Spring 5-2020

Derivatives Use and Risk Taking: Evidence from Alternative Mutual Funds

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Derivatives Use and Risk Taking: Evidence from Alternative Mutual Funds

An honors thesis presented to the
Department of Finance,
University at Albany, State University of New York
in partial fulfillment of the requirements
for graduation with Honors in Finance
and
graduation from The Honors College

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Research Advisor: Ying Wang

May 2020

Abstract

I provide new empirical evidence on the effect of derivatives usage on the risk and performance of a group of mutual funds mimicking hedge fund strategies, namely alternative mutual funds (AMFs). Using data on a sample of 914 AMFs from Morningstar during 2002-2017, I show that while the use of derivatives does impact the performance of AMFs, it significantly increases AMFs' total and idiosyncratic volatilities, even after we control for various fund characteristics. This positive relation between the use of derivatives and the risk-taking of AMFs is particularly strong during the crisis period, and Bear Market, Long-Short Credit, Managed Futures, and Multialternative funds. Overall, the result is in contrast to the documented negative or insignificant relation between derivatives usage and performance for hedge funds or traditional mutual funds, suggesting that AMFs as a group tend to use derivatives for speculative purposes.

Keywords: Alternative mutual funds, use of derivatives, fund risk, fund performance, speculation, financial crisis

Acknowledgements

I have had the privilege to work with many incredible individuals as I conducted my thesis. My advisor, Ying Wang, not only guided me but went above and beyond to help me conduct my research and develop my hypothesis. I also want to thank the rest of the Department of Finance including David Smith and Na Dai who sparked my passion for finance and enriched my financial knowledge.

I also want to thank my family for always encouraging me and pushing me to be my best.

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1. Introduction

In this paper, I investigate the role derivatives have in alternative mutual funds (AMF) and how they impact risk and performance. This research takes into account the different fund styles, as well as time periods of AMFs. Alternative mutual funds are SEC-registered mutual funds that hold non-traditional investments and or use complex investment and trading strategies. These alternative vehicles include derivatives, shorting securities, buying and selling options, pairs trading, and more. Since AMFs include a wide range of investment strategies, they are designed to meet various investment needs. The majority of alternative mutual funds try to minimize fluctuations in the value of their investments and reduce risks. The reduction of risk comes from using complex trading strategies and spreading their investments among different asset classes. Some different asset classes include real estate, start-up companies, or commodities. These investments can sometimes provide greater diversification and different returns than more traditional investments such as stocks and bonds. Along with reducing risk, some AMFs try to generate above-market returns relative to other mutual funds with a similar benchmark.

Many alternative mutual funds have similar strategies to those of hedge funds, which is why sometimes AMFs are marketed as “hedge fund-like” options to retail investors (SEC, 2017). Though these funds do act similar, there are a few differences that separate them. Some benefits that AMFs provide that hedge funds do not, include being regulated, open to the public, and potentially having lower fees. By being open to the public, not only does it allow any investor to purchase shares, but also increases the data availability compared to hedge funds. Another major difference between the two types of funds is that hedge funds are typically less liquid and have longer lock-up periods than AMFs; investors typically have access to their capital on a daily basis in alt funds. With this being said, alternative mutual funds promise the upside of hedge funds, while providing the liquidity of traditional mutual funds.

Alternative mutual funds have proven to provide a variety of benefits that other funds cannot, and because of this, alternative investments have experienced rapid growth over the past two decades. In recent analysis by the SEC, the assets under management in AMFs grew from $320.4 billion in 2010, to $469.3 billion in 2014 (SEC, 2015). With lower yields and a decreasing number of public companies in the equities market, investors look to increase their allocations to major alternative categories. According to Preqin, “The alternative investment industry is expected to grow by 59 percent by 2023, reaching $14 trillion in assets in five years’ time” (McElhaney, 2018). Data shows that some of the category’s investors are looking to invest in include private equity, infrastructure, and private debt.

Also, past volatility has motivated investors to seek returns elsewhere besides traditional markets. For example, after the Financial Crisis of 2008, investors were encouraged to seek investment opportunities that would hedge some downside risk with diversification (Lewis, 2016).

Financial innovations have provided more exposure of alternative investments to retail investors, allowing them to gain experience with AMFs. As their experience grows, more of this untapped market is being satisfied by the diversification these funds provide. Although investors are gaining exposure to AMFs and have the understanding that they involve high flexible investment strategies, there are still uncertainties that revolve around the use of derivatives and how they impact the funds risk and performance.

I review literature that discuss the general use of derivatives, as well as their use in other types of funds. In the empirical literature I review, the analysts examine the use of derivatives in other types of funds, like mutual and hedge funds. In Koski and Pontiff's research they analyzed the use of derivatives in equity mutual funds and they find that there is variation in the risk levels which is associated to the fund's investment objective, rather than the derivative itself (1995). My hedge fund literature looks at the impact derivatives have on the risk and performance and Chen (2011) finds that there is a negative link between the use of derivatives and fund risk levels. Along with this Chen discovers that derivatives, similar to the mutual fund literature, do not have a significant relation with fund performance.

In this paper, I provide an empirical analysis of the derivative use in alternative mutual funds to shed light on the role these securities have on the risk and performance of these funds. Since AMFs are relatively new, especially for individual investors, this analysis gives a better understanding if derivatives are used in more of a speculative role or hedging role.

In my research I expect that implementing derivatives for speculative purposes will increase risk exposure, and on the other hand, implementing derivatives for hedging purposes will have a decrease effect on the fund's risk level. I use my data sample of 914 AMFs, that are sourced from Morningstar, and run regressions to calculate the risk and returns for each of these funds between 2002 and 2017. I also use a 10-factor model, which is based off Hsieh's 7 factor model used in hedge funds to calculate the raw and adjusted returns. Using these results, I am able to calculate two risk measures, total volatility and idiosyncratic volatility, by taking the standard deviation of the raw and adjusted returns respectively.

The rest of the paper proceeds as follows. Section 2 discusses more my literature review in greater detail. In Section 3, I present my initial hypotheses and reasonings behind them. Section 4 presents my data and key variables and Section 5 discusses the methodologies behind my study. In Section 6, I present my empirical results regarding the relation between the use of derivatives and risk and in Section 7 I conclude.

2. Literature Review:

With limited research on derivative use in AMFs, this paper will give investors more insight, as well as compare results to other types of funds (traditional mutual funds, hedge funds). By looking at the use of derivatives in a variety of funds, investors will have a better understanding of these investment strategies.

The theoretical literature of Robert C. Merton (1995) proposes that derivatives provide investors with efficiency benefits in the form of reduced transaction costs and improved risk control. Some observers see that the growth in derivative use as a fad-like, but a more likely explanation is the vast saving in transaction costs derived from their use (Merton, 1995). Technology also plays a large role in the reduction of transaction costs and risk mitigation. The adoption of new financial technology, especially technology designed to help manage risk has encouraged users to incorporate derivative securities into their portfolios.

The empirical work performed by Fong, Gallagher and Ng (2005) on the use of derivatives by investment managers provides investors with the implications these securities have on portfolios' performance and risk. With recent shifts in financial markets and increased volatility, investors are becoming more exposed to a broad range of risks. This exposure has led to the increasing use of derivatives in portfolio for risk management. They performed this research using a database comprising the monthly holdings and daily trades of investment managers, which provided evidence on the performance and risk effect of the derivative users. At the beginning of their research they believe that the use of derivatives causes significant impacts on performance and risk of investment managers, but their results showed that there was no significant difference in both portfolio performance and risk across derivative users and non-users in mutual funds (Fong et al., 2005).

The researched performed on the use of derivatives by investment managers can also be compared by the research conducted by Koski and Pontiff (1999). In this empirical study, the researchers focus on the use of derivatives, specifically in the mutual fund industry. Their paper analyzes the use of derivatives by equity mutual funds by comparing the return characteristics of derivative-using funds and non-users (Koski & Pontiff, 1999). They also decide to study portfolio return instead of individual trading in derivatives since the ability to trade these securities may affect managers' decisions to trade non-derivatives. The first thing to distinguish when looking at any type of fund, is to determine if derivatives are being used to speculate or to hedge. Depending on the type of fund it is may dictate the amount of risk they experience. From their sample of 679 general equity mutual funds, only 21% use derivative securities (Koski & Pontiff, 1999). To retrieve results associated with risk, the researchers use the variables of standard deviation, idiosyncratic risk, and beta. They find that there were substantial variations in risk associated with investment objectives, but not with derivative use (derivative users have neither increased risk due to speculation nor decreased risk from hedging (Koski & Pontiff, 1999)). This finding negates the popular association of the derivatives with increased risk exposure. Looking into the impact derivatives have on performance, Koski and

Pontiff computed a multivariate analog to Jensen's alpha for the different fund types. Using a regression, results showed that there was no significant difference in performance (measured by alpha) between derivative users and non-users.

The paper *On the Use of Options by Mutual Funds: Do They Know What They Are Doing?* also looks into the use of options by mutual funds. In this study, Cici and Palacios use detailed option holdings data to shed light on how mutual funds employ options and what type of mutual funds/managers use options and how they impact the funds risk and performance. It seems that options were typically used for income generation and portfolio hedging. The results this paper generated disapproves the view that managers of mutual funds that use options have abilities to generate proprietary information leading to superior fund performance compared to non-derivative users (Cici & Palacios, 2011). It was also discovered that option-using mutual funds typically do not engage in extreme portfolio risk levels, rather they have lower systematic risk levels than non-users (Cici & Palacios, 2011). These findings disprove the higher risk level stigma associated with option users, and instead shows how options are used for risk management and risk hedging purposes.

These studies support the notion that derivatives do not have any significant impact to the risk and performance of traditional mutual funds, but research done on hedge funds seem to show different results. Since hedge funds act differently than traditional mutual funds one would assume that derivatives have a different effect on their risk and performance. It is also to take into account the different investment objectives from each of these funds; based off these objectives, derivatives can be efficiently implemented.

The hedge fund industry is an attractive setting to study the motives for using derivatives, especially when researching their impact on AMFs, since they act in similar manners. Hedge funds are different than mutual funds in that they are unregulated and can implement a wide range of trading securities (i.e. use derivatives broadly to earn higher returns on information production) (Aragon & Martin, 2012). To see if derivatives play a speculative role in investment management, G.O Aragon and Spencer Martin deciphered eight years of required disclosures by 250 hedge fund managers. Prior to this research, findings showed no speculative role for derivatives in mutual fund management, but instead mainly a hedging role. Aragon and Martin's (2012) results show that after-fee portfolio returns for derivative-users are larger than non-users and have lower return standard deviation.

I believe the research that was conducted by Chen on derivative use and risk taking in the hedge fund industry is the most comparable to my research in regard to security usage since the proportion of hedge funds using derivatives is over 3 times as large as other mutual funds. Chen examines a large sample of hedge funds, where 71% of the funds traded derivatives (Chen, 2011). To conduct his research, Chen examines 3 essential aspects of hedge fund risk profiles. This includes comparing risk measures between derivatives users and nonusers by performing regressions. Chen also uses regressions to investigate whether or not derivatives users exhibit different propensity to shift risk. And finally, Chen analyzes the failure rate of derivatives using hedge funds to see if they occur more likely than nonusers or see if they help mitigate unfavorable influences from the market. Chen's results confirm the fact that derivative-using hedge funds, on average, displayed lower risk under several measures of volatility (Chen, 2011). It was also seen that derivative users engage less in risk shifting compared to non-users. Looking at the performance of derivative-using hedge funds, it seemed that after-fee risk-adjusted performance is similar to non-derivative users. Derivatives also proved that they are especially useful in mitigating risk when it comes to unusual/severe market conditions.

After looking at the research that has been done on mutual funds and hedge funds, it can be concluded that derivatives play a different role in each and have a different impact on the funds' risk and performance.

3. Hypotheses:

One of my testable hypotheses is that derivative use and AMFs' risk has a **positive** relationship. This hypothesis is associated with speculative AMFs, where their investment objective is to generate above-market returns, and therefore increasing their risk exposure. As stated earlier, hedge funds act similar to alternative mutual funds, in regard to types of investment vehicles. Since research has found that derivatives help mitigate risk and lower risk levels, I predict that this will likely be the same for AMFs, like the results found in Chen's research (2011). I also believe derivatives will be able to **positively** affect the performance of alternative mutual funds.

H_1: Derivative use and AMFs' risk has a positive relationship

H_{10}: Derivative use and AMFs' risk does not have a positive relationship

H_2: Using derivatives will have a positive impact on AMFs' performance

H_{20}: Using derivatives will have not have a positive impact on AMFs' performance

4. Data and Variables:

My data sample consists of 914 AMFs that were sourced from Morningstar during the time period of 2002 to 2017. This sample period provides different economic states and shows how derivative-using AMFs performed and how their use changed over time. From these funds include different types of AMFs, including Long/Short, Currency, Fixed Income, Multialternative, and more. By looking at a wide range of alternative mutual funds, it provides better insight into each funds' ability to reduce risk and performance level.

The variables I incorporate into my research consists of my independent, dependent, and control variables. My main independent variable is derivative usage, which is used by approximately 73% of AMFs, compared to only 29% of traditional mutual funds (SEC, 2017). This variable includes a variety of financial securities that can be used by funds for speculative or hedging purposes. The control variable fund size represents the total amount of money managed as a standalone portfolio across share classes. This helps gauge a product's size, agility, and popularity. Another control variable, age indicates the maturity level of the different AMFs by incorporating its inception and obsolete date. The flow (control variable) of a fund represents the demand for securities, or in my case the demand for entering into derivative using alternative mutual funds; this allows us to gauge investors sentiment within this asset class. The turnover ratio (control variable) follows each fund's trading activity by taking the lesser of the purchases and dividing by the average monthly net assets. And the final control variable, expense ratio, shows the percentage of fund assets used to pay for operating expenses and management fees, administrative fees, and all other asset-based costs incurred by the fund (except brokerage fees).

By evaluating these variables, I am able to calculate the risk experienced by the funds' as well as their performance (dependent variables).

5. Methodologies:

To conduct my research, I identify alternative mutual funds that use derivatives and those that do not. By analyzing the two different types of funds, it makes it easier to see the impact of derivatives. I also perform regressions to identify each funds' performance and risk and look at these measures during different economic states, including pre-crisis, crisis, and post crisis. In these regressions, the variables that were used included the use of derivatives (independent variable), fund size, age, flow, expense and turnover ratio (control variables).

$$\mathbf{Risk}_{\mathbf{i,\,t}} \,/\, \mathbf{Return}_{\mathbf{i,\,t}} = a + bD_{i,t-1} + cX_{i,\,t-1} + \varepsilon_{i,\,t}$$

The ten risk factors I focus on include Trend-Following (bond, currency, and commodity), Equity-Oriented (equity market and size spread factors), Bond-Oriented (bond market and credit spread factors), and Emerging Market (emerging market index). Below is the 10 factors model I performed to conduct my return measures.

$$\mathbf{R}_{\mathbf{i,\,t}} = a + b_{i,EM}\, EM + b_{i,SIZE}\, SIZE_{t} + b_{i,BM}\, BM_{t} + b_{i,CREDIT}\, CREDIT_{t} + b_{i,MSEMKF}\, MSEMKF_{t} + b_{i,PTFSBD}\, PTFSBD_{t} + b_{i,PTFSFX}\, PTFSFX_{t} + b_{i,PTFSCOM}\, PTFSCOM_{t} + b_{i,PTFSIR}\, PTFSIR_{t} + b_{i,PTFSSTK}\, PTFSSTK_{t} + \varepsilon_{i,\,t}$$

The regressions performed use a sample that beings in 2002 and ends in 2017. I believe this is very important since it shows how AMFs performed, as well as how much volatility they experienced, during different economic environments. It also can show if fund managers adjust their mindset and alter the securities they use, given the pressures they face from the economy.

Since alternative mutual funds act similar to hedge funds, I think it would be appropriate to use the David A. Hsieh's hedge fund risk factors to capture the risk of AMFs.

His first risk factor is a popular strategy commonly referred to as "Trend-Following". This is a self-described strategy for the majority of commodity trading advisors (Fung & Hsieh, 2004). It includes the Bond Trend-Following Factor, Currency Trend-Following Factor, and Commodity Trend-Following Factor. Hsieh's results from this strategy found that returns from trend following funds were uncorrelated with standard equity, bond, and currency indices, but also that those returns exhibited option-like features with large and positive returns during the best and worst months.

The second risk factor used is the Equity-oriented Risk Factor, which includes the Equity Market Factor and the Size Spread Factor. The Equity Market Factor uses the Standard & Poor's 500 index monthly total return and the Size Spread Factor and subtracts both from the Russell 2000 index monthly total return.

The third risk factor is the Bond-oriented Risk Factors, which includes the Bond Market Factor and the Credit Spread Factor. These factors focus on the monthly change in the 10-year treasury constant maturity yield and difference between the monthly change in the Moody's Baa yield and the 10-year treasury constant maturity yield, respectively.

Hsieh recently incorporated an eighth factor to his model with the Emerging Market Risk Factor, which is also included in my results. This risk factor uses the IFC Emerging Market index monthly total return.

6. Empirical Analysis:

This section presents my main empirical results regarding the relation between derivative use and alternative mutual fund risk. I perform regression analysis in Table 3, which includes all time periods (pre-crisis, crisis, and post-crisis) and focuses on multiple fund characteristics. Table 4 takes the data acquired from the overall sample and categorizes the different types of AMFs. These funds include the US Fund Bear Market, US Fund Long-Short Credit, US Fund Long-Short Equity, US Fund Market Neutral, US Fund Multialternative, US Fund Multicurrency, US Fund Options-based, and US Fund Trading-Leveraged Equity. This table provides investors with better insight into how different alternative mutual funds use derivatives and their impact on the funds' overall risk.

An important aspect to this research includes the use of derivatives in different time periods. Specific economic environments require different financial tools and securities to combat risk and by analyzing the U.S. economy at different points of its cycle, my results show the role derivatives played during each phase. Table 6 shows the volatility derivative-using AMFs experience during a pre-crisis time period (2002-2007) using the control variables, fund size, age, flow, turnover ratio, and expense ratio. Next, I examine the use of derivatives in alternative mutual funds during a crisis period; in my research I focused on the most recent recession (2007-2009). In Table 5, it shows how effective the different types of AMFs were at mitigating risk and performing during The Great Recession, while using the same control variables as mentioned prior. And then to finalize the analysis of different economic conditions, Table 7 discusses the volatility and idiosyncratic volatility the sample of AMFs experienced during a post-crisis economy (2009-2017).

Table 2 is able to show the correlation between derivative usage and the other control characteristics (fund size, flow, age, turnover ratio, and expense ratio) with the returns and volatility experienced by the AMFs of my sample. And then finally, Table 1 provides a summary of my data and results I uncovered.

6.1 Correlation

Taking a closer look at Table 2, my results reveal that many of my variables are correlated to the risk exposure of my sample of 914 alternative mutual funds. More specifically, it shows that derivative usage has a positive correlation of 14.3% to volatility and a negative correlation to performance with -1.3%. This supports my original hypothesis, which originally stated that using derivatives in AMFs would have a positive relationship with risk in the case of speculative AMFs. Other variables that had strong positive correlations to volatility were, the fund's age at 20.2%, flow with 9.1%, turnover ratio with 13.7%, and expense ratio with a 5.7% correlation. One variable that shows a negative correlation was the size of the fund with -34.8%, which makes sense since the larger the fund size, the more likely it is diversified, and therefore mitigating risk.

6.2 Overall Risk Regression

The results from the regression of AMF risk can be viewed on Table 3, which includes pre-crisis, crisis, and post-crisis periods. This table shows that overall, derivatives have a strong positive relationship with both volatility and idiosyncratic volatility at 107% and 14.4%, and a significance level of 10% (***). It also shows that all of my controlled variables (age, size, flow, turnover and expense ratio) have high significance levels. The funds' age, flow, turnover ratio and expense ratio had positive relationships with volatility, while fund size had a negative relationship. Table 4 provides greater detail of the results found on Table 3, by breaking the sample into the different types of alternative mutual funds.

6.3 Pre-Crisis Regression

Focusing on the risk exposure of these funds during a pre-crisis period, Table 6 shows the regression of derivative usage in AMFs prior to 2007. These results show derivatives having a very strong relationship with volatility at 37.6% and 13.7% with idiosyncratic volatility. It seems that each funds' age and size have a negative relationship with risk exposure/volatility with -65.8% and -5.9% respectively. These negative relationships can stem from the fact that more mature funds are less volatile and that the large funds provide more diversity, which help with combating market risk. This table also shows the turnover ratio in the sample of alternative mutual funds having a positive relationship with volatility/idiosyncratic volatility at 15.8%. This makes sense since it includes the trading activity of the fund and with more movement comes more market exposure, but I was surprised at how impactful this plays in a pre-crisis time period.

6.4 Crisis Regression

A crisis period within an economy can be difficult to navigate and I initially believed that AMFs, especially those using derivatives, would provide a great source of diversification to portfolios, but looking at Table 5 reveals the opposite. Table 5 breaks up the different types of alternative mutual funds within the sample and displays each of their volatility and returns. The funds that display a very significant relationship between derivatives and volatility/idiosyncratic volatility were the US Fund Bear Market, US Fund Market Neutral, US Fund Multialternative, US Fund Multicurrency, US Fund Options-Based, US Fund Trading – Inverse Debt, and the US Fund Trading – Leveraged Debt.

First, looking at the US Fund Bear Market, derivatives have an extremely strong positive relationship with volatility with 145.1% and idiosyncratic volatility with 28.9%. The use of derivatives show a significant level of 10% (***), indicating their main purpose is used for speculation purposes. The unfavorable market did not respond well with the use of derivative securities in this type of AMF overall, but the larger and more mature funds would be better off since those two controlled variables showed a negative relationship with volatility and idiosyncratic volatility. The age variable was indicated to have a significance level of 10% (***) at -226.1% and fund size also had a significance level of 10% (***) at -17.4%. Looking at the performance side of the table, it showed that derivatives and returns and adjusted returns had a positive relationship with 40.5% and 23.5% respectively, but they did not hold much significance. With this being said, it seems that the derivatives used in US Fund Bear Market plays a speculative role, rather than a hedging role and are more focused on returns than risk mitigation.

Next, looking at the US Fund Long-Short Credit, it produces different results than the US Fund Bear Market in that derivatives had a negative relationship with the fund’s volatility at -196.8% but has low significance (especially compared to other types of alternative mutual funds). The variables that play a major role (in terms of volatility) in this type of AMF are the turnover and expense ratio. The turnover ratio displays a negative relationship with volatility/idiosyncratic volatility at -60.9% and a 10% (***) significance level, while the expense ratio experienced a significant positive relationship at 10% (***). Once again, I disregard the returns and adjusted returns in this type of alternative mutual fund due to lack of significance.

The US Fund Long-Short Equity funds reveal that there was really no significance found between derivative usage the fund's risk exposure and returns. The variables that did show significance were the fund's age, size, turnover ratio, and expense ratio, which each had a significance level of 10% (***). Along with US Fund Long-Short Equity, the US Fund Managed Futures showed a lack of significance derivatives had on the fund's volatility/idiosyncratic during a crisis period but did show a strong negative relationship with the fund's returns and adjusted returns.

The US Fund Market Neutral was another type of AMF that shows a negative relationship with the fund's volatility at -36.7% and a significance level of 10% (***). Fund size, flow, turnover and expense ratio also show negative relationships with volatility at -7.2%, -137.7%, -9.1%, and -1707.5% respectively with significance levels of 5% (size and flow) and 10% (***) (turnover and expense ratio).

Similar to the US Fund Bear Market, derivative usage in US Fund Multialternative has a strong positive relationship at 441% and a significance level of 10% (***) with risk. The US Fund Multicurrency and US Options-based funds also have a significantly positive relationship between derivatives and volatility with 43.3% and 45.4%. Since these funds offer exposure to several different investment tactics, it seems that in a crisis period this ends up exposing them to the unfavorable market, rather than protecting them. With this being said, these types of funds seem to play more of a speculative role, rather than a hedging role and are focused more on generating returns.

US Fund Trading – Inverse Debt funds reveal that each of our variables, derivatives and the control variables (age, size, flow, and turnover and expense ratio) have significance levels of 10% (***) in relation to risk, with derivatives being negative at -39.1%. On the other hand, performance lacked significance from each variable.

And the last type of fund that shows derivatives having a very significant impact on volatility/idiosyncratic was the US Fund Trading – Leveraged Debt. The results for this type of alternative mutual fund indicated that it was speculative rather than a hedging fund with a derivative relationship of 266.8%.

6.5 Post-Crisis

Looking at Table 7, which reports the volatility and idiosyncratic volatility experienced by my sample in a post-crisis period (after 2009), I found that post-crisis periods were very similar to pre-crisis periods and crisis period in that my sample of funds, majority of them use derivatives for speculation purposes. In the post-crisis period, derivatives have a positive relationship with volatility at 84.7% and 8.6% with idiosyncratic volatility, with both having significance levels of 10% (***). One difference I relationship difference I saw between pre and post crisis was for the fund's age. During post-crisis, age has a positive relationship with volatility at 145.5% and a significance level of 10% (***).

7. Conclusion

Alternative investments have become more popular with investors in recent years due to more accessibility and a proven source of diversification. There have been multiple studies performed to look at the impact these securities have on different types of funds, like traditional mutual funds and hedge funds, which are performed by Cici, Gjergji, Palacio (2011) and Chen (2011). Derivatives are securities that have been used in many high flexible investment strategies, like those found in alternative mutual funds, but there is little knowledge on the effect these securities have on the funds' risk and performance. Although there have been studies, like Chen's (2011), that discusses the impact derivatives have on hedge funds, which are similar-acting funds to AMFs, to the best of my knowledge there have been no studies that specifically focus on derivative use in alternative mutual funds. My research provides the first empirical evidence to shed light on the effect's derivatives have on the volatility of AMFs.

This paper analyzes 914 alternative mutual funds between 2002-2017 and shows that derivative usage has a positive correlation with risk. Looking at different economic states, I found that this relationship is extremely strong in each phase, pre-crisis, crisis, and post-crisis, with the most impact occurring during a crisis period (July 2007 to March 2009). Overall, derivatives show a high significance level in relation to volatility with 107% and 14.4% for idiosyncratic volatility. A possible explanation for this may be that the funds studied are speculative funds, whose goal is to generate higher returns, rather than hedging funds (whose goal is to mitigate risk exposure). The majority of the funds in my sample use derivatives for speculative purposes, but one fund that does not is the market neutral fund. This type of fund has a history of using securities for hedging purposes and this is exemplified in each time period, especially in my crisis period. Here, this is the only fund that demonstrated a significant negative relationship between derivatives and risk. I also find that the relationship between derivatives and returns lacked significance, which corresponds to what other funds (mutual and hedge funds) experienced in the literature I review.

By looking into the impact derivatives play on the risk in alternative mutual funds, investors will now have better understanding of the role these securities play in the AMF space, which is rapidly growing, and will be able to determine the usefulness of them in their portfolio.

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Table 1: Derivative Summary Statistics

The sample includes 914 U.S. Alternative Mutual Funds during January 2002 – December 2017.This table reports summary statistics of my key variables, including Fund Size (mtna), Flow (mflow), Turnover Ratio (tr), Expense Ratio (exp), Age (age), Risk (VOL/IDVOL), Derivative Usage (der) and Returns (mret/mretadj).

NAME	N	Min	P25	Mean	Median	P75	Max	STD
Return	54792	-16.72	-1.26	0.16	0.24	1.63	15.89	4.34
Adj. Return	54792	-21.20	-1.39	-0.12	-0.04	1.22	22.20	4.19
Volatility	35190	0.03	1.42	3.44	2.39	4.65	14.21	2.79
Id. Volatility	35190	0.01	0.53	1.22	0.89	1.48	9.26	1.09
Derivative	47840	0.00	0.00	0.55	1.00	1.00	1.00	0.50
Age	54792	0.04	1.66	5.81	3.84	8.28	27.95	5.75
log Age	54792	0.05	0.98	1.60	1.58	2.23	3.37	0.81
Fund Size	54792	111671	13863773	285463425	46434428	188990214	4550079334	700516997
log Fund Size	54792	11.62	16.44	17.72	17.65	19.06	22.24	2.00
Flow	53242	-0.58	-0.03	0.07	0.00	0.05	3.02	0.41
Turnover Ratio	39588	0.00	0.42	2.94	1.31	3.12	33.21	5.02
Expense Ratio	46109	0.00	0.01	0.02	0.02	0.02	0.04	0.01

Table 2: Correlation between Key Variables

The sample includes 914 U.S. Alternative Mutual Funds during January 2002-December 2017. This table reports the correlation coefficients (in percentage) among the key variables.

Variable	Return	Adj. Return	Volatility	Id. Volatility	Derivative	Age	Fund Size	Flow	Turnover Ratio	Expense Ratio
Return	1.000	0.960***	-0.010*	-0.002	-0.013***	0.002	0.005	-0.009**	0.005	-0.004
Adj. Return		1.000	-0.020***	-0.012**	-0.011**	0.004	0.024***	-0.013***	0.000	-0.006
Volatility			1.000	0.706***	0.143***	0.202***	-0.348***	0.091***	0.137***	0.057***
Id. Volatility				1.000	0.033***	0.028***	-0.292***	0.058***	0.119***	0.124***
Derivative					1.000	0.038***	0.105***	0.006	0.003	-0.056***
Age						1.000	0.294***	-0.139***	0.045***	-0.105***
Fund Size							1.000	-0.073***	-0.136***	-0.085***
Flow								1.000	0.071***	0.003
Turnover Ratio									1.000	0.094***
Expense Ratio										1.000

Table 3: Regression of AMFs

The table reports regression results of derivative use in AMFs. The dependent variables are volatility (vol) and idiosyncratic risk (idvol). The independent variable is derivative usage and control variables include Fund Size (logmtna), Age (logage), Flow (mflow), Turnover Ratio (tr), and Expense Ratio (exp). ***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

Parameter	Volatility	Id. Volatility	Return	Adj. Return
Intercept	6.091***	2.011**	1.185	0.213
	(2.70)	(2.12)	(0.31)	(0.06)
Derivative	1.070***	0.144***	-0.028	-0.030
	(37.63)	(12.06)	(-0.65)	(-0.71)
Log(Age)	1.123***	0.140***	0.149***	0.150***
	(48.16)	(14.25)	(4.83)	(4.89)
Log(Fund Size)	-0.521***	-0.144***	-0.057***	-0.022*
	(-69.57)	(-45.78)	(-5.07)	(-1.94)
Flow	0.681***	0.161***	0.027	0.029
	(13.65)	(7.68)	(0.38)	(0.41)
Turnover Ratio	0.024***	0.011***	0.003	0.003
	(8.38)	(8.88)	(0.76)	(0.59)
Expense Ratio	26.137***	18.576***	-1.221	-1.234
	(13.10)	(22.14)	(-0.41)	(-0.41)
AdjRsq	0.326	0.152	0.167	0.032
Time FE	Yes	Yes	Yes	Yes
Number of Observation	26807	26807	34308	34308

Table 4: Overall Regression for Different Fund Categories

The table reports regression results of derivative use in different AMFs. The dependent variables are volatility (vol) and idiosyncratic risk (idvol). The independent variable is derivative usage and control variables include Fund Size (logmtna), Age (logage), Flow (mflow), Turnover Ratio (tr), and Expense Ratio (exp). ***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

(a)

US Fund Bear Market

Parameter	**Volatility**	**Id. Volatility**
Intercept	18.547***	3.819***
	(22.65)	(10.85)
Derivative	1.230***	0.207***
	(9.51)	(3.72)
Log Age	-2.153***	-0.963***
	(-19.41)	(-20.19)
Log Fund Size	-0.512***	-0.081***
	(-17.23)	(-6.37)
Flow	0.389***	0.076
	(2.87)	(1.31)
Turnover Ratio	-0.079***	0.010***
	(-8.82)	(2.65)
Expense Ratio	12.723	41.909***
	(1.30)	(9.96)
AdjRsq	0.677	0.573
Time FE	Yes	Yes
Number of Observation	1422	1422

US Fund Long-Short Credit

Parameter	**Volatility**	**Id. Volatility**
Intercept	1.854***	1.425***
	(7.44)	(8.89)
Derivative	0.193***	0.105***
	(4.16)	(3.54)
Log Age	-0.041	0.007
	(-1.27)	(0.36)
Log Fund Size	-0.053***	-0.058***
	(-4.89)	(-8.42)
Flow	-1.204***	-0.752***
	(-5.31)	(-5.16)
Turnover Ratio	-0.047***	-0.005
	(-3.38)	(-0.58)
Expense Ratio	12.462***	6.570***
	(3.50)	(2.87)
AdjRsq	0.254	0.269
Time FE	Yes	Yes
Number of Observation	677	677

US Fund Long-Short Equity

Parameter	**Volatility**	**Id. Volatility**
Intercept	3.807***	1.965***
	(19.41)	(19.49)
Derivative	-0.007	0.055***
	(-0.23)	(3.45)
Log Age	0.039	0.017
	(1.27)	(1.09)
Log Fund Size	-0.084***	-0.063***
	(-9.88)	(-14.47)
Flow	0.196*	0.246***
	(1.75)	(4.27)
Turnover Ratio	-0.006**	0.011***
	(-2.30)	(7.43)
Expense Ratio	7.447***	14.241***
	(3.71)	(13.81)
AdjRsq	0.283	0.207
Time FE	Yes	Yes
Number of Observation	5761	5761

US Fund Managed Futures

Parameter	Volatility	Id. Volatility
Intercept	2.365***	1.611***
	(10.06)	(11.71)
Derivative	0.121***	0.155***
	(2.79)	(6.12)
Log Age	-0.009	0.037
	(-0.12)	(0.85)
Log Fund Size	0.040***	-0.001
	(3.83)	(-0.19)
Flow	0.060	-0.013
	(0.57)	(-0.21)
Turnover Ratio	-0.021***	-0.023***
	(-5.31)	(-9.74)
Expense Ratio	-9.947***	-12.822***
	(-3.26)	(-7.18)
AdjRsq	0.180	0.167
Time FE	Yes	Yes
Number of Observation	1521	1521

US Fund Market Neutral

Parameter	Volatility	Id. Volatility
Intercept	1.719***	0.965***
	(9.28)	(11.42)
Derivative	-0.006	-0.008
	(-0.20)	(-0.58)
Log Age	-0.255***	-0.210***
	(-10.38)	(-18.73)
Log Fund Size	0.012	0.011***
	(1.64)	(3.22)
Flow	-0.007	-0.018
	(-0.06)	(-0.34)
Turnover Ratio	-0.032***	-0.006**
	(-5.55)	(-2.32)
Expense Ratio	5.247***	8.469***
	(2.77)	(9.81)
AdjRsq	0.163	0.330
Time FE	Yes	Yes
Number of Observation	3523	3523

US Fund Trading--Leveraged Equity

Parameter	Volatility	Id. Volatility
Intercept	13.159***	7.598***
	(21.55)	(13.93)
Derivative	0.357***	-0.815***
	(5.82)	(-14.88)
Age	-2.659***	-0.834***
	(-33.30)	(-11.69)
Fund Size	0.110***	-0.155***
	(4.70)	(-7.45)
Flow	-0.156***	-0.012
	(-2.82)	(-0.24)
Turnover Ratio	-0.029***	0.012**
	(-5.46)	(2.56)
Expense Ratio	-20.108	9.764
	(-1.16)	(0.63)
AdjRsq	0.529	0.150
Time FE	Yes	Yes
Number of Observation	4286	4286

US Fund Multialternative

Parameter	Volatility	Id. Volatility
Intercept	2.925***	0.727
	(3.19)	(1.62)
Derivative	0.149***	0.154***
	(5.34)	(11.29)
Age	0.333***	-0.004
	(13.12)	(-0.30)
Fund Size	-0.147***	-0.043***
	(-19.31)	(-11.55)
Flow	-0.238**	-0.100**
	(-2.45)	(-2.10)
Turnover Ratio	-0.034***	0.011***
	(-5.40)	(3.46)
Expense Ratio	-11.425***	5.320***
	(-7.03)	(6.68)
AdjRsq	0.447	0.138
Time FE	Yes	Yes
Number of Observation	5771	5771

US Fund Multicurrency

Parameter	Volatility	Id. Volatility
Intercept	-0.700	0.855***
	(-1.31)	(3.46)
Derivative	-0.148**	-0.110***
	(-2.07)	(-3.33)
Age	-0.411***	-0.280***
	(-5.12)	(-7.52)
Fund Size	0.126***	0.016
	(5.76)	(1.57)
Flow	0.294*	0.082
	(1.94)	(1.16)
Turnover Ratio	0.008	-0.011*
	(0.63)	(-1.87)
Expense Ratio	135.503**	74.819***
	(17.89)	(21.36)
AdjRsq	0.259	0.395
Time FE	Yes	Yes
Number of Observation	1063	1063

US Fund Options-Based

Parameter	Volatility	Id. Volatility
Intercept	2.265***	0.205*
	(9.03)	(1.89)
Derivative	0.031	-0.018
	(0.64)	(-0.86)
Age	-0.071**	-0.007
	(-2.40)	(-0.54)
Fund Size	-0.036***	0.002
	(-3.17)	(0.40)
Flow	-0.083	-0.104
	(-0.52)	(-1.51)
Turnover Ratio	-0.041***	0.002
	(-4.53)	(0.52)
Expense Ratio	52.885***	39.423***
	(11.18)	(19.31)
AdjRsq	0.390	0.267
Time FE	Yes	Yes
Number of Observation	1691	1691

(b)

Derivative Significance

Fund Type	**Volatility**	**Id. Volatility**	**Return**	**Adj. Return**
US Fund Bear Market	(+)***	(+)***		
US Fund Long-Short Credit	(+)***	(+)***	(-) *	(-) **
US Fund Long-Short Equity		(+)***		
US Fund Managed Futures	(+)***	(+)***		
US Fund Market Neutral				
US Fund Multialternative	(+)***	(+)***		

***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

Table 5: Crisis: Regression of AMF Risk

The table reports regression results of derivative use in AMFs during a crisis time period (2007-2009). The dependent variables are volatility (vol), idiosyncratic risk (idvol), monthly raw returns (mret), and monthly adjusted returns (mretadj). The independent variable is derivative usage and control variables include Fund Size (logmtna), Age (logage), Flow (mflow), Turnover Ratio (tr), and Expense Ratio (exp). ***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

(a)

US Fund Bear Market

Parameter	Volatility	Id. Volatility
Intercept	14.280***	5.333***
	(7.00)	(6.58)
Derivative	1.451***	0.289*
	(3.92)	(1.97)
Log Age	-2.261***	-0.943***
	(-10.28)	(-10.80)
Log Fund Size	-0.274***	-0.095**
	(-2.93)	(-2.55)
Flow	0.325	-0.145
	(1.02)	(-1.15)
Turnover Ratio	-0.174***	-0.061***
	(-4.24)	(-3.73)
Expense Ratio	55.634	39.335***
	(1.55)	(2.76)
AdjRsq	276	276
Time FE	Yes	Yes
Number of Observations	227	227

US Fund Long-Short Credit

Parameter	Volatility	Id. Volatility
Intercept	-32.709***	-21.789***
	(-4.65)	(-3.93)
Derivative	-1.968	2.401
	(-0.35)	(0.55)
Log Age	-2.542	-0.160
	(-0.88)	(-0.07)
Log Fund Size	0.119	-0.390
	(0.19)	(-0.78)
Flow	-0.074	0.033
	(-0.09)	(0.05)
Turnover Ratio	-0.609***	-0.496***
	(-5.40)	(-5.57)
Expense Ratio	4264.592***	3273.964***
	(7.15)	(6.96)
AdjRsq	67	67
Time FE	Yes	Yes
Number of Observations	34	34

US Fund Long-Short Equity

Parameter	Volatility	Id. Volatility
Intercept	2.501***	0.778***
	(4.13)	(2.82)
Derivative	0.022	0.035
	(0.20)	(0.70)
Log Age	-0.250**	0.106**
	(-2.27)	(2.12)
Log Fund Size	0.121***	0.023*
	(4.16)	(1.70)
Flow	-0.481*	0.105
	(-1.92)	(0.92)
Turnover Ratio	0.081***	0.033***
	(7.40)	(6.57)
Expense Ratio	-32.876***	1.228
	(-3.86)	(0.32)
AdjRsq	60	60
Time FE	Yes	Yes
Number of Observations	527	527

US Fund Managed Futures

Parameter	Volatility	Id. Volatility
Intercept	2.053***	2.809***
	(3.49)	(8.73)
Derivative	-0.048	-0.029
	(-0.53)	(-0.59)
Log Age	-0.173**	-0.315***
	(-2.38)	(-7.92)
Log Fund Size	-0.011	-0.056***
	(-0.47)	(-4.18)
Flow	0.002	0.317*
	(0.00)	(1.79)
Turnover Ratio	-0.029	-0.044***
	(-1.52)	(-4.21)
Expense Ratio	35.904***	14.143***
	(6.00)	(4.31)
AdjRsq	40	40
Time FE	Yes	Yes
Number of Observations	14	14

US Fund Market Neutral

Parameter	Volatility	Id. Volatility
Intercept	4.627***	1.270***
	(7.36)	(3.64)
Derivative	-0.367***	0.041
	(-2.96)	(0.59)
Log Age	0.423***	0.126**
	(4.43)	(2.38)
Log Fund Size	-0.072**	-0.024
	(-2.00)	(-1.20)
Flow	-1.377**	0.078
	(-2.26)	(0.23)
Turnover Ratio	-0.091***	0.025*
	(-3.60)	(1.79)
Expense Ratio	-17.075***	0.614
	(-3.38)	(0.22)
AdjRsq	20	20
Time FE	Yes	Yes
Number of Observations	356	356

US Fund Multialternative

Parameter	Volatility	Id. Volatility
Intercept	22.843***	3.363*
	(3.68)	(1.80)
Derivative	4.410***	1.563***
	(8.14)	(9.58)
Log Age	0.065	0.033
	(0.51)	(0.84)
Log Fund Size	-1.293***	-0.301***
	(-4.84)	(-3.74)
Flow	-2.858***	-0.361
	(-3.02)	(-1.26)
Turnover Ratio	-0.786*	-0.409***
	(-1.81)	(-3.13)
Expense Ratio	465.778**	346.086***
	(2.51)	(6.20)
AdjRsq	40	40
Time FE	Yes	Yes
Number of Observations	348	348

US Fund Multicurrency

Parameter	Volatility	Id. Volatility
Intercept	7.747***	6.098***
	(7.34)	(10.03)
Derivative	0.433***	0.159**
	(3.75)	(2.40)
Log Age	1.406***	1.017***
	(7.20)	(9.04)
Log Fund Size	-0.462***	-0.408***
	(-6.46)	(-9.89)
Flow	-1.175	-0.008
	(-0.79)	(-0.01)
Turnover Ratio	0.226	0.017
	(1.57)	(0.20)
Expense Ratio	21.690	-3.630
	(0.59)	(-0.17)
AdjRsq	216	216
Time FE	Yes	Yes
Number of Observations	94	94

US Fund Options-Based

Parameter	Volatility	Id. Volatility
Intercept	3.053*	1.146
	(1.82)	(1.64)
Derivative	0.454**	0.157*
	(2.18)	(1.81)
Log Age	-2.087***	0.324
	(-4.47)	(1.67)
Log Fund Size	0.338**	-0.059
	(2.33)	(-0.99)
Flow	0.215	0.054
	(1.05)	(0.64)
Turnover Ratio	0.089	-0.019
	(1.35)	(-0.69)
Expense Ratio	19.113***	-2.767
	(3.15)	(-1.10)
Time FE	Yes	Yes
Number of Observations	64	64

US Fund Trading-- Inverse Debt

Parameter	**Volatility**	**Id. Volatility**
Intercept	-7.015***	26.085***
	(.)	(.)
Derivative	-0.391***	-7.124***
	(.)	(.)
Log Age	9.036***	-1.767***
	(.)	(.)
Log Fund Size	0.332***	-0.539***
	(.)	(.)
Flow	-1.270***	-2.795***
	(.)	(.)
Turnover Ratio	-0.095***	-0.280***
	(.)	(.)
Expense Ratio	0.000***	0.000***
	(.)	(.)
Time FE	Yes	Yes
Number of Observations	60	60

US Fund Trading-- Leveraged Commodities

Parameter	**Volatility**	**Id. Volatility**
Intercept	5.475	5.755*
	(0.65)	(1.86)
Derivative	-0.432*	0.074
	(-1.90)	(0.89)
Log Age	-2.530	-0.537
	(-0.93)	(-0.53)
Log Fund Size	0.615**	-0.107
	(2.76)	(-1.30)
Flow	-0.215*	0.036
	(-1.93)	(0.88)
Turnover Ratio	-0.079***	-0.002
	(-3.82)	(-0.24)
Expense Ratio	-313.996	-128.409
	(-0.74)	(-0.83)
Time FE	Yes	Yes
Number of Observations	20	20

US Fund Trading-- Leveraged Debt

Parameter	**Volatility**	**Id. Volatility**
Intercept	-0.697	-4.820**
	(-0.23)	(-2.16)
Derivative	2.668***	1.306**
	(3.11)	(2.04)
Log Age	-1.297***	-0.835***
	(-4.74)	(-4.10)
Log Fund Size	0.237**	0.292***
	(2.44)	(4.05)
Flow	0.092	-0.247
	(0.28)	(-1.00)
Turnover Ratio	0.119***	0.024*
	(6.37)	(1.75)
Expense Ratio	304.402***	160.407**
	(3.39)	(2.40)
Time FE	Yes	Yes
Number of Observations	60	60

US Fund Trading-- Leveraged Equity

Parameter	**Volatility**	**Id. Volatility**
Intercept	0.716	0.727
	0.987	0.985
Derivative	0.439	0.343
	0.397	0.541
Log Age	0.625	0.185
	0.884	0.932
Log Fund Size	0.986	0.968
	0.995	0.961
Flow	1.000	1.000
	0.987	0.971
Turnover Ratio	0.701	0.411
	0.675	0.688
Expense Ratio	0.953	0.944
	0.403	0.301
Time FE	Yes	Yes
Number of Observations	319	319

(b)

Derivative Significance

Fund Type	**Volatility**	**Id. Volatility**
US Fund Bear Market	(+) ***	(+) *
US Fund Long-Short Credit		
US Fund Long-Short Equity		
US Fund Managed Futures		
US Fund Market Neutral	(-) ***	
US Fund Multialternative	(+) ***	(+) ***

***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

Table 6: Pre-Crisis: Regression of AMF Risk

The table reports regression results of derivative use in AMFs during a pre-crisis time period (before 2007). The dependent variables are volatility (vol) and idiosyncratic risk (idvol). The independent variable is derivative usage and control variables include Fund Size (logmtna), Age (logage), Flow (mflow), Turnover Ratio (tr), and Expense Ratio (exp). ***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

(a)

Parameter	Volatility	Id. Volatility
Intercept	4.321***	2.280***
	(8.41)	(10.34)
Derivative	0.376***	0.137***
	(4.22)	(3.58)
Log Age	-0.658***	-0.148***
	(-8.27)	(-4.34)
Log Fund Size	-0.059**	-0.073***
	(-2.53)	(-7.29)
Flow	-0.084	0.223***
	(-0.52)	(3.23)
Turnover Ratio	0.158***	0.027***
	(15.36)	(6.04)
Expense Ratio	-0.155	7.151***
	(-0.02)	(2.65)
AdjRsq	0.220	0.154
Time FE	Yes	Yes
Number of Observation	1769	1769

(b)

Derivative Significance

Fund Type	**Volatility**	**Id. Volatility**
US Fund Bear Market	(+) ***	(+) ***
US Fund Long-Short Credit	(+) ***	(+) ***
US Fund Long-Short Equity		(+) ***
US Fund Managed Futures	N/A	N/A
US Fund Market Neutral		
US Fund Multialternative	(-) ***	

***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

Table 7: Post-Crisis: Regression of AMF Risk

The table reports regression results of derivative use in AMFs during a post-crisis time period (after 2009). The dependent variables are volatility (vol) and idiosyncratic risk (idvol). The independent variable is derivative usage and control variables include Fund Size (logmtna), Age (logage), Flow (mflow), Turnover Ratio (tr), and Expense Ratio (exp). ***, **, * indicate the significance levels at 1%, 5%, and 10%, respectively.

(a)

Parameter	**Volatility**	**Id. Volatility**
Intercept	5.325**	1.913**
	(2.55)	(2.03)
Derivative	0.847***	0.086***
	(28.17)	(6.35)
Age	1.455***	0.225***
	(59.90)	(20.52)
Fund Size	-0.508***	-0.145***
	(-64.89)	(-41.09)
Flow	0.692***	0.154***
	(13.11)	(6.46)
Turnover Ratio	0.005*	0.003*
	(1.79)	(1.93)
Expense Ratio	28.710***	18.400***
	(13.73)	(19.50)
AdjRsq	0.329	0.120
Time FE	Yes	Yes
Number of Observation	20659	20659

(b)

Derivative Significance

Fund Type	**Volatility**	**Id. Volatility**
US Fund Bear Market	(+) **	(-) ***
US Fund Long-Short Credit	(+) ***	(+) ***
US Fund Long-Short Equity		(+) ***
US Fund Managed Futures	(+) ***	(+) ***
US Fund Market Neutral	(-) **	(-) *
US Fund Multialternative	(+) ***	(+) ***