deviation of daily fund returns.

$$\sigma_t^i = a_0 + a_l l_t + a_1 FF_t + a_2 \times X_{t-1}^i + e_t^i \tag{5}$$

The control variables in X_{t-1} are the same as in previous regressions, and standard errors are also clustered by Morningstar Category. The results from this model are reported in Table (7).

The first column reports the risk counterpart to the relationship between the Fed Funds rate and mutual fund returns, i.e., that mutual fund volatility is inversely related to the policy rate. Column (2) includes both the Fed Funds rate and the low-rate dummy. All of these results are consistent with higher mutual fund volatility during low rate periods, as we observe a negative and significant coefficient on FF_t and a positive and significant coefficient on l_t. However, Column (3) shows that these results may be driven mostly by benchmark risk behavior. Controlling for benchmark volatility, we observe insignificant coefficients on these policy variables.

In the last two column, we report the results of a similar specification measuring risk with "tracking error"–defined as the squared deviation from the benchmark $(\Delta_t^i)^2$. Our past results have indicated that benchmark spread tends to increase during low rate periods, but this isolates for whether this increase is associated with greater overall deviation from the benchmark. The results in Column (4) reflect higher risk taking, as we find that low rate periods are associated with higher tracking error.

This evidence sheds light on the relationship between mutual fund risk and return during periods of unconventionary monetary policy. Consistent with the conventional risk-return tradeoff, low-interest rate periods are associated with both higher risk *and* higher return. However, it remains difficult to determine whether a particular fund's riskiness has increased or decreased as we only observe a single realization of each fund's return series and have limited information on the ex-ante riskiness of their fund assets.[2]

Fortunately, there remain other potential sources of variation. To study this relationship further, we exploit variation within Morningstar's assigned Fund Category designation. Strong cross-sectional variation of fund-level results, denoted by σ_t^j, within categories is another indicator of risk taking. If we index categories by j, we can specify our model as:

$$\sigma_t^j = a_0 + a_l l_t + a_1 FF_t + a_2 \times X_{t-1}^i + e_t^i \tag{6}$$

Here, we aggregate controls within categories by taking an asset-weighted average for each period. The results from this analysis are reported in Table (8).

The first two columns measure the standard deviation of benchmark spread across funds within the same category, $\sigma_t^{j\Delta}$. This standard deviation is calculated weighting by fund assets in order to mimic an aggregate "category portfolio." Columns (1) and (2) report results that are consistent with increased risk taking during low rate periods. In Column (2) we find both a negative coefficient on FF_t and a positive one on l_t; and both are significant at the 1% level. In fact, low rate periods are associated with a 22.7% higher standard deviation (in levels) across fund benchmark spreads.

In addition to indicating higher risk levels, the divergence in benchmark spreads also indicates that funds may also be exhibiting greater heterogeneity in risk taking itself. This is the phenomenon that was observed for MMFs– illustrated in Figure (2) and documented in Kacperczyk and Schnabl (2013)– during similar low rate periods.

In the last two columns of Table (8), we attempt to measure cross-sectional variation in fund risk taking more directly. In particular, we measure the cross-sectional standard deviation of fund level realized volatility, $\sigma_t^{j\sigma}$, to analyze whether funds' risk-taking behavior is diverging as well. Here, we observe evidence consistent with increased variation in risk-taking activity. Lower Fed Funds rates are associated with higher *volatility of* realized volatility as well.

Combined with results from Table (4), these observations indicate that mutual funds reach for yield during periods of unconventional monetary pol-

[2]Morningstar provides quarterly updates of fund asset allocation from S-12 filings. This frequency provides additional challenges in interpolating fund holdings, but results– using volatility calculated by combining daily individual stock returns with reported asset portfolios–were similar.

icy and achieve higher returns by taking on greater risk. We find this evidence both at the individual fund level, and in the cross section at the category level.

Moreover, we also observe that cross-sectional variation in funds' risk-taking behavior increases, which suggests that some funds may reach for yield more than others. In the following subsection we will analyze this cross-sectional heterogeneity in detail and identify fund characteristics that lead to greater reaching for yield.

3.5 Fund Heterogeneity

Related studies on MMFs found that funds' risk-taking behavior was strongly influenced by reputational concerns (Di Maggio and Kacperczyk, 2014; Kacperczyk and Schnabl, 2013). In particular, these studies used the existence of a fund sponsor as a proxy for the magnitude of these concerns. We apply a similar approach here for our sample of AEMFs, using heterogeneity to confirm reaching for yield behavior.

We focus on two separate measures of heterogeneity that we believe to influence funds' incentive to reach for yield.

First, we categorize funds by their focus on institutional investors. Institutional funds hold the majority of MMF assets[3] and Figure (3) illustrated that the institutional MMF flows tend to be more elastic. Thus, we expect AEMFs with institutional shares to have a greater incentive to compete for these flows. We define the variable $INST_t^i$ as 1 if a fund's institutional asset share is in the upper quartile, and $NINST_t^i$ as 1 if in the lower quartile.

Second, we expect size to help separate our sample as smaller funds may have a greater proportional benefit from attracting new investment and are more exposed to the fixed cost motivation for reaching for yield. Further, larger funds may be subject to a reputational cost. The variable BIG_t^i is defined as 1 if a fund is in the upper quartile of size in any given period, and $SMALL_t^i$ is similarly defined for the lower quartile of size.

Thus, we expect to observe more reaching for yield among smaller funds and those with greater institutional assets. To formalize this analysis, we consider the following model where $UPPER_t^i, LOWER_t^i$ are placeholders for the quartile dummies above. Since low-rate dummies provided most of

[3]According to the ICI, as of May 2012 institutional funds held 64% of assets

the variation in previous analyses, we focus on this interaction:

$$\left\{r_t^i, \Delta_t^i, \sigma_t^i \left(\Delta_t^i\right)^2\right\} = a_0 + a_l l_t + a_U l_t UPPER_t^i + a_L l_t LOWER_t^i + a_1 FF_t + a_2 \times X_{t-1}^i + e_t^i \qquad (7)$$

Table (9) lists our results for $INST_t^i$ and $NINST_t^i$. Columns (1)-(4) report the results for $r_t^i, \Delta_t^i, \sigma_t^i \left(\Delta_t^i\right)^2$, respectively. Across all specifications, we observe–consistent with our earlier regressions–that the coefficient on l_t is positive. Moreover, we find that the regression coefficients are consistent with our reaching for yield hypothesis. Funds with greater institutional asset shares are associated with higher return, benchmark spread, and volatility during low interest rate periods. During these periods, corresponding measures for funds in the lower quartile of institutional assets are statistically indistinguishable from those in the middle quartiles, except that they exhibit some additional tracking error at 10% significance.

Our results for size heterogeneity are also broadly consistent with our reaching for yield hypothesis. Table (10) reports our analysis of the BIG_t^i and $SMALL_t^i$ quartile interactions. As before, we observe that the coefficient on l_t remains positive across all specifications. Further, during low rate periods larger funds in our sample are associated with lower returns, benchmark spreads, and tracking error. Although larger funds exhibit higher volatility, these results–combined with increased tracking error for smaller funds–point to weaker reaching for yield for larger funds. This is consistent with these funds having less incentive to compete for new flows.

Put together, our analysis strongly supports the connection between incentives and reaching for yield. We find several specific points to support our hypothesis: First, funds with greater institutional assets respond to low rates with higher returns, benchmark spreads, and volatility than funds with lower institutional asset shares. Second, during the same low rate periods smaller funds exhibit higher tracking error relative to larger funds. Lastly, results for larger funds are broadly consistent with these funds being less sensitive to the incentives provided by new flows, as they exhibit lower returns, benchmark spread, and tracking error than smaller funds.

3.6 Event Studies

In addition to cross-sectional heterogeneity, our panel also permits us to exploit discrete events to study longitudinal variation in greater detail. In this subsection, we present event study evidence in order to support our previous empirical results. Our primary identification uses Fed announcements regarding low-rate policy and asset purchases as monetary policy surprise events. We collect returns at a weekly frequency to improve our estimates around short-lived surprises.

To isolate Fed announcements, we begin by identifying five announcements that provided or extended forward guidance of low-interest rates. The dates of these announcements and others are summarized well in Engen et al. (2015). As in Di Maggio and Kacperczyk (2014), this provides five individual announcements. The specific wording around these zero interest rate policy events is provided in Table (1).

Table 1: Low-Rate Policy Announcements.

Date	Announcement
12/16/2008	0 to .25 percent target range
3/18/2009	"for an extended period"
8/9/2011	"at least through mid 2013"
1/25/2012	"at least through late 2014"
9/13/2012	"at least through mid 2015"

Since we are interested in mutual fund returns, we also augment these dates with other Fed announcements regarding the scale of asset purchases and other significant updates. Due to significant overlap between these announcements and those related to low-rate policy, we restrict our attention to announcements made after the last low-rate announcement, i.e., after 9/13/2012.

This provides us with the dates below in Table (2)

Table 2: Important Announcements post 9/2012.

Date	Announcement
12/12/2012	"The Committee also will purchase longer-term Treasury securities after its program to extend the average maturity of its holdings of Treasury securities is completed at the end of the year, initially at a pace of $45 billion per month."
3/20/2013	"until the outlook for the labor market has improved substantially"
6/19/2013	"The Committee sees the downside risks to the outlook for the economy and the labor market as having diminished since the fall."
9/18/2013	"However, the Committee decided to await more evidence that progress will be sustained before adjusting the pace of its purchases."

On these dates, we estimate the surprise component of these announcements by measuring the change in both equity markets (measured by the S&P500) and interest rates (measured by the Treasury yield curve.) For the S&P500, we use a simple measure of daily market return on the date of the announcement. Mirroring the methodology of Buraschi et al. (2014) and Di Maggio and Kacperczyk (2014), we measure the surprise component contained in interest rates by looking at the change in the first principal component of the yield curve on the date of announcement.[4] For simplicity, we use the constant maturity rates published by the Federal Reserve Board of Governors and represent the yield curve with the 6-month, 1-year, 5-year, 10-year, and 30-year rates. Finally, we normalize surprise announcements by their standard deviation and so that positive values correspond to "positive" market surprises.

In all, our sample begins with 9 possible events. Since we use weekly data, we pare down this sample in order to eliminate events that would otherwise generate an overlap between estimation windows. Our longest specification uses a two-month pre-window and a four-month post-window. Thus, any events within 6 months are removed by prioritizing the magnitude of the S&P500 surprise. This method eliminates four of these dates, and

[4]This principal component measures the "average level" and explains approximately 97% of variation in these rates.

leaves us with five remaining events for our analysis:[5] 12/16/2008, 8/9/2011, 1/25/2012, 12/12/2012, and 6/19/2013.

If we index events by the superscript k, we can summarize our model as follows:

$$\{r_t^i, \Delta_t^i, \sigma_t^i\} = a_0 + a_k S_t^k E_t + a_2 \times X_k^i + e_t^i \tag{8}$$

In this equation, the surprise component for each event is given by S_t^k, and the event indicator by E_t. We set our control variables X_k to their values at the beginning of the pre-event window to control for any endogenous changes in their values due to the event. Further, we use event and fund fixed effects and cluster standard errors by Morningstar category.

The first three columns of Table (11) describe our first set of results for r_t^i across all surprise measures. Column (1) reports results for using a constant event indicator across all events. We observe that this fails to generate any significance in the coefficient; since some of our announcement surprises are negative, this result is not surprising.

Columns (2) and (3) report the results using surprise measured by S&P return and change in the yield curve. Controlling for benchmark return, both of these specifications indicate a positive and significant surprise effect on fund returns. This is consistent with the results provided in our previous panel regressions. However, performing the same exercise for benchmark spread Δ_t^i does not generate this result. Across all of these specifications, a standard-deviation move in either S&P return or yield level component generates a positive effect on annualized fund return of over 1%.

Given these results on funds' increasing yield after these events, we turn our attention to their risk taking behavior. In particular, we mirror our earlier panel regressions and look at the behavior of both weekly standard deviation, and weekly spread of this standard deviation relative to that of the benchmark. These results are reported in Table (12).

Columns (1) and (2) report regression results for volatility and the volatility spread relative to the benchmark, respectively. We note positive and significant coefficients for both of these specifications–consistent with increased risk taking following positive Fed announcements, and contemporaneous with higher returns reported in Table (11). However, given that these announce-

[5] Although 6/19/2013 ranked lower than 9/18/2013, we choose to keep 6/19/2013 in the sample as our largest positive interest rate surprise. Our results are robust to this specification.

ments are also likely to generate large return movements (and we have confirmed this is the case), such announcements mechanically increase the realized standard deviation of fund returns.

To control for this effect, Columns (3) and (4) present results from the same model but with the event period removed from the analysis. Specifically, we restrict our attention to weeks preceding and after the event, excluding the week in which the announcement was made. These results confirm our earlier claim that these announcements are associated with higher volatility, as the reported coefficients are smaller than those from the first two columns. However, our results are still consistent with increased risk taking following these announcements: we find positive and significant coefficients for these specifications as well.

Finally, we measure the quality of this risk-return tradeoff by using the Sharpe Ratio measure. Column (5) reports the effect of the yield surprise on a fund's realized Sharpe Ratio. We find that the risk-return tradeoff is in fact strongly negative–the increased risk greatly offsets the benefit of the increased return. A single standard deviation surprise component is associated with a decrease of 0.42 in Sharpe Ratio.

Thus, evidence from our event study analysis is strongly consistent with the reaching for yield behavior we reported in our panel regressions. Following Fed announcements of low rate policy and asset purchases, we find an increase in both fund return and fund volatility, even after adjusting for those of their benchmarks. These increases combine to provide lower Sharpe Ratios following these announcements, as the increased risk strongly outweighs the higher returns.

4 Conclusion

The recent financial crisis necessitated the use of a number of unprecedented policy measures. Of these, quantitative easing and near-zero rate policy were of the greatest interest and consequence to the general economy. Studying these policies in greater detail is of utmost importance.

Towards this goal, our paper serves as an early foray into the potential ramifications of pursuing these unconventionary measures. We document a number of novel insights.

First, we draw a strong parallel and highlight strong complementarities between the behavior of MMFs and AEMFs during the height of the recent financial crisis. The evidence appears to indicate that the same incentives and dynamics that led to MMF outflows provided strong competitive pressures for AEMFs.

Second, we demonstrate–through a variety of empirical methods–that under these pressures, AEMFs responded to low interest rates by increasing their risk to generate higher returns. To the extent that investors value the Sharpe Ratio as a method of risk-adjustment, this increased risk taking did not appear to be in investors' best interest. Furthermore, this risk taking was inconsistent with the risk channel for unconventionary monetary policy, as we demonstrate that this risk taking was excessive by controlling for various benchmark measures.

Appendix

VARIABLES	(1) f_{t+1}	(2) f_{t+1}	(3) f_{t+1}	(4) f_{t+1}
r_t^i	0.133***			0.0358***
	(0.0168)			(0.00803)
Δ_t^i		0.104***		0.0821***
		(0.0190)		(0.0171)
SR_t^i			0.00943***	0.00300*
			(0.000828)	(0.00161)
r_t^{ib}	-0.0830***			
	(0.0167)			
Observations	176,507	176,507	171,101	171,101
Number of Funds	2,128	2,128	2,067	2,067
Controls	Y	Y	Y	Y
Year/Fund FE	Y	Y	Y	Y

Table 3: Flow-Performance Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, Fed Funds rate, logarithm of total fund assets (interacted with year), age, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) r_t^i	(2) r_t^i	(3) r_t^i
FF_t	13.75***	-1.473**	0.471
	(1.804)	(0.587)	(0.829)
l_t			0.0907***
			(0.0321)
r_t^{ib}		0.915***	0.919***
		(0.0102)	(0.0101)
Observations	177,192	177,192	177,192
Number of Funds	2,130	2,130	2,130
Controls	Y	Y	Y
Year/Fund FE	Y	Y	Y

Table 4: Return Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) Δ_t^i	(2) Δ_t^i
FF_t	-2.885***	1.193
	(0.620)	(0.828)
l_t		0.185***
		(0.0364)
Observations	177,192	177,192
Number of Funds	2,130	2,130
Controls	Y	Y
Year/Fund FE	Y	Y

Table 5: Benchmark Spread Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) SR_t^i	(2) SR_t^i	(3) SR_t^i	(4) SR_t^i
FF_t	30.35*	9.315	-6.012**	-7.134
	(16.72)	(29.99)	(2.808)	(4.542)
l_t		-0.952*		-0.0509
		(0.569)		(0.0982)
SR_t^{ib}			0.937***	0.937***
			(0.00565)	(0.00566)
Observations	171,762	171,762	171,762	171,762
Number of Funds	2,069	2,069	2,069	2,069
Controls	Y	Y	Y	Y
Year/Fund FE	Y	Y	Y	Y

Table 6: Sharpe Ratio Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) σ_t^i	(2) σ_t^i	(3) σ_t^i	(4) $(\Delta_t^i)^2$
FF_t	-9.604***	-0.992	0.0306	0.391
	(1.008)	(0.621)	(0.102)	(0.400)
l_t		0.390***	-0.000214	0.148***
		(0.0173)	(0.00684)	(0.0248)
σ_t^{ib}			0.925***	
			(0.00922)	
Observations	171,763	171,763	171,763	177,192
Number of Funds	2,069	2,069	2,069	2,130
Controls	Y	Y	Y	Y
Year/Fund FE	Y	Y	Y	Y

Table 7: Risk Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) $\sigma_t^{j\Delta}$	(2) $\sigma_t^{j\Delta}$	(3) $\sigma_t^{j\sigma}$	(4) $\sigma_t^{j\sigma}$
FF_t	-5.771***	-3.428***	-0.893***	-0.607***
	(1.021)	(0.565)	(0.138)	(0.109)
l_t		0.227***		0.0277***
		(0.0163)		(0.00484)
Observations	990	990	990	990
Controls	Y	Y	Y	Y
Category/Year FE	Y	Y	Y	Y

Table 8: Cross-Sectional Risk Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. For each Morningstar category, controls include the asset-weighted averages of the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund category fixed effects. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) r_t^i	(2) Δ_t^i	(3) σ_t^i	(4) $(\Delta_t^i)^2$
$INST_t^i \times l_t$	0.00708**	0.00569**	0.00209**	-0.00280
	(0.00307)	(0.00252)	(0.000907)	(0.00416)
$NINST_t^i \times l_t$	0.000942	0.000124	-0.00114	0.00913***
	(0.00342)	(0.00293)	(0.000845)	(0.00331)
FF_t	0.498	1.194	-0.994	0.416
	(0.829)	(0.828)	(0.621)	(0.406)
l_t	0.0895***	0.183***	0.390***	0.147***
	(0.0323)	(0.0362)	(0.0173)	(0.0246)
r_t^{ib}	0.919***			
	(0.0103)			
Observations	171,763	177,192	171,763	171,763
Number of Funds	2,069	2,130	2,069	2,069
Controls	Y	Y	Y	Y
Year/Fund FE	Y	Y	Y	Y

Table 9: Institutional Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. This specification also includes institutional share quartile dummies. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) r_t^i	(2) Δ_t^i	(3) σ_t^i	(4) $(\Delta_t^i)^2$
$BIG_t^i \times l_t$	-0.0312***	-0.0318***	0.0112***	-0.0245*
	(0.00677)	(0.00662)	(0.00299)	(0.0146)
$SMALL_t^i \times l_t$	0.00513	0.00525	-0.0124***	0.0777***
	(0.00732)	(0.00715)	(0.00239)	(0.0166)
FF_t	0.513	1.224	-0.979	0.444
	(0.825)	(0.830)	(0.622)	(0.414)
l_t	0.0934***	0.189***	0.388***	0.133***
	(0.0317)	(0.0359)	(0.0172)	(0.0231)
r_t^{ib}	0.918***			
	(0.0102)			
Observations	177,192	177,192	171,763	177,192
Number of Funds	2,130	2,130	2,069	2,130
Controls	Y	Y	Y	Y
Year/Fund FE	Y	Y	Y	Y

Table 10: Size Regressions. Our dataset is comprised of all actively managed mutual funds from January 2005 to December 2014. Controls include the expense ratio, logarithm of total fund assets (interacted with year), age, fund flow, and cross-sectional standard deviation of fund flows. We apply year and fund fixed effects, and standard errors are clustered by Morningstar Category and Year. Significance markers are standard: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

VARIABLES	(1) r_t^i	(2) r_t^i	(3) r_t^i	(4) Δ_t^i
Event	0.0353			
	(0.0255)			
S&P Surprise		0.0116**		
		(0.00508)		
Yield Surprise			0.0171**	0.00824
			(0.00728)	(0.00762)
r_t^{ib}	0.950***	0.950***	0.950***	
	(0.0105)	(0.0105)	(0.0105)	
Observations	148,313	148,313	148,313	148,313
Number of Funds	1,825	1,825	1,825	1,825
Controls	Y	Y	Y	Y
Event Included	Y	Y	Y	Y

Table 11: Return and Spread Event Studies. Our dataset includes weekly data for 8 weeks prior, and 12 weeks following each of 5 Federal Reserve announcement dates: 12/16/2008, 8/9/2011, 1/25/2012, 12/12/2012, and 6/19/2013. Controls include the values of expense ratio, Fed Funds rate, logarithm of total fund assets, age, and cross-sectional standard deviation of fund flows set at the period just before the pre-event window. Standard errors are clustered by Morningstar Category and Event.

VARIABLES	(1) σ_t^i	(2) $\sigma_t^i - \sigma_t^{iB}$	(3) σ_t^i	(4) $\sigma_t^i - \sigma_t^{iB}$	(5) SR_t^i
Yield Surprise	0.0169***	0.0188***	0.00912***	0.0136***	-0.695***
	(0.00217)	(0.00137)	(0.00145)	(0.00230)	(0.0745)
σ_t^{ib}	0.858***		0.754***		
	(0.0318)		(0.0346)		
SR_t^{ib}					1.307***
					(0.0432)
Observations	148,312	148,312	141,254	141,254	146,902
Number of Funds	1,825	1,825	1,825	1,825	1,825
Controls	Y	Y	Y	Y	Y
Event Included	Y	Y	N	N	N

Table 12: Risk Event Studies. Our dataset includes weekly data for 8 weeks prior, and 12 weeks following each of 5 Federal Reserve announcement dates: 12/16/2008, 8/9/2011, 1/25/2012, 12/12/2012, and 6/19/2013. Controls include the values of expense ratio, Fed Funds rate, logarithm of total fund assets, age, and cross-sectional standard deviation of fund flows set at the period just before the pre-event window. Standard errors are clustered by Morningstar Category and Event.

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