(Ab)Use of Leverage, Short Sales, and Options by Mutual Funds

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Abstract

We study the use of leverage, short sales, and options by equity mutual funds and find that their use is associated with poor performance. We find evidence that moral hazard and agency costs drive this underperformance. Funds that use these complex instruments hold riskier equity positions and attempt to use the instruments to reduce the risk of their portfolios, but in an imperfect and costly way. Furthermore, the negative outcomes associated with complex instrument use dissipate in funds that are well-monitored, well-incentivized, and transparent. Our results suggest that investors are better off choosing simplicity over complexity.

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Keywords: mutual funds, leverage, short sales, options, complex instruments, performance, risk, agency costs, moral hazard

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1. Introduction

Over the past fifteen years there has been a rise in the complexity of mutual funds as more funds are given the authority to use leverage, short sales, and options. Over this period 42.5% of domestic equity funds have reported using at least one of these instruments. In theory, these *complex instruments* should enable sophisticated investors to better exploit profitable trading opportunities.[1] For example, Frazzini and Pedersen (2014) provide evidence that leverage and margin constraints drive up prices on high-beta stocks relative to their low-beta counterparts. This effect leads to a profitable "betting against beta" strategy for unconstrained investors, such as mutual funds with access to complex instruments. Funds may also use complex instruments to manage and hedge risk, reduce transaction costs and costs associated with fund flows (e.g., Merton, 1995; Koski and Pontiff, 1999; and Deli and Varma, 2002).

However, in practice, there is concern that the same attributes that allow complex instrument users to reap outsized gains will expose them to severe losses when the market turns against them, or when they use the instruments without understanding their implications on the return distribution. In the words of Warren Buffet, "Only when the tide goes out do you discover who has been swimming naked". Anecdotal evidence provides support for this concern. For example, the use of derivatives resulted in some funds suffering large losses during the 2008 subprime mortgage crisis.[2] Furthermore, complex instruments may be used by fund managers for opportunistic reasons. In response, the Securities and Exchange Commission (SEC) has proposed new rules designed to limit the amount of risk funds can take as they pursue these increasingly complex portfolio strategies.[3]

The double-sided nature of these instruments raises the following question: Does complex instrument use by mutual funds benefit or harm fund shareholders? To address this question we extract information on the use of leverage, short sales, and options by domestic equity funds from

[1] We use the term *complex instruments* to describe a variety of complicated investment strategies (using leverage, short sales, and options) that mutual funds may adopt.
[2] See "Seeking More Clarity on Derivatives in Mutual Funds" The Wall Street Journal, June 15, 2015.
[3] https://www.sec.gov/rules/proposed/2015/ic-31933.pdf

Form N-SAR filings, which are semi-annual reports that mutual funds are required to file with the SEC.[4] The data allow us to identify if funds are allowed to use and actually use each complex instrument. We merge this data with the CRSP mutual fund database, which provides daily net mutual fund returns and other fund characteristics. Using panel regressions, we first examine the relation between complex instrument use and future fund outcomes. We select a lead-lag specification to address endogeneity concerns and focus on the subsample of funds that are allowed to use complex instruments. We start by studying how complex instrument use affects fund performance. We use returns in excess of the risk-free rate and the Carhart (1997) four-factor alphas to measure performance. We also estimate the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007), which is robust to potential biases created by nonlinearity and asymmetry likely to be present in the returns for funds that use complex instruments.

Employing a composite measure of complex instrument use, which is a dummy variable that indicates if the fund uses at least one of the three instruments (leverage, short sales, and options), we find that the actual use of these instruments is associated with lower excess returns, four-factor alphas, and MPPM that are economically and statistically significant. Specifically, composite measure use is associated with 0.59% lower annual excess return, 0.46% lower annual four-factor alpha, and 0.64% lower MPPM. We also use an instrumental-variable approach to address the endogenous nature of a fund's decision to use complex instruments. As our instrument, we adopt the proportion of other funds in the same fund family that are using complex instruments. We again find a significant negative relation between complex instrument use and fund performance.

We next explore two possible explanations for the underperformance of funds that use complex instruments. First, insurance-like effects of complex instruments, especially options and short sales, can create a moral hazard problem for the fund. For example, a fund manager could be less worried about the risk of her non-complex (i.e., equity) positions given that she could use

[4] https://www.sec.gov/about/forms/formn-sar.pdf

complex instruments to reduce portfolio risk. To test the validity of this explanation we examine the association between the riskiness of the fund's equity positions and complex instrument use. We find that funds that use complex instruments have higher risk (standard deviation, beta, and idiosyncratic volatility) in their equity holdings than funds that choose not to use these instruments.[5] This result also suggests that funds do not use complex instruments to overcome constraints that can lead to suboptimal portfolios. Specifically, they are not taking advantage of the low-beta anomaly by buying and leveraging low-beta stocks.

We also look at the relation between complex instruments and fund risk. For our composite measure, we find no relation between complex instrument use and standard deviation. However, we observe lower beta exposure and higher idiosyncratic volatility.[6] This proportional shift in the risk exposure of the fund may not be optimal for fund shareholders as funds are trading away a rewarded risk for an unrewarded one. To further test whether the moral hazard problem could be a contributing factor to explain underperformance, we sort funds into three groups according to the standard deviation of their equity positions. We observe a monotonic relation between the risk of the underlying equity positions and underperformance associated with complex instrument use.

The second explanation for the underperformance of funds that use complex instruments is related to agency costs. Given that complex instruments can serve as powerful tools to change portfolio risk, funds may use them to alter their distribution of returns for opportunistic motives.[7] We find that complex instrument use is associated with higher risk in the subsample of funds that experience poor performance. Consistent with potential opportunistic motives for complex

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[5] We also consider the effect of simply being allowed to use complex instruments on fund risk. Consistent with moral hazard, we find that complex instrument authorization is associated with higher levels of total and systematic risk at the fund.

[6] To isolate the impact of complex instrument use on fund risk, we develop risk gap measures that we define as the difference between the realized risk of the fund and the risk of the fund's underlying equity holdings. With the exception of leverage, we find a strong negative relation between use and the standard deviation and beta exposure risk gap measures, which is consistent with funds using those complex instruments to hedge.

[7] For example, mutual funds may manipulate their risk exposure in response to the non-linear relation between fund flow and performance (Brown et al., 1996; Chevalier and Ellison, 1997; and Sirri and Tufano, 1998).

instrument use harming fund shareholders, the negative performance associated with complex instrument use is more severe in funds that use them following poor performance.

Although complex instrument use is associated with poor performance in aggregate, it is plausible that some subgroups of funds use complex instruments with positive results. In particular, if moral hazard and agency costs are (at least partially) responsible for the underperformance then the outcomes of complex instrument use should be more favorable when they are employed in settings with strong monitoring (internal and external), by well-incentivized managers, and along with high transparency regarding their use. Specifically, we measure internal monitoring by the presence of institutional shareholders and independent directors; external monitoring using the shock to litigation risk around the 2003 mutual fund trading scandal; managerial incentives using the tenure of the fund manager; and transparency using the fund's disclosure of complex instrument use in its summary prospectus. In each of these settings we find that the harmful effects associated with complex instrument use are neutralized. This finding is useful information for the SEC as they craft new regulation for complex instrument use by mutual funds.

The finding that complex instruments are not always harmful to fund shareholders motivate us to explore two additional settings that, ex-ante, may be associated with a positive use of complex instruments. First, we consider whether some funds use complex instruments to exploit the low-beta anomaly. Although we earlier observed that funds using complex instruments tend to invest in higher beta equity portfolios, when we condition on the subgroup of funds investing in low-beta equities, we observe that their use of complex instruments is associated with significant positive performance (1.34% per year using the four-factor alpha). Second, if funds use complex instruments to manage fund flows, in particular to reduce costs associated with outflows, then complex instrument use in this setting may have a positive effect on fund performance. Inconsistent with this prediction, we find that funds that use complex instruments after both inflows and outflows experience poor performance.

Finally, we perform a series of tests to ensure the robustness of our results. If complex instrument use is indeed harmful to fund shareholders, we expect these effects to be stronger among the heaviest users. We distinguish between heavy and light users using balance sheet information. We find that heavy users exhibit significantly worse performance than light users. Next, for options, we use holdings information to investigate different types of strategies (e.g., put vs. call and covered vs. naked positions). Among all the option strategies investigated, we are unable to find that options usage is associated with positive performance. We also examine the relation between complex instrument use and both fund fees, measured using the net expense ratio, and trading costs, proxied by the turnover ratio. The use of these instruments is associated with higher fees and turnover ratio, which suggests the impact of complex instruments on these costs may represent an additional channel through which complex instrument use impact fund returns. Given that complex instruments can be used to alter the return distribution, we also examine the higher moments of the fund return distribution using skewness and kurtosis. We find that their use is associated with more negative skewness and greater kurtosis, which ceteris paribus is undesirable for shareholders.

Our paper contributes to the literature that investigates the use of complicated investment strategies by mutual funds by showing that complex instrument use is harmful to fund shareholders. This result is novel as previous studies have found that these instruments have either no effect or a positive effect. Specifically, Koski and Pontiff (1999) were the first to study the use of derivatives by equity mutual funds. Using a 1992-1994 sample period, they document that derivative users have risk exposure and return performance that are similar to non-users, and that managers may use derivatives to attenuate the impact of fund flows on fund risk.[8] In this paper, we use more detailed information about complex instrument positions instead of relying on survey evidence as done by Koski and Pontiff (1999), and given the significant changes in the growth of

[8] Other papers investigate the use of derivatives by mutual funds in Canada (Johnson and Yu, 2004), Australia (Pinnuck, 2004), and the UK (Fletcher et al., 2002) with similar results to Koski and Pontiff (1999). Also there are papers that study the use of derivatives by other institutional investors such as hedge funds (see Aragon and Martin, 2011; and Chen, 2011). Hedge funds, however, are very different from mutual funds since they are lightly regulated, open only to a limited number of investors, and less constrained in using derivatives for speculation.

mutual funds and their complexity since 1994, it is important to provide a new assessment of the effects of complex instruments on shareholder outcomes.

The most closely related papers to ours that also use N-SAR data are Deli and Varma (2002), Almazan et al. (2004), Chen et al. (2013), and Natter et al. (2016). Deli and Varma (2002) examine the benefits and costs of allowing mutual funds to invest in derivatives. In line with a cost-reduction explanation, they find that the use of derivatives among mutual funds is associated with transaction-cost benefits. However, they do not examine whether these cost reductions lead to better fund performance. Almazan et al. (2004) do not examine actual use, but instead focus on the decision to allow or restrict complex instrument use. They find that restrictions are more common when there is weaker governance and less managerial career concerns. However, they find that there is no difference in performance between low- and high-constraint funds.

We differ from the most recent papers in several ways. First, Chen et al. (2013) focus on short selling whereas Natter et al. (2016) focus on options. We take a broader perspective by also considering leverage in addition to both options and short selling. We argue that considering the effect of leverage is important as it is more common than short selling and used as frequently as options. Second, we differ in our empirical design. The focus of both Chen et al. (2013) and Natter et al. (2016) is the contemporaneous relation between complex instrument use and performance.[9] In contrast, we consider a lead-lag relation and instrumental variable approach that is important for inferring casual effects. Third, we provide a deeper analysis of the economic impact associated with complex instruments by considering moral hazard in addition to agency costs. Finally, our mutual fund sample is much larger than those used by both papers, which, together with the differences in empirical design, explain some of the divergent findings.[10] Indeed, our paper shows

[9] In one (Table 5) of their eight tables Chen et al. (2013) consider a lead-lag relation. However, their analysis is conducted on a small dataset comprising 5,515 observations. In contrast, our dataset is almost an order of magnitude larger with 49,811 observations.
[10] A lead-lag relation is also used by Cici and Palacios (2015). They examine the use of exchange-traded options and find, consistent with our study, that the use of options by equity mutual funds is not associated with performance benefits.

that although, consistent with Chen et al. (2013) and Natter et al. (2016), there may be some funds that use complex instruments to the benefit of fund shareholders, in aggregate, these benefits are not sufficiently high to offset the costs and the net effect for investors is negative. Warren Buffet is famously quoted as saying that "derivatives are financial weapons of mass destruction."[11] The poor shareholder outcomes associated with complex instrument use provide some ammunition for this claim.

2. Hypothesis Development

There are potentially both benefits and costs for funds that use complex instruments. Among the benefits, complex instruments could be used to efficiently exploit superior information and take advantage of market inefficiencies. All three instruments allow investors to increase stock exposure through implicit or explicit leverage. Short sales and options also allow investors to execute bearish bets. Furthermore, options can also be used to reduce transaction costs (Merton, 1995). All three complex instruments can also be useful for reducing costs associated with fund flows and the opportunity costs of holding cash (Deli and Varma, 2002). All these uses predict that mutual funds improve their performance by using complex instruments.

As pointed out by the existing literature for the case of derivatives (Koski and Pontiff, 1999, and Deli and Varma. 2002) there are potential agency costs associated with the use of complex instruments. For example, Brown et al. (1996) and Chevalier and Ellison (1997) show that poorly performing funds have an incentive to increase fund risk. Complex instruments could be used as a tool by managers to alter the risk-return distribution of their portfolios for opportunistic motives. If agency costs drive complex instrument use, we predict that their use will be associated with worse performance and this relationship will be especially strong in an environment where agency costs are higher such as with funds with poor governance. We expect to observe settings in which management is well monitored (both internally and externally) and is

[11] See Chairman's Letter (www.berkshirehathaway.com/letters/2002pdf.pdf) in the 2002 Berkshire Hathaway Annual Report

transparent about the use of complex instruments to be associated with good governance and thus better use of complex instruments. Career concerns are also a mechanism that can reduce agency problems (Fama, 1980). Given that career concerns are larger among young managers (Chevalier and Ellison, 1999), we also expect a stronger relationship for long-tenured managers compared to short-tenured managers.

Another potential cost, which has not been highlighted by the existing mutual fund literature, is related to moral hazard created by the insurance-like effects of complex instruments, especially options and short sales. For example, a fund manager could be less worried about the risk of her equity investments given that she could use complex instruments to reduce portfolio risk. In this case, we expect funds that use complex instruments will hold riskier underlying securities than those that do not, and similarly funds that have bylaws allowing them to use complex instruments will take more risk than those that are prohibited.

Complex instruments may also influence fund risk in ways that are both beneficial and harmful to shareholders. On the one hand, complex instruments may be used to manage risk. For example, short sales can be used to hedge away unwanted risks, leverage as part of risk parity strategies, and options can be used in both capacities. If these instruments are used for hedging then we predict that their use will be associated with lower risk, while use as part of a risk parity strategy predicts the underlying securities the fund invests in will have lower risk. On the other hand, these instruments can be used as tools for speculation, in which case we expect their use to be associated with higher fund risk. Ultimately, the effect of these instruments on fund risk is an empirical question and we therefore investigate which type of risk is affected by funds that use complex instruments. In particular, we examine the effect of their use on total, systematic, and idiosyncratic risk, as well as whether higher-moment risks are also affected. Higher moment risks could be affected if for example managers use options to hedge against extreme returns. It is unclear how the complex instruments' effect on risk will influence fund performance.

To summarize, if benefits are greater than costs we should observe a positive effect on performance for funds that use complex instruments. If agency costs matter we expect that the negative effects can be neutralized in funds that have good monitoring and governance. Finally, depending on whether complex instruments are used for hedging or speculation we expect that these instruments lower or increase risk, respectively.

3. Data

Although mutual funds are often perceived as long-only 'plain vanilla' investment vehicles, they are often allowed to use a variety of complex investment strategies. However, in addition to voluntary investment restrictions that mutual funds can adopt, the Investment Company Act imposes some restrictions. In particular, Section 18 of the Act regulates the use of leverage. Whereas long option positions are not treated as leverage because they do not require further payments aside from the initial price, uncovered written options and short selling are regulated as a form of leverage. Open-end funds can use leverage as long as they maintain the asset coverage requirement of at least 300% (i.e., the fund's net assets plus market value of the written options and/or the securities sold short divided by market value of the written options and/or the securities sold short is at least 300%).[12]

We extract data on mutual funds' investment practices from the SEC's Form N-SAR that registered investment companies have to file twice a year. We download these filings from the SEC's EDGAR FTP server. We extract data on investment practices (Question 70), income statement (Question 72), and balance sheet (Question 74) items. In particular, Question 70 asks with a "yes" or "no" answer whether or not a mutual fund had the authorization to use and if it actually used different complex instruments during the reporting period. We focus on the following complex instruments: leverage (Question 70O), short selling (Question 70R), options on equities

[12] As explained by Chen et al. (2013), the SEC has progressively relaxed restrictions on short selling over time. In particular, mutual funds would be compliant with the asset coverage restriction if they held a sufficient amount in segregated accounts to cover the market value of the securities sold short. Moreover, the Taxpayer Relief Act of 1997 made it easier for mutual funds to use short sales by repealing the "short-short" rule that limited gains from short-term positions to less than 30% of income.

(Question 70B), options on stock indices (Question 70D), options on futures (Question 70G), and options on stock index futures (Question 70H).[13] We group together the options, and for each complex instrument, we compute the proportion of funds each year that are allowed to use the instrument and that actually use the instrument. In addition to examining the permission to use separately leverage, short sales, and options, we calculate a composite measure which is a dummy variable that takes the value of one if a fund is allowed to use at least one of the complex instruments. We also develop a composite complex instrument use variable which identifies if a fund uses at least one of the complex instruments.

We include both form N-SAR-A, which covers the first half of the reporting year, and form N-SAR-B which covers the full year, filed from January 1999 through December 2015 for a total of 104,849 individual filings.[14] Because of the semi-annual reporting requirement of the N-SAR, our dataset is structured at the semi-annual-fund level. Throughout the paper we refer to each semi-annual period as a semester. N-SAR filings are available since 1994, but we start in 1999 because daily mutual fund net-return data are available only from 1999. Then, we drop filings if they are filed more than 90 days after the end of the reporting period and if the income statement and balance sheet items are not reported at the fund level. There are 101,074 filings remaining that contain on average 3.7 funds per filing given that a registrant typically files information for more than one fund at a time. Our collection process distinguishes which set of information filed by the registrant pertains to each fund.

We take several steps to insure that our sample contains only domestic open-end equity mutual funds. We keep a fund if it is an open-end investment company (Question 27) and if it invests in equity securities (Question 66.A). We drop funds that invest primarily in debt securities (Question 62.A), balanced funds (Question 67), funds that have more than 50% of its net assets at

[13] According to form N-SAR instructions leverage should not include the practice of borrowing money from a bank for temporary or emergency purposes, and not for investment, in an amount not exceeding 5% of net assets.
[14] The N-SAR-A is usually filed in June and the N-SAR-B is usually filed in December. However in the case of a fiscal year end which does not align with these months, we use data from the most recent filing preceding either June or December.

the end of the current period invested in i) the securities of issuers engaged primarily in the production or distribution of precious metals (Question 68.A); or ii) the securities of issuers located primarily in countries other than the United States (Question 68.B). We also exclude index funds (Question 69). We check the fund names and if the name suggests that the fund focuses on commodities, fixed income securities, international stocks, preferred and/or convertible securities, real estate, or if it is an ETF or an index fund then we drop those funds. After applying these filters, our sample contains 153,488 fund-filing combinations.

We next match the data from the N-SAR filings to the CRSP mutual fund database for access to more information such as net returns and fund characteristics. Given that there is no common identifier, the matching is done using fund names. Specifically, we use a computer algorithm together with manual checks. From 2006, tickers are reported on N-SAR filings. We match those tickers to the CRSP mutual fund database for cross-checking and additional matches. Once we match funds from N-SAR to CRSP mutual funds through fund names or tickers, we use the CRSP class group information (crsp_cl_grp) to combine multiple share classes of a single fund. Overall, we match 119,565 fund-filing combinations to a CRSP class group for a success rate of 77.9%. Finally, we include three more filters. We eliminate funds with total assets less than $5 million, funds not classified as domestic equity funds by CRSP, and funds with non-equity assets greater than 25% of total assets.[15] The final sample includes 4,793 funds for 61,980 fund-semester observations. This is significantly larger than the sample used by recent papers such as Chen et al. (2013), 2,066 funds, Natter et al. (2015), 2,576 funds, and Cici and Palacios (2016), 2,509 funds.

We use daily net mutual fund returns from CRSP to compute performance and risk measures.[16] Given that the frequency of the filings is semiannual, we compute the performance and risk measures every six months requiring a minimum of 100 daily observations. Using data at

[15] Non-equity assets is defined as the sum of short-term debt securities (Question 74C), long-term securities including convertible debt (Question 74D), preferred securities (Question 74E), and other investments (Question 74I).

[16] The information provided by CRSP is at the share class level. We compute value-weighted daily fund net returns across multiple share classes using the latest total net assets as weights. We apply the same process for fund characteristics with the exception of age, which is based on the oldest share class.

the daily frequency is important to obtain more precise estimates of the fund risk measures (e.g., Busse 1999). Furthermore, obtaining the measure every semester allows us to use panel data regressions, which are better able to capture the time-series variation in the relation between complex instrument use and outcomes.

Finally, to construct holdings-based measures we use data from the intersection of Thomson Reuters mutual fund holdings database and the CRSP mutual fund database. Thomson Reuters provides information on equity mutual funds' stock holdings at the quarterly or semi-annual frequency. We select the report date closest to June and December. This ensures that the period for which we compute the return of the equity holdings matches the period used for the overall fund returns. We match the holdings with the CRSP daily security returns to compute value-weighted fund gross returns that are used to obtain performance and risk measures during six-month periods after the report date.

3.1 Univariate Results

Figure 1 reports time-series trends in complex instrument use by funds. Over our 17-year sample period, there has been an increase of funds allowed to use at least one complex instrument, from 95.3% of funds in 1999 to 99.2% in 2015. Although not shown in the figure, when we look at the proportion of funds allowed to use all three instruments the rise is more dramatic, from 25.7% in 1999 to 62.6% in 2015. This increase is present across all three instruments. For example, the proportion of funds allowed to use options increased from 86.9% to 93.7%, for short selling from 35.5% to 71.2% and for leverage from 78.5% to 90.1%. However, despite a reduction in the constraints faced by mutual funds, the increase in actual use has been relatively modest. For example, in 1999 16.6% of funds used at least one complex instrument compared to 17.3% of funds in 2015. Options and leverage use have actually decreased, however short selling use has increased almost threefold, from 1.7% to 4.7% over the sample period. There is also some cyclicality in the use of these instruments. After 2000, coinciding with the dot com bubble bursting, there was a drop in leverage use by funds. There was also a drop in the use of all three complex instruments after 2003 and then another one after 2008, coinciding with increased scrutiny from regulators concerning the use of these instruments following the financial crises. When we look at the entire life of funds we find that 42.5% of funds in our sample use a complex instrument at least once. For individual instruments 25.3% use options, 9.3% short sell and 20.6% use leverage.

Next, we examine how fund characteristics vary by complex instrument use (see Table 1). Our fund characteristics are defined as follows: Fund Size – assets under management (AUM), as reported in Question 74N in N-SAR; Fund Family Size – the aggregate fund size within the fund's family as classified by CRSP; Expense Ratio – fees reported in N-SAR data scaled by fund size;[18] Fund Age –the number of years since the fund's inception as reported by CRSP; Institutional Ownership - proportion of fund's AUM composed of institutional share classes as reported by CRSP; Fund Flows - the proportional change of the funds AUM adjusted for the return of the fund as in Chevalier and Ellison (1997); Excess Return – annualized net fund return minus the risk-free rate; Standard Deviation – annualized standard deviation of the excess returns.

The results presented in Table 1 show that the characteristics of funds that are not allowed to use, choose not to use and actually use complex instruments are generally very different.[19] For example, funds that are not allowed to use complex instruments tend to be larger, older, have lower fees, higher fund flows, lower levels of institutional ownership, lower returns, and lower standard deviations than funds that are allowed to use these instruments. The existence of these differences motivates us to focus on the subsample of funds that are allowed to use complex instruments when examining the relationship between complex instrument use and fund outcomes. This distinction contrasts with the previous literature, which tends to consider only users and non-users without accounting for the existence of fund bylaws that allow complex instrument use.

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[18] To measure a fund's fees, we start with the total expenses reported in its N-SAR filings. We subtract expense reimbursements, interest expenses and other expenses from this figure, then scale by total assets and then annualize the figure if the N-SAR is for a reporting period of less than 12 months to arrive at the fund's net expense ratio. We subtract out interest expenses and other expenses as complex instruments can mechanically add to these expenses (for example dividends paid on shorted stocks are counted in other expenses) and including these items in the expense ratios figure would bias us towards finding a relation between complex instruments and higher fees. This is also the reason why we do not use the expense ratio from CRSP because it is not clear if it includes interest expenses.

[19] For example, for the composite measure, in unreported tests we find that all the differences are statistically significant except for the difference in standard deviation between not allowed to use and use.

4. Complex Instrument Use and Fund Performance

Given the heterogeneity in the motivations for complex instrument use, it is unclear if they are being used to benefit or harm fund performance. For example, using complex instruments to manage fund flows or to exploit superior information may lead to outperformance. However, agency induced use of complex instruments may expose fund shareholders to unnecessary costs and unrewarded risks. In this section, we empirically address whether the positive or negative effects are dominant.

We run panel data regressions to analyze the consequences of complex instrument use on fund performance. We only consider funds that have permission to use complex instruments during the respective reporting period. Thus, the comparison group includes funds that are allowed to use complex instruments but choose not to employ them in a given semester. Throughout our paper, we focus on the association between current complex instrument use and future outcomes. The use of a lead-lag specification helps us to address endogeneity concerns resulting from some of our outcome variables potentially driving complex instrument use. For example, if funds use complex instruments in an attempt to 'double down' after bad performance, in a contemporaneous setting the direction of causality between bad performance and complex instrument use would be ambiguous. This approach is also advantageous as it more accurately reflects an actionable investment strategy for a mutual fund investor based on the fund's complex instrument use.

Our dependent variables are three different fund performance measures. In particular, we use the fund's net returns in excess of the risk-free rate and the fund's Carhart (1997) four-factor alphas computed from daily net returns. Furthermore, the nonlinearity and asymmetry in the returns associated with complex instruments could create a bias in the four-factor alphas. To address this concern, we also use the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007) as an alternative dependent variable. Compared to traditional performance measures, MPPM is more difficult for complex instrument users to game.[20]

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[20] The MPPM can be interpreted as the annualized geometric excess return certainty equivalent of a particular fund. Goetzmann et al. (2007) show four conditions that are met by the MPPM but not by other traditional performance

Our independent variables of interest are our various complex instrument use dummy variables. Our control variables include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, level of institutional ownership, and fund flows.[21] Additionally, we include fund style-time interactive fixed effects. All independent variables are lagged one semester. Each column of our tables reports the results of two separate regressions. A regression where the composite measure dummy (Row 1) is our variable of interest, and where leverage, short sales, and options are our dummy variables of interest (Row 2-4). The regressions take the following form where *i* indicates the fund and *t* refers to the semester:

$$Fund\ Performance_{i,t} = \beta_0 + \sum_{j=1}^{J} \beta_j \cdot Complex\ Instrument\ Use_{i,j,t-1} + \sum_{k=J+1}^{J+K} \beta_k \cdot Controls_{i,k,t-1} + FE_{Fund\ Style*Time} + \varepsilon_{i,t} \quad (1)$$

The first row of Table 2 presents results for the composite measure. The results show that complex instrument use is associated with significantly negative annualized excess returns (-0.594%), alphas (-0.458%), and MPPM (-0.636%). This finding suggests that complex instrument use is harmful to investors. In the next three rows, we examine the use of the individual complex instruments. We find that using leverage (-0.360%), short sales (-0.731%), and options (-0.668%) are all associated with lower annualized excess returns in the following semester, although the relationship is only statistically significant with respect to options. We also find that all three

measures. These conditions are: (1) recognize arbitrage opportunities; (2) be concave; (3) be time separable; and (4) have a power form to be consistent with an economic equilibrium. The MPPM measure is computed for each semester and fund using a coefficient of relative risk aversion equal to 3, which is the value suggested by Goetzmann et al. (2007).

[21] We do not include expense ratio and turnover as controls because they are potential channels through which complex instrument use affects fund performance. In the robustness section we examine how expense ratio and turnover are related to complex instrument use. We also show that our results are robust when we include these fund characteristics as control variables.

instruments are associated with lower alpha and MPPM, but that the relation is only significant with respect to leverage.[23]

4.1 Instrumental Variable Approach

In the previous analysis, to control for endogeneity, we regress lagged indicators of complex strategies as predictive variables to determine future performance. One concern is that the use of complex strategies is likely to be very persistent and so lagging the predictive variables in the regression is insufficient to control for endogeneity. Therefore, to further address endogeneity concerns, we identify an instrumental variable that predicts mutual fund complex instrument use but is otherwise uncorrelated with mutual fund performance. We select the proportion of other funds within the mutual fund family that use complex instruments to serve as our instrument. We argue that this instrument satisfies the instrumental variable exclusion restriction – namely, it affects the fund's performance only through the fund's own complex instrument use. The estimates for the instrumental variable are calculated using two-stage least squares. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables:

$$Complex\ Instrument\ Use_{i,t} = \alpha_0 + \sum_{j=1}^{J} \alpha_j \cdot Family\ Complex\ Instrument\ Use_{i,j,t-1}$$

$$+ \sum_{k=J+1}^{J+K} \alpha_k \cdot Controls_{i,k,t-1} + FE_{Fund\ Style*Time} + \varepsilon_{i,t} \qquad (2)$$

In the second stage, we replace complex instrument use with the value instrumented by family complex instrument use:

[23] The lack of a positive alpha associated with short sale positions is in contrast to Chen et al. (2013). See Section 6 for a comparison between our results and Chen et al. (2013).

$$Fund\ Performance_{i,t} = \beta_0 + \sum_{j=1}^{J} \beta_j \cdot Predicted\ Complex\ Instrument\ Use_{i,j,t}$$

$$+ \sum_{k=J+1}^{J+K} \beta_k \cdot Controls_{i,k,t-1} + FE_{Fund\ Style*Time} + \varepsilon_{i,t} \qquad (3)$$

We measure complex instrument use using our composite measure, as well as our three individual complex instruments, leverage, short sales, and options. Control variables include those used in our main tests. In Panel A of Table 3, we show that family complex instrument use is a strong (and positive) predictive factor for fund complex instrument use for the composite measure (column 1). Furthermore, in the second through fourth columns we show that for each individual complex instrument the family's use of that specific complex is the most important predictor of the fund's use of that instrument.

In Panel B, we examine the relation between predicted complex instrument use and fund performance. Consistent with our main results, we find a negative relation. In fact, for the composite measure, after controlling for endogeneity using the instrumental variable approach, we find that our results strengthen with respect to both our coefficient estimates and their statistical significance. With respect for the individual instruments, we continue to find a negative relation between their use and fund returns, although the significance of the coefficients depend on the measure of performance used.

5. Why Does Complex Instrument Use Lead to Underperformance?

As documented in the previous section, funds that use complex instruments are associated with lower performance relative to funds that are permitted but do not use complex instruments. In this section, we explore two possible explanations for this underperformance. The first explanation if related to moral hazard, where funds that use complex instruments take more risk in their non-complex instrument positions. They use complex instruments to hedge some of the risk, but they do it in an imperfect and costly way. The second explanation is related to agency problems. In particular, the convex relation between fund flows and performance may incentivize managers to manipulate their risk exposure. Therefore, we examine if there is evidence of risk shifting and if this has an effect on performance. We also consider situations where fund agency problems are held in check and expect the negative outcomes associated with complex instruments use to be neutralized. Finally, we examine settings in which complex instrument use is more likely to have a positive effect on the fund performance.

5.1 Moral Hazard

Complex instruments, especially options and short sales, can be used by fund managers to hedge the risk of their investments. One concern is that if they are used for insurance purposes, they can create a moral hazard problem. For example, a fund manager could be less worried about the risk of her equity investments given that she could use complex instruments to reduce portfolio risk. We test if this is the case by examining the relation between complex instruments use and the underlying equity holdings of the fund. We use the same regression framework of equation (1) where the dependent variable is a risk measure. We measure total risk using the standard deviation of returns, systematic risk using the fund's CAPM beta exposure, and unsystematic risk using the fund's idiosyncratic risk as computed from the four-factor model.

The first row of Table 4 Panel A shows results for the composite measure. Consistent with complex instrument users holding riskier equity portfolios, we find that these funds have a significantly higher equity standard deviation (0.451), equity beta exposure (0.017), and equity idiosyncratic volatility (0.407) than funds that choose not to use complex instruments.

We also examine the relation between the individual complex instruments and fund equity risk. We find that leverage use is associated with higher fund equity risk as measured by the standard deviation, beta exposure, and idiosyncratic volatility. The finding that funds that use leverage buy higher beta stocks is counter-intuitive as past research suggests investor preference for high-risk stocks is driven by leverage constraints (see, for example, Frazzini and Pedersen, 2014). One might expect a sophisticated investor to use leverage to overcome leverage constraints and capture the low-beta premium by implementing a betting-against-beta strategy. Instead, we find mutual funds do the opposite; they buy high-beta stocks when they have access to leverage suggesting that their preference for high-beta stocks is unrelated to the leverage constraints. It appears that these funds are risk seekers that load up on risk through both their equity positions and the use of leverage. Later in the paper we examine whether some funds use complex instruments to exploit the low-beta anomaly. We also find that short sales and option use are associated with equity positions that have returns with higher standard deviation, and higher idiosyncratic volatility relative to the equity portfolios of funds that choose not to use the complex instruments.

We next examine the relation between complex instrument use and risk computed at the fund level. The first row of Table 4 Panel B shows results for the composite measure. We find no significant relation between complex instrument use and standard deviation. Funds that use at least one complex instrument have lower betas (-0.023), but also higher idiosyncratic volatility (0.394). These results are consistent with funds using complex instruments to reduce only the systematic risk rather than the idiosyncratic risk.[24]

Concerning the relation between the individual complex instruments and fund risk, because each complex instrument has a distinct nature, we do not expect their impact on firm risk to be uniform. We find that leverage use amplifies fund's standard deviation (0.557), beta exposure (0.029) and idiosyncratic volatility (0.285). This result is unsurprising. In contrast to the other complex instruments, which have the potential to be used as hedging or speculative tools, leverage mechanically increases risk. With that said, firms that use leverage need not have greater risk. For example, a risk parity or betting against beta strategy, in which lower risk assets are levered up could lead to portfolios that use leverage and have similar levels of risk as portfolios that do not use leverage. In contrast, we find that both short sales and option use decreases funds' standard

[24] We also examine the relation between predicted complex instrument use and fund risk after controlling for endogeneity using the instrumental variable approach adopted in the previous section. In untabulated results, we find evidence that predicted complex instrument use is associated higher standard deviation and idiosyncratic volatility.

deviation and beta exposure, but are associated with higher idiosyncratic volatility. Natter et al. (2015) also document that the use of options is associated with lower systematic risk, but they do not examine idiosyncratic risk.[25]

If the moral hazard explanation is valid, we also expect that simply being allowed to use complex instruments would encourage funds to take more risk in their other positions. To test whether this is the case we use a dummy variable for a fund that is allowed to use complex instruments, and expand our sample to include all domestic equity mutual funds rather than just those that are allowed to use the instruments. Appendix Table 1 reports our results. Consistent with a moral hazard problem, relative to funds that are not allowed, we find that funds that are allowed to use complex instruments have significantly higher standard deviations (0.641) and beta exposures (0.039).

Modern portfolio theory dictates that investors should eliminate their exposure to unsystematic risk, which is unrewarded by financial markets, so that they are only exposed to systematic risk, which is rewarded. Given this paradigm, it is curious, and potentially harmful to shareholders, that complex instrument use increases the fund's exposure to unsystematic risk while at the same time decreasing the fund's exposure to systematic risk. The decrease in rewarded risk may explain our earlier finding that funds that use complex instruments have lower excess returns than those that do not.

5.2 Moral Hazard Behavior, Complex Instrument Use and Fund Returns

We next examine if the moral hazard problems is one of the culprits for the poor performance associated with complex instrument use. To test if this is the case, each semester we sort funds into quintiles, based on their equity standard deviation observed at semester *t-1*. We partition the sample into funds with the low equity standard deviations (bottom quintile), middle

[25] We construct "risk gap" measures, which are defined as the difference in the fund's actual risk and the risk of their underlying equity holdings. The assumption is that the gap between the actual risk and equity risk for the fund is explained by the fund's complex instrument use. In untabulated results, consistent with mutual funds using complex instruments to reduce systematic risk, we find evidence that the composite measure is associated with a lower beta exposure gap (-0.035).

equity standard deviations (middle three quintiles), and high equity standard deviations (top quintile). Examining different subsamples allows us to compare how the outcomes of funds that use complex instruments vary with different equity risk exposure. Within each subsample, we use the instrumental variable approach to examine the consequence of the predicted use of complex instruments at time *t* on fund outcomes at time *t*. Using the instrumental variable approach allows us to control for endogeneity, which is likely to be more severe when we condition on the subsamples based on fund outcomes.[27] Table 5 presents the results of this analysis and are consistent with the notion that the moral hazard problem, at least partially, drives the poor returns associated with complex instrument use. Specifically, in the subsample of funds with low equity standard deviation, which are the least symptomatic of the moral hazard problem, we find complex instrument use is associated with positive although insignificant performance measures. In contrast, we observe the most negative relation between complex instrument use and performance in the subsample of funds that hold the riskiest equity positions.

5.3 Risk Shifting

Past research highlights that the non-linear relation between fund flows and performance may incentivize managers to manipulate their risk exposure. For example, poor performing fund managers may use complex instruments to pursue a 'doubling down' strategy where they increase risk exposure to catch up to their better performing peers, and good performing managers may use complex instruments to lock in gains. In this section, we examine if funds use complex instruments to shift risk following bad and good performance, and if this behavior has an impact on fund returns.

To test if this is the case, each semester we sort funds into quintiles, based on their four-factor alpha observed at semester *t-1*. We partition the sample into funds with the low four-factor alpha (bottom quintile), middle four-factor alpha (middle three quintiles) and high four-factor

[27] In unreported tests, we replicate this analysis (as well as the risk-shifting analysis) using the non-instrumented complex instrument variables and find similar results.

alpha (top quintile). Examining different subsamples allows us to examine if complex instrument use affects funds differently conditional on recent performance. Within each subsample, we use the instrumental variable approach to examine the consequence of the predicted use of complex instruments at time *t* on fund outcomes at time *t*. Using the instrumental variable approach allows us to control for endogeneity, which is likely to be more severe when we condition on the subsamples based on fund outcomes.

If funds use complex instruments to risk shift, we would expect that laggard (leading) funds might use complex instruments to increase (decrease) risk. In Table 6, we find that complex instruments are associated with a significant increase in risk as measured by the standard deviation of net fund returns in the low four-factor alpha quintile (0.634), but insignificant changes in risk in the middle (0.267) and high (-0.023) four-factor alpha subsamples.

Using the instrumental-variable approach, we next examine how complex instrument use in each four-factor alpha subsample is related to fund performance. Consistent with complex instruments use motivated by risk shifting having a detrimental effect on fund shareholders, we find that use by funds that are performing poorly is associated with the worst performance with a magnitude ranging from -2.26% to -2.6% per year.

5.4 Complex Instrument Use and Agency Problem

The above results provide support that for some funds complex instrument use is driven by agency considerations. If this is the case, we expect the negative outcomes associated with their use to subside in settings where fund agency problems are held in check. We explore three settings where we expect this to be the case: (1) if the fund is well monitored; (2) if the fund's manager is affected by career concerns; and (3) if the fund is transparent in its disclosures. We expect each setting to be associated with lower agency costs and hence less negative association between complex instruments and performance. In Table 7 we examine how complex instrument outcomes vary in each setting.

We first examine complex instrument use by well-monitored funds. We proxy for fund monitoring quality using two measures: (1) if the fund has institutional shareholders (identified by the presence of institutional share classes); and (2) if the fund's board independence is in the top quintile of the sample.[30] In the subsample of institutional funds, we find that complex instrument use is not associated with significant negative performance, and in funds with high board independence complex instrument use is associated with positive performance, which are statistically significant when our performance measure is excess return and MPPM.

Next, we examine complex instrument use by fund managers who are more sensitive to career concerns. Specifically, we identify in the bottom quintile of our sample with respect to their tenure at the fund. Managers who are relatively new in their job are more likely to face more career concerns. In contrast to the full sample, we find that complex instrument use by these funds is not associated with negative returns across all three measures of performance.

Last, we examine complex instrument use by funds who are transparent about their use. Since 2009, funds have been required to disclose their summary prospectuses to the SEC each quarter in Form 497K. Funds are required to discuss their investment objectives and summarize their strategies at the beginning of the summary prospectus. We web crawl these forms and search the filings using a dictionary of terms associated with complex instrument use. If the fund discusses complex instruments at the beginning of the prospectus we define it as being a highly transparent fund.[31] In contrast to the full sample analysis, we find that complex instrument use by these funds is not associated with negative returns.

In conclusion, although there is evidence of negative association between complex instrument use and fund performance, there are some settings in which these negative effects can be neutralized. If agency considerations are one of the motives for the use of complex instruments then another setting where the negative effects could be mitigated is when there is a significant

[30] We use board independence data manually collected by Calluzzo and Dong (2014). They collect director data from mutual fund N-30D and N-SAR filings from 1994 through 2011. As such, we exclude years after 2011 from this analysis.

[31] Specifically, for each fund we identify the first line in which one of the words from our dictionary appears. We then scale the lines position by the total number of lines in the fund's summary prospectus. If the scaled line position is in the top quintile of the sample, we define the fund as being highly transparent with respect to their complex instrument use. Our complex instrument dictionary includes the following words: short sale, short sell, short, sold short, sell short, shorting, short position, shorted, borrow, leveraged position, leverage, derivatives position, options strategy, options position, call option, put option, covered call, naked call, naked put, and naked position.

increase in litigation risk. One important event that increases this risk is the mutual fund trading scandal in 2003. This scandal started in the fall of 2003 and involved 24 mutual fund families, which went under investigation for permitting some investors to engage in late trading or market timing. One advantage of using the trading scandal is that it represents an exogenous shock and hence addresses endogeneity concerns that could be present in the relation between complex instruments use and performance. This event may have increased the likelihood of being litigated for breach of fiduciary responsibility for the mutual fund industry and in particular for the funds affected by the scandal. Therefore, we posit that in the period after 2003 the agency-induced use of complex instruments will be reduced, which will be reflected in less negative effects for using these instruments. Furthermore, this prediction would be particularly strong for funds affected by the scandal.[32]

Table 8 presents regression results testing these predictions. When we condition on the event, we find that the negative association between the use of complex instruments and performance is higher during the pre-2003 sample period. During the post-2003 period the coefficient is still negative and significant for excess returns and MPPM. When we consider the affected funds the difference between the two sample periods is much stronger and during the post-2003 period the coefficient becomes positive although not statistically significant.

5.5 Potential Positive Uses of Complex Instruments

The results above provide evidence that use of complex instruments is associated with negative performance and only when we conditions on settings where agency costs are reduced this negative association disappears. In this section we further explore other settings that ex-ante should be associated with a positive use of complex instruments. It is possible that if we focus on some subgroups of funds we might find a different result for the relation between complex instrument use and performance. In particular, we first consider funds that use complex

[32] We obtain a list of mutual funds affected by the scandal from Qian and Başak (2017).

instruments to try to exploit the low-beta anomaly. Next, we consider funds that use complex instruments to reduce the costs associated with fund flows.

5.5.1 Betting Against Beta

The finding that funds that use complex instruments, and in particular leverage, buy higher beta stocks is counter-intuitive as past research suggests investor preference for high-risk stocks is driven by leverage constraints (e.g., Frazzini and Pedersen, 2014). One might expect a sophisticated investor to use leverage to avoid investing in risky stocks and instead capture the low-beta premium by implementing a betting-against-beta strategy. Instead, we find mutual funds do the opposite; they buy high-beta stocks when they have access to leverage suggesting that their preference for high-beta stocks is unrelated to the leverage constraints. It appears that these funds are risk seekers that load up on risk through both their equity positions and the use of leverage. These results are for the average fund that use complex instrument. It is possible that if we focus on funds that try to exploit the low-beta anomaly the results would be different. To test if this is the case in Table 9 we use the earlier instrumental variable approach where we condition on different portfolio beta computed from the equity holdings. Interestingly, funds that invest in low-beta securities and use complex instruments are associated with significant positive performance ranging from 1.34% to 1.38% per year. By contrast, funds that invest in high-beta securities and use complex instruments are associated with significant negative performance ranging from -1.72% to -2.31% per year.

5.5.2 Fund Flow Management

Another explanation for complex instrument use is that funds may use them to reduce costs associated with fund flows. This explanation would be consistent with a good use of complex instruments and there is some indirect evidence for derivatives use by Deli and Varma (2002). Table 10 presents the results of this analysis. We first examine the effect of fund flow environment on fund outcomes considering our composite measure of complex instrument use. We measure net fund flows as the change in fund flows scaled by the fund's assets over the semester, and partition the sample into funds that experience low net flows (bottom quintile), middle net flows (middle three quintiles), and high net flows (top quintile). If funds use complex instrument to mitigate the liquidity shocks associated with large fund flows, we expect to find a more positive association between complex instrument use and fund performance in the group of funds that use these instruments following negative net flows than in the other groups.[33] Inconsistent with complex instruments improving the fund's ability to manage liquidity, we find that complex instrument use is associated with negative returns across all three subgroups.

6. Additional Analyses and Robustness

6.1 Light vs. Heavy Users of Complex Instruments

If the effects documented above on performance are driven by the actual use of complex instruments, then we expect that these effects will be stronger when we consider the heaviest users. To test if this is the case, we use balance sheet information to identify heavy and light users of complex instruments.[37] To measure the size of short sale positions we use Question 74R2 (short sales), to measure the size of options positions we sum Question 74G (options on equities), 74H (options on all futures). Among users of each instrument, as proportion of total fund assets (listed in Question 74N), we find that the average short sale position is 18.3%, and the average option position is 1.6%. Because of the embedded leverage in options the impact on the fund's portfolio is likely larger than implied by the magnitude of these positions. Because there is no specific question that identifies a fund's level of leverage,[38] to proxy for leverage we use a fund's interest expenses (Question 72P) scaled by fund assets (Question 74N). Because interest rates are time-varying, we rank the scaled interest expense by time. Heavy (light) users are defined as funds that

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[33] For the bottom quintile flows are never positive. They are on average -2.5% and range between -7% and negative -0.08%.

[37] Because balance sheet data only captures holdings at the end of the reporting period, it is susceptible to window dressing concerns. This concern is also discussed by Natter et al. (2016) and is the main reason why we rely on the question 70 data, which gives yes or no responses to if the fund used each instrument over the entire reporting period. Consistent with window dressing being a concern, we find that 46.6% of funds that disclose using options in question 70 do not report options on their balance sheet.

[38] Question 74Q (senior long-term debt) does not adequately capture the use of leverage because it is not well populated for users of leverage.

hold a given complex instrument above (below) the median level for a given semester conditional on a positive value on the balance sheet for the specified instrument. To compute the heavy and light user composite measure we assign a score for each instrument: 0 if there is a no position in the instrument indicated on the balance sheet, 1 if they are defined as a light user of that instrument; and 2 if they are defined as heavy user of that instrument. We sum the score of each of the three instruments. If the composite score is above (below) the median for the semester, conditional on a non-zero score, the fund is designated as a heavy (light) composite.

Appendix Table 2 reports the panel regression results when we use the heavy and light user dummies.[40] Consistent with a direct impact of complex instrument use on performance, we find that the results are different for heavy users versus light users. Using the composite measure, we find that the negative effect on excess returns, four-factor alphas and MPPM is significantly greater for heavy users. The results for the individual instruments suggest that this is driven by heavy users of leverage and short sales.

6.2 Fund performance and specific option strategies

When we examine light and heavy options use we do not find consistent evidence that heavy options leads to underperformance. This result draws attention to the multi-faceted nature of options, both with respect to the motives for their use, and their effect on the return distribution. Using a variable that capture the use of options without distinguishing between call, put, and type of position, could be too coarse and hide evidence that some option strategies could actually work in delivering positive abnormal performance. Moreover, a strategy that is specific to options is that mutual funds use options to generate income (Natter et al., 2016). Cici and Palacios (2015) document that one of the most popular use of options by mutual funds is for income generation through writing of call options. This strategy has the potential to generate the appearance of

[40] We also compute the average value of short selling, long options, and written options scaled by total assets. Heavy users of short-selling held positions that are worth 29.8% of the assets. Heavy users of long options held positions that are worth 1.8% of the assets. Heavy users of written options held positions that are worth 1.4% of the assets.

superior performance (e.g., Goetzmann et al., 2007), but it is unclear if this strategy generates abnormal returns after using a manipulation-proof performance measure.

To understand the impact of different options strategies on performance and risk we need option holdings information. These data are available from CRSP Mutual Fund database since 2008.[41] We use the holdings with report date closest to the end of the semester. Given that there is no identifier for options, we identify option positions using the security name field in the database.[42] Once we identify the options, we match the underlying equity position to a ticker which is typically provided in the security name field and we check if a fund has a long or short position in the underlying security. In this way we can determine whether an option position is covered or naked.

We first examine some summary statistics of fund option strategies. Among funds that use options, the most common positions are long call (49.4%), followed by short call (41.8%), long put (39.3%), and short put (22.2%). With respect to covered and naked positions; funds prefer to cover written calls (80.1% vs. 37.6% among funds that write calls) but leave puts naked (95.6% vs. 11.5% among funds that write puts).[43] Covered call and naked put strategies both generate income in uptrending markets and are exposed to losses in down trending markets.

Appendix Table 3 provide results for the effect of different option uses on performance and risk. No matter how we cut the data we do not find any evidence of significant positive relation between a particular option strategy and performance. By contrast, there is evidence that the use of put and written call are associated with significant negative excess return and MPPM. The

[41] Cici and Palacios (2015) also use options holdings data from CRSP starting from 2003. However, Schwarz and Potter (2016) discuss that the data before 2008 coming from Morningstar provided inaccurate position information whereas the data starting in 2008 coming from Lipper are accurate. They recommend avoiding the holdings data from CRSP for the period prior to 2008.
[42] We are only able to identify the option position for 32% of funds that disclose using options in question 70 of their N-SAR filings in our sample. This is due to potential window dressing and to the use of a name search algorithm to identify options.
[43] These statistics do not add to 100% because some funds use multiple strategies (i.e. among funds that write puts some use covered puts and naked puts).

negative effect of the written calls appear to be driven by the naked calls. When we examine risk, there is evidence that increase in idiosyncratic risk is driven by calls, in particular bought and covered calls, whereas the reduction is systematic risk is driven by long puts, covered puts, and naked calls. With respect to the higher order risks, we find that the more negative skewness is driven by both long and covered calls, whereas the increase in kurtosis is driven by long and covered puts, and by naked calls.

6.3 Complex Instruments Use and Expense Ratio and Trading Costs

A fund's expense ratio and trading activity generate costs to fund shareholders, and have been shown to be negatively associated with fund returns (e.g., Carhart, 1997). We posit that complex instrument use can affects both of these costs, and if this is the case than they may represent an indirect channel through which complex instruments influence fund performance. Therefore, we prefer not to account for these costs using control variables in our main regressions, as their inclusion may cause us to underestimate the effect of complex instruments on fund performance. In this section, we estimate the effect of complex instrument use on the fund's expense ratio and trading activity, which we proxy for using turnover ratio. We then re-estimate our main regression to determine if our results persist after including each of these ratios as controls variables.

6.3.1 Expense Ratio

We first examine the relation between complex instrument use and fund fees. Much as hedge funds have higher fees than mutual funds, we expect that mutual funds that pursue complex investment strategies will have higher fees than mutual funds that pursue simpler strategies. To measure a fund's expense ratio we start with the total expenses reported in its N-SAR filing. We subtract expense reimbursements, interest expenses and other expenses from this figure and then scale by total assets and then annualize the figure if the N-SAR is for a reporting period of less than 12 months to arrive at the fund's net expense ratio. We subtract out interest expenses and other expenses as complex instruments can mechanically add to these expenses (for example dividends paid on shorted stocks are counted in other expenses) and including these items in the expense ratios figure would bias us towards finding a positive relation between complex instrument use and fees. This is also a reason why we do not use the expense ratio from CRSP because it is not clear if it includes interest expenses.

We estimate the regression model in equation (1) with expense ratio as the dependent variable. The results presented in the first column of Appendix Table 4 provided evidence that investors pay a premium to access funds that use complex instruments. Specifically, the coefficient on the composite measure indicates that using at least one of the three complex instruments is associated with a 0.072% annual increase in net expense ratio. This figure is statistically significant at the one percent level. Next, we estimate regressions that include dummy variables that indicate the use of leverage, short sales, and options. We find that funds that use short sales (0.136%) and options (0.100%) are associated with higher fees, whereas the relation between leverage use and fees is insignificant. Taken together, the results provide evidence that investors pay to access funds that use complex instruments. This result is unsurprising and aligns with the intuition that the more complex the product, the more it will cost.[45]

Our results suggest that expense ratio is an indirect channel through which complex instruments affect fund performance. We next include expense ratio in our IV regressions on fund performance to determine if complex instruments influence fund performance beyond their effect on fund fees. We prefer to use the IV regression given the endogenous relation between fund fees and complex instrument use. The second through forth columns of Appendix Table 4 present the results. Consistent with expense ratio being an indirect channel through which complex instrument use affects fund performance, we find that the coefficients on the complex instrument use variables is generally lower than our earlier analysis. However, consistent with complex instrument use

[45] It is worth noting that the above analysis focuses only on funds that are allowed to use complex instruments. Our univariate results in Table 1 show that investors pay a premium to access funds with these bylaws. In unreported regressions we find that being allowed to use complex instruments is associated with a 0.099% larger expense ratio. Therefore, the combined effect of being allowed to and actually using complex instruments is a more economically meaningful 0.171% (0.072% + 0.099%) compared to funds that are restricted from using complex instruments.

affecting fund performance through additional channels beside expense ratio, we find that complex instrument use continues to be negatively related fund performance across our three performance measures.

6.3.1 Trading Costs

We next examine the relation between complex instrument use and trading activity, measured using turnover ratio.[46] Complex instrument use has the potential to both increase and decrease fund turnover. On the one hand, as pointed out by Deli and Varma (2002) complex instruments can reduce the need to buy and sell stocks as a response to flow shocks and thus reduce turnover. On the other hand, much as moral hazard associated with complex instrument use increases the riskiness of the equity positions mutual funds take, it may also manifest in the aggressiveness with which the funds trade. It is ultimately an empirical question which effect dominates, and if complex instruments have a positive or negative impact on fund turnover. We measure a fund's turnover ratio using the figure reported on N-SAR question 74D which we annualize to adjust for unequal reporting periods.

We estimate the regression model in equation (1) with turnover ratio as the dependent variable. The results presented in the first column of Appendix Table 5 provided evidence that investors that use complex instruments have higher turnover ratios. Specifically, the coefficient on the composite measure indicates that using at least one of the three complex instruments is associated with a 20% annual increase in turnover ratio. This figure is statistically significant at the one percent level. Next, we estimate regressions that include dummy variables that indicate the use of leverage, short sales, and options. We find that funds that the use of leverage (12.9%), short sales (52.9%), and options (16.1%) are all associated with higher turnover ratios. All these estimates are all economically large as the average fund in our sample has an 88.1% turnover ratio.

[46] Trading costs are difficult to measure and follow the literature (e.g., Carhart, 1997) in using turnover ratio as a proxy. Although trading costs are mechanically associated with lower shareholder returns, there is mixed evidence on the relation between turnover ratio and fund performance as turnover may also proxy for the informed trading (e.g., Grinblatt and Titman, 1993; and Wermers, 2000). In Appendix Table 5 we report a negative, although statistically insignificant relation between fund turnover ratio and returns in our sample.

As trading generates transactions costs our results suggest that the turnover ratio may be an indirect channel through which complex instruments affect fund performance. We next include turnover ratio in our IV regressions on fund performance to determine if complex instruments influence fund performance beyond their effect on fund fees. The second through forth column of Appendix Table 5 present the results. Consistent with turnover ratio being an indirect channel through which complex instrument use effects fund performance, we find that the coefficients on the complex instrument use variables is generally lower than our earlier analysis. However, consistent with complex instrument use affecting fund performance through additional channels beside turnover ratio, we find that complex instrument use continues to be negatively related fund performance across our three performance measures.

6.4 Complex Instruments and Higher Order Risk

Given that complex instruments can be used to alter the return distribution, we also examine the relation between complex instruments and higher moments of the fund return distribution using skewness and kurtosis. For instance, writing covered call options truncates upside gains and creates more negatively skewed return distributions. Appendix Table 6 presents the results. With respect to the higher order risks, the negative coefficient with respect to skewness (-0.009) suggests that users are more exposed to the left tail of the distribution, and the positive coefficient with respect to kurtosis (0.040) suggests that these funds have fatter tails. Therefore, complex instrument use is associated with undesirable outcomes such as more left skewness and higher kurtosis in the funds' return distributions. When we examine the individual complex instruments, it appears that these negative effects are coming from short sales and option uses rather than leverage.

6.5 Comparison with Related Literature

Almazan, Brown, Carlson, and Chapman (ABCC, 2004) using N-SAR filings data construct a "constraint score" to capture the cumulative impact of the constraints imposed on mutual funds. In particular, the score is constructed placing equal weights on constraints imposed on three different categories: derivatives, illiquid assets, and leverage. ABCC find that using their score to divide funds into low- and high- constraint funds produce similar performance. We find instead that low-constraint funds, in particular funds that are not constrained to invest and actually invest in complex securities, deliver poor performance.

To ensure that the difference between our findings and ABCC is not driven by the difference in the construction of the constraint measure and/or by the methodology, we replicate the analysis of ABCC on our sample of funds using a similar methodology and both their score and our composite measure.[47] In particular, every six months we sort funds into terciles according to the ABCC score or the composite measure. The bottom (top) tercile includes low (high) constraint funds. We then compute equally-weighted fund portfolio returns during the next six months using monthly returns. We use monthly instead of daily returns to be consistent with ABCC. We rebalance the portfolios every six months and we end up with a time-series of excess returns for each portfolio, which we can regress on the four factors to obtain the four-factor alpha. Appendix Table 7 presents the results. The worst performing funds are the unconstrained funds with almost -1% annual alpha, which is marginally significant for the ABCC score. The alpha of the constrained funds is negative but the magnitude is more than halved and the difference between the constrained and unconstrained funds is statistically significant for both the ABCC score and the composite score. Hence, the difference between our results and ABCC are likely to stem from sample differences rather than from a different definition of the constraint measure or a different methodology.

We also compare our results with Natter et al. (2016) and Chen et al. (2013) who also employ N-SAR data to examine mutual funds that use options and short selling, respectively. Similar to Natter et al. (2016), we find that options use is associated with a reduction in systematic risk. Furthermore, the increase in both left skewness and four-factor alpha, but not MPPM, is

[47] Our composite measure is constructed somewhat differently from ABCC. For the derivatives we did not include stock index futures and instead included options on futures and options on stock index futures. Furthermore, we did not consider restricted securities and margin purchases. The main reason for excluding some of the questions is that we excluded investments for which we could not quantify the magnitude in the balance sheet.

consistent with the frequent use of a covered call income generating strategy as suggested by Natter et al. (2016). With respect to Chen et al. (2013), both our paper and their paper find that short selling is associated with a reduction in market beta exposure.

Our main results are different from the findings of Natter et al. (2016) and Chen et al. (2013). In particular, our findings suggest that the overall impact of complex instrument use on fund shareholders is negative rather than positive. We relate our contrasting findings to differences in our empirical approach and our larger sample size. A main difference in our empirical approach is that we examine lead-lag relationships to avoid endogeneity issues. For example, we find a negative relationship, albeit weak, between a fund being in the bottom alpha tercile and subsequent short sale use, which may bias results in an empirical design that examines a contemporaneous relation between short sales use and fund returns. In untabulated tests we replicate our Tables 4 and 5 using a contemporaneous specification. We find that the relation between complex instrument use and fund performance is weaker but still negative for all performance measures and significant for the four-factor alpha. The relation with respect to risk is very similar in magnitude and statistical significance across all five variables. These results suggest that the difference between our findings and previous papers is not entirely driven by our lead-lag empirical design. An additional difference is that we compute our risk and return measures using daily rather than monthly mutual fund return data.[48] Using the daily frequency is important for estimating the measures every semester. Semester-level measures allow us to perform panel regressions instead of cross-sectional regressions, and to obtain more precise estimates of performance and risk (e.g., Busse, 1999).

7. Conclusion

Like the righteous and iniquitous angels in *The Shepherd of Hermas*, complex instruments are dual-natured with the ability to either lead funds to safety or to the temptation to seek higher risk. This negative potential has raised concerns at the SEC which is considering reforms designed

[48] In some of their analyses Natter et al. (2016) use daily data, but their performance and risk measures are computed using a rather short window length of one month.

to limit complex instrument use by mutual funds in an effort to protect investors that invest in these funds. Whether the use of complex instruments helps or harms fund shareholders is ultimately an empirical question that we address in this paper using a comprehensive dataset of mutual funds that use leverage, short sales, and options.

Our results suggest that the use of complex instruments is associated with lower performance and changes in risk that are harmful to shareholders (i.e., higher unsystematic risk, more negative skewness, and greater kurtosis). One concern is that the perceived safety generated by providing funds with the possibility of using complex instruments creates a moral hazard problem and alters their risk-taking behavior. Indeed, we find that funds that use complex instruments take more risk, both systematic and idiosyncratic, in their equity positions. We then find that funds use complex instruments to try to hedge away this increased risk, but only manage to decrease their beta exposure, not their idiosyncratic risk or higher-moment risk. As financial theory suggests, only systematic risk is rewarded in financial markets. Thus, increasing the relative proportion of idiosyncratic risk in the fund's risk profile, while simultaneously changing the distribution of returns to increase higher moment risks, can be harmful to shareholders. We also provide evidence that agency-induced motives are a contributing factor for the underperformance of funds that use complex instruments. In settings where agency problems are held in check the negative effects dissipate.

By highlighting concerns about the use of complex instruments by mutual funds, our research provides useful information for regulators. In aggregate, we find that these instruments can have a harmful effect on fund investors, which suggests that the concerns of regulators are justified. At the same time, in environments where their use is well monitored, disclosed in a transparent way, and when they are used in moderation, their harmful effects seem to be neutralized. Overall, it appears that mutual fund investors are better off choosing simplicity. This finding is consistent with DeMiguel et al. (2009) who show, in a different context, that a simple equal-weighted portfolio strategy outperforms more complicated strategies based on portfolio optimization. Célérier and Vallée (2013) also argue that, in the market for structured products, complexity serves as a moat that allows institutions to charge high fees in increasingly competitive markets for financial products. The question remains, if these funds underperform, why do they exist in equilibrium? One explanation is that these funds cater to an investor bias towards complexity. This bias may be reinforced by SEC regulations that restrict retail investors who earn less than $200,000 a year or have less than $1,000,000 net worth from investing in hedge funds. Investors may think that accessing complex hedge-fund like investment strategies facilitates outperformance. This explanation is consistent with our finding that complex instrument use is more common in funds held predominantly by retail investors.

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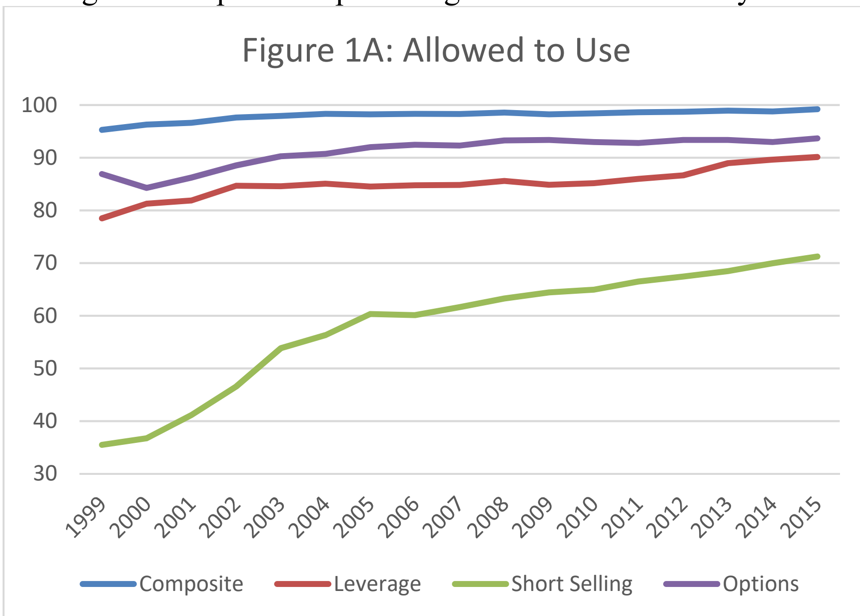
Figure 1
Complex Instrument Use over Time

These figures report the percentage of domestic equity funds that are allowed to use and actually use complex instruments over the 1999-2015 sample period. Figure 1A reports the percentage of funds that are allowed to use each complex instrument. Figure 1B reports the percentage of funds that actually use each complex instrument.



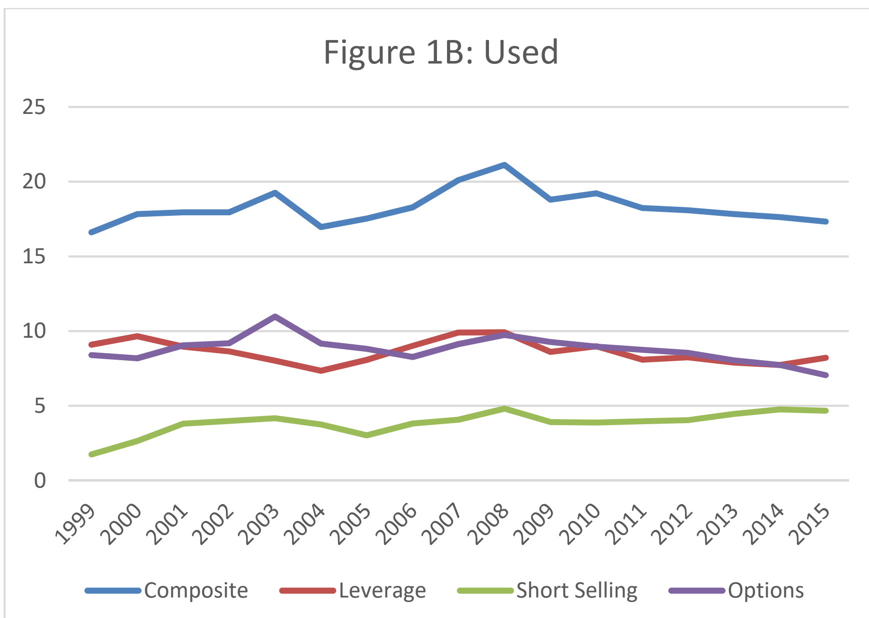


Table 1
Fund Characteristics by Complex Instrument Use

This table reports mean fund characteristics by complex instrument use. It reports the fund size (millions), fund family size (millions), annual expense ratio (%), age (years), the percentage of AUM in the institutional share classes, six-month fund flow (%), annualized excess return (%), and standard deviation of returns (%). Columns 1-3 report summary statistics for our composite measure, columns 4-6 for options, columns 7-9 for short selling, and columns 10-12 for leverage. Columns 1, 4, 7, 10 report mean values of each measure for funds that are not allowed to use each complex instrument. Columns 2, 5, 8, 11 report mean values of each measure for funds that although permitted, do not use each complex instrument. Columns 3, 6, 9, 12 report mean values of each measure for funds that use each complex instrument.

	At Least One Complex Instrument			Options			Short Sales			Leverage		
	Not Allowed	Don't Use	Use	Not Allowed	Don't Use	Use	Not Allowed	Don't Use	Use	Not Allowed	Don't Use	Use
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fund Size	2397	1287	971	1839	1198	1234	1139	1351	1033	1191	1320	766
Family Size	130999	148783	87720	73992	149213	95252	87268	179232	62810	112663	148045	92656
Expense Ratio	1.02	1.09	1.21	1.11	1.10	1.24	1.12	1.10	1.27	1.18	1.09	1.21
Fund Age	12.16	11.71	11.48	12.04	11.57	12.22	11.71	11.85	8.63	11.90	11.65	11.38
Institutional Ownership	13.00	30.66	24.41	20.56	31.07	21.27	29.51	29.37	26.34	23.22	30.73	26.24
Fund Flow	0.75	0.37	0.23	0.62	0.31	0.28	0.42	0.25	0.71	0.29	0.40	-0.16
Excess Return	3.36	6.43	4.52	4.69	6.33	4.84	4.45	7.44	2.58	5.15	6.37	4.79
Standard Dev.	17.82	18.55	18.20	18.11	18.56	17.92	18.73	18.50	15.30	18.50	18.38	19.15

Table 2
Fund Performance and Complex Instrument Use

This table reports results from panel regressions of fund performance on complex instrument use and a set of controls. All the explanatory variables are observed six months before the dependent variable. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. For each column, two separate regressions are estimated. The first row reports results using our composite complex instrument dummy variable, which takes the value of one if at least one of the complex instruments under consideration is used. The next three rows report results for dummy variables capturing the use of leverage, short sales, and options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Composite	-0.594	-0.458	-0.636
	(0.003)	(0.004)	(0.005)
Leverage	-0.360	-0.773	-0.699
	(0.147)	(0.000)	(0.014)
Short Sales	-0.731	-0.124	-0.215
	(0.323)	(0.815)	(0.790)
Options	-0.668	-0.132	-0.454
	(0.012)	(0.526)	(0.126)

Table 3
Instrumental Variable Approach

This table shows the results of a two-stage least squares regression. In the first stage (Panel A) we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance (Panel B) on the predicted complex instrument use from the first stage and control variables. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. In both panels standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

Panel A: First Stage	Composite	Leverage	Short Sales	Options
	(1)	(2)	(3)	(4)
Family-Level Composite	0.619			
	(0.000)			
Family-Level Leverage		0.744	0.005	-0.009
		(0.000)	(0.523)	(0.521)
Family-Level Short Sales		0.002	0.345	0.003
		(0.939)	(0.000)	(0.926)
Family-Level Options		-0.028	-0.052	0.559
		(0.011)	(0.016)	(0.000)

Panel B: Second Stage Performance	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Composite	-1.536	-1.290	-1.848
	(0.004)	(0.003)	(0.003)
Leverage	-0.601	-1.103	-1.165
	(0.195)	(0.004)	(0.029)
Short Sales	-8.866	-3.413	-9.268
	(0.023)	(0.232)	(0.038)
Options	-1.325	-1.136	-0.940
	(0.186)	(0.163)	(0.401)

Table 4
Risk and Complex Instrument Use

This table reports results from panel regressions of equity (Panel A) and fund (Panel B) risk on complex instrument use and a set of controls. All the explanatory variables are observed six months before the dependent variable. Risk is measured using the standard deviation of returns (1), CAPM beta (2), idiosyncratic volatility as computed from the four-factor model (3). The equity (fund) risk measures are computed from equity holdings (net) daily returns data observed during a six-month period. The standard deviation and the idiosyncratic volatility are reported on an annualized basis and expressed in percentages. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. For each column, two separate regressions are estimated. The first row reports results using our composite complex instrument dummy variable, which takes the value of one if at least one of the complex instruments under consideration is used. The next three rows report results for dummy variables capturing the use of leverage, short sales, and options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

Panel A	Equity Standard Deviation	Equity Beta Exposure	Equity Idiosyncratic Volatility
	(1)	(2)	(3)
Composite	0.451	0.017	0.407
	(0.000)	(0.000)	(0.000)
Leverage	0.394	0.018	0.173
	(0.002)	(0.003)	(0.041)
Short Sales	0.542	0.006	0.954
	(0.099)	(0.701)	(0.000)
Options	0.292	0.008	0.413
	(0.024)	(0.196)	(0.000)

Panel B	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)
Composite	-0.077	-0.023	0.394
	(0.484)	(0.001)	(0.000)
Leverage	0.557	0.029	0.285
	(0.000)	(0.000)	(0.000)
Short Sales	-1.355	-0.147	0.812
	(0.001)	(0.000)	(0.000)
Options	-0.493	-0.039	0.285
	(0.002)	(0.000)	(0.001)

Table 5
Moral Hazard and Fund Performance

This table examines the relation between complex instrument use and fund performance for different equity standard deviation exposure. Specifically, we replicate our earlier return analysis for different subsamples based on the quintiles of the fund's equity standard deviation at semester *t-1*: low equity standard deviations (bottom quintile), middle equity standard deviations (middle three quintiles), and high equity standard deviations (top quintile). The equity standard deviation is computed from equity holdings daily returns data observed during a six-month period. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We used an instrumental variable approach to control for endogeneity. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage and control variables. The table shows only the results for the second stage. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Low Equity Standard Deviation	0.373	0.193	0.197
	(0.610)	(0.761)	(0.794)
Middle Equity Standard Deviation	-0.371	-0.694	-0.438
	(0.421)	(0.081)	(0.374)
High Equity Standard Deviation	-1.512	-0.862	-1.429
	(0.171)	(0.358)	(0.272)

Table 6
Risk Taking and Fund Performance

This table examines the relation between complex instrument use and fund risk and performance for different past performance ranking. Specifically, we replicate our earlier risk and return analysis for different subsamples based on the quintiles of the fund's four-factor alpha at semester *t-1*: low four-factor alpha (bottom quintile), middle four-factor alpha (middle three quintiles) and high four-factor alpha (top quintile). Fund risk is measured by the standard deviation computed from daily net returns data observed during a six-month period. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We use an instrumental variable approach to control for endogeneity. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage and control variables. The table shows only the results for the second stage. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Standard Deviation	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)	(4)
Low Four-Factor Alpha	0.634	-2.259	-2.267	-2.600
	(0.081)	(0.021)	(0.006)	(0.015)
Middle Four-Factor Alpha	0.267	-0.927	-1.000	-1.135
	(0.187)	(0.052)	(0.010)	(0.031)
High Four-Factor Alpha	-0.023	-1.405	0.114	-1.502
	(0.938)	(0.114)	(0.865)	(0.119)

Table 7

Monitoring Quality and Performance Associated with Complex Instrument Use

This table examines how different environments for complex instrument use affects fund performance. Specifically, we replicate our earlier return analysis for four different subsamples based on the fund's institutional ownership, board independence, manager tenure, and prospectus transparency. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Institutional Fund	-0.281	-0.092	-0.274
	(0.157)	(0.544)	(0.195)
High Board Independence	0.651	0.256	0.582
	(0.027)	(0.350)	(0.059)
Short Tenure Fund Manager	0.059	0.424	0.295
	(0.899)	(0.234)	(0.556)
High Prospectus Transparency	-0.161	0.027	0.078
	(0.839)	(0.963)	(0.915)

Table 8
Fund Performance around the Mutual Fund Late Trading Scandal

This table examines how different motivations for complex instrument use affect fund performance. Specifically, we replicate our earlier return analysis before and after the 2003 mutual fund late trading scandal and among funds that belong to fund families that were and were not implicated by the scandal. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
All Funds			
Pre 2003	-1.886	-1.573	-2.094
	(0.059)	(0.026)	(0.072)
Post 2003	-0.318	-0.164	-0.283
	(0.030)	(0.219)	(0.049)
Scandal-Affected Funds			
Pre 2003	-6.679	-3.620	-7.255
	(0.026)	(0.098)	(0.039)
Post 2003	0.601	0.054	0.767
	(0.282)	(0.907)	(0.155)
Unaffected Funds			
Pre 2003	-1.176	-1.231	-1.337
	(0.259)	(0.095)	(0.271)
Post 2003	-0.342	-0.167	-0.318
	(0.024)	(0.229)	(0.033)

Table 9
Equity Beta and Fund Performance

This table examines the relation between complex instrument use and fund performance for different equity beta exposure. Specifically, we replicate our earlier risk and return analysis for four different subsamples based on the quintiles of the fund's equity beta at semester *t-1*. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We used an instrumental variable approach to control for endogeneity. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage and control variables. The table shows only the results for the second stage. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Low Equity Beta	1.389	1.342	1.357
	(0.072)	(0.066)	(0.089)
Middle Equity Beta	-0.487	-0.681	-0.617
	(0.297)	(0.086)	(0.215)
High Equity Beta	-2.123	-1.718	-2.307
	(0.056)	(0.060)	(0.076)

Table 10

Fund Flow Management and Fund Performance

This table the relation between complex instrument use and fund performance for different net fund flows rankings. Specifically, we replicate our earlier return analysis for four different subsamples based on the quintiles of the fund's flows at semester *t-1*. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We used an instrumental variable approach to control for endogeneity. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage and control variables. The table shows only the results for the second stage. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Low Net Flows	-1.259	-1.295	-1.524
	(0.083)	(0.026)	(0.062)
Middle Net Flows	-1.652	-1.212	-1.934
	(0.012)	(0.028)	(0.009)
High Net Flows	-0.940	-1.002	-1.198
	(0.329)	(0.173)	(0.266)

Internet Appendix

to accompany

(Ab)Use of Leverage, Short Sales, and Options by Mutual Funds

Appendix Table 1
Complex Instrument Allowance and Fund Risk

This table reports results from panel regressions of fund risk on being allowed to use complex instruments and actual use and a set of controls. All the explanatory variables are observed six months before the dependent variable. Fund risk is measured by the standard deviation of returns (1), CAPM beta (2), and the four-factor model idiosyncratic volatility (3) of net returns. All measures are computed using the daily fund net returns observed during a six-month period, reported on an annualized basis and expressed in percentages. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Two separate regressions are estimated. The first two rows report results using our composite complex instrument variables. The next six rows report results for Leverage, Short Sales, and Options Use variables. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)
Composite Used	-0.074	-0.023	0.397
	(0.499)	(0.001)	(0.000)
Composite Allowed	0.641	0.039	-0.066
	(0.030)	(0.013)	(0.714)
Leverage Used	0.532	0.027	0.266
	(0.000)	(0.000)	(0.001)
Short Sales Used	-1.484	-0.153	0.731
	(0.000)	(0.000)	(0.001)
Options Used	-0.537	-0.042	0.288
	(0.001)	(0.000)	(0.001)
Leverage Allowed	0.306	0.020	0.026
	(0.001)	(0.000)	(0.674)
Short Sales Allowed	0.272	0.011	0.231
	(0.000)	(0.003)	(0.000)
Options Allowed	0.389	0.025	-0.174
	(0.010)	(0.003)	(0.056)

Appendix Table 2
Light and Heavy Users of Complex Instruments and Fund Performance

This table reports results from panel regressions of fund performance on the level of complex instrument use and a set of controls. All the explanatory variables are observed six months before the dependent variable. We use information reported in each fund's balance sheet to define funds as light (below median) and heavy (above median) complex instrument users. Fund performance is measured by fund net returns in excess of the risk-free rate (1), four-factor alphas (2), and MPPM (3). All measures are computed using the daily fund net returns observed during a six-month period, reported on an annualized basis and expressed in percentages. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. For each column, two separate regressions are estimated. The first two rows report results using our heavy and light composite complex instrument dummy variables. The last six rows report results for heavy and light Leverage, Short Sales, and Options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses. We also report the p-value for the test of the difference between the coefficients on Composite Light and Composite Heavy.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Composite Light (A)	-0.045	0.168	-0.012
	(0.859)	(0.383)	(0.966)
Composite Heavy (B)	-1.260	-0.756	-1.026
	(0.015)	(0.082)	(0.082)
p-value (A-B)	0.023	0.034	0.088
Leverage Light	-0.087	-0.543	-0.295
	(0.850)	(0.107)	(0.561)
Leverage Heavy	-0.871	-1.689	-1.573
	(0.163)	(0.005)	(0.035)
Short Sales Light	0.817	0.727	1.062
	(0.283)	(0.124)	(0.190)
Short Sales Heavy	-2.071	0.204	-0.397
	(0.068)	(0.728)	(0.723)
Options Light	-0.788	-0.076	-0.572
	(0.024)	(0.794)	(0.140)
Option Heavy	-0.515	0.547	0.282
	(0.276)	(0.180)	(0.568)

Appendix Table 3
Option Strategies and Fund Performance

This table reports results from panel regressions of fund performance on dummy variables capturing different option strategies and a set of controls. All the explanatory variables are observed six months before the dependent variable. We use holdings information from CRSP to define funds as users of call and put, as long/short call and put, as user of covered/naked call and put strategies. A covered (naked) call is defined as a short position in a call with (without) a long position in the underlying equity security. A covered (naked) put is defined as a short position in a put with (without) a short position in the underlying equity security. Fund performance is measured by fund net returns in excess of the risk-free rate (1), four-factor alphas (2), and MPPM (3). All measures are computed using the daily fund net returns observed during a six-month period, reported on an annualized basis and expressed in percentages. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Call	-0.321	-0.013	-0.393
	(0.403)	(0.968)	(0.295)
Put	-1.901	-0.597	-1.255
	(0.001)	(0.113)	(0.021)
Bought Call	0.377	-0.349	-0.046
	(0.449)	(0.382)	(0.922)
Written Call	-1.607	0.220	-1.117
	(0.002)	(0.620)	(0.024)
Bought Put	-1.199	-0.083	-0.404
	(0.060)	(0.838)	(0.505)
Written Put	-0.703	-0.857	-1.029
	(0.352)	(0.143)	(0.202)
Covered Call	-0.066	-0.083	-0.186
	(0.875)	(0.808)	(0.645)
Naked Call	-1.986	0.622	-1.510
	(0.014)	(0.393)	(0.044)
Covered Put	-1.708	-0.534	-0.948
	(0.010)	(0.225)	(0.144)
Naked Put	-1.619	-0.954	-1.391
	(0.015)	(0.073)	(0.048)

Appendix Table 4
Complex Instrument Use and Expense Ratio

This table reports in column 1 results from panel regressions of fund net expense ratio on complex instrument use and a set of controls and in columns 2-4 results from panel regressions of fund performance on complex instrument use, expense ratio, and a set of controls. All the explanatory variables are observed six months before the dependent variable. Fund net expense ratio is calculated by subtracting expense reimbursements, interest expenses and other expenses from a fund's total expenses and scaling by the fund's total assets. The figure is then annualized. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We used an instrumental variable approach to control for endogeneity in columns 2-4. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage, expense ratio, and control variables. The table shows only the results for the second stage. Our set of controls (unreported in the table) includes the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of TNA in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. The first two rows reports results using our composite complex instrument dummy variable, which takes the value of one if at least one of the complex instruments under consideration is used. The next four rows report results for dummy variables capturing the use of leverage, short sales, and options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

		IV Results		
	Expense Ratio	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)	(4)
Composite	0.072	-1.331	-1.058	-1.585
	(0.000)	(0.010)	(0.011)	(0.008)
Expense Ratio		-1.279	-1.300	-1.418
		(0.000)	(0.000)	(0.000)
Leverage	0.007	-0.647	-1.127	-1.220
	(0.631)	(0.158)	(0.003)	(0.020)
Short Sales	0.136	-8.243	-2.652	-8.418
	(0.000)	(0.033)	(0.349)	(0.059)
Options	0.100	-0.979	-0.716	-0.465
	(0.000)	(0.321)	(0.367)	(0.672)
Expense Ratio		-1.044	-1.236	-1.418
		(0.000)	(0.000)	(0.000)

Appendix Table 5
Complex Instrument Use and Turnover Ratio

This table reports in column 1 results from panel regressions of fund turnover ratio on complex instrument use and a set of controls and in columns 2-4 results from panel regressions of fund performance on complex instrument use, turnover ratio, and a set of controls. All the explanatory variables are observed six months before the dependent variable. Fund turnover ratio is calculated from NSAR files. Fund performance is measured using net returns in excess of the risk-free rate (1), four-factor alphas (2), and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All measures are computed from daily fund net return data observed during a six-month period, reported on an annualized basis and expressed in percentages. We used an instrumental variable approach to control for endogeneity in columns 2-4. In the first stage, we regress fund complex instrument use in a semester on the proportion of other funds in the family using complex instruments and control variables. In the second stage, we regress fund performance on the predicted complex instrument use from the first stage, turnover ratio, and control variables. The table shows only the results for the second stage. Our set of controls (unreported in the table) includes the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of TNA in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. The first two rows reports results using our composite complex instrument dummy variable, which takes the value of one if at least one of the complex instruments under consideration is used. The next four rows report results for dummy variables capturing the use of leverage, short sales, and options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

		IV Results		
	Turnover Ratio	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)	(4)
Composite	0.200	-1.416	-1.064	-1.663
	(0.000)	(0.007)	(0.011)	(0.006)
Turnover Ratio		-0.491	-0.928	-0.632
		(0.000)	(0.000)	(0.000)
Leverage	0.129	-0.358	-0.887	-0.632
	(0.000)	(0.007)	(0.000)	(0.000)
Short Sales	0.529	-0.538	-0.949	-1.055
	(0.000)	(0.245)	(0.011)	(0.047)
Options	0.161	-8.397	-2.251	-8.440
	(0.000)	(0.031)	(0.418)	(0.058)
Turnover Ratio		-1.345	-1.182	-0.972
		(0.173)	(0.127)	(0.372)

Appendix Table 6
Complex Instruments and Higher Order Risk

This table reports results from panel regressions of higher order fund risk on complex instrument use and a set of controls. All the explanatory variables are observed six months before the dependent variable. Higher order fund risk is measured using skewness (1), and kurtosis (2) of fund returns. Both measures are computed from daily fund net return data observed during a six-month period. Our controls (unreported in the table) include the log of the fund's AUM, the log of the fund family's AUM, the log of the fund's age, the proportion of AUM in the institutional share classes, and fund flows. Additionally, we include time x fund-style fixed effects with fund style measured using the fund's CRSP objective code. For each column, two separate regressions are estimated. The first row reports results using our composite complex instrument dummy variable, which takes the value of one if at least one of the complex instruments under consideration is used. The next three rows report results for dummy variables capturing the use of leverage, short sales, and options. Standard errors are clustered at the fund level and *p-values* are reported below the coefficient estimates in parentheses.

	Skewness	Kurtosis
	(1)	(2)
Composite	-0.009	0.040
	(0.000)	(0.040)
Leverage	-0.002	-0.001
	(0.482)	(0.962)
Short Sales	-0.023	0.146
	(0.020)	(0.073)
Options	-0.011	0.115
	(0.000)	(0.000)

Appendix Table 7
Performance of Unconstrained and Constrained funds

This table presents the four-factor alphas of portfolio of funds sorted according the ABCC score or the composite score. The ABCC score is defined in Almazan et al. (2004). The composite score is defined in the main text and is based on whether a fund is allowed to use complex instruments such as leverage, short selling, and options. *p-values* are reported in parentheses.

	ABCC score	**Composite score**
Unconstrained	-0.999	-0.901
	(0.078)	(0.123)
Medium constrained	-0.338	-0.269
	(0.552)	(0.748)
Most constrained	-0.452	-0.319
	(0.406)	(0.554)
Most constrained - constrained	0.548	0.582
	(0.037)	(0.039)