Complex Instrument Allowance at Mutual Funds

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This draft: November 2019

Abstract

We study the loosening of restrictions on the use of leverage, derivatives, and illiquid assets by mutual funds. In contrast to previous studies, we find that the allowance of these complex instruments is associated with poor performance and higher risk. The underperformance is most acute during market downturns and among weakly monitored funds. We also find that mutual funds that actually use these instruments underperform. Overall, our results suggest caution in allowing funds to use these complex instruments.

JEL Classification: G11, G23
Keywords: mutual funds, complex instruments, leverage, derivatives, illiquid assets, borrowing, margin, short selling, options, futures, restricted securities, performance, risk

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1. Introduction

In 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 and derivatives, and invest in illiquid assets. The increase in the allowance of these *complex instruments*[1] raises the question of whether this trend has benefited or harmed mutual fund investors. On the one hand, Almazan, Brown, Carlson, and Chapman (2004, henceforth ABCC) examine complex instrument allowance and find that in aggregate they have no effect on fund performance. They argue that their findings provide support for an optimal contracting equilibrium where complex instrument restrictions substitute for fund monitoring. On the other hand, practitioners and regulators have raised concerns that allowing funds to use these instruments may expose investors to severe losses. Anecdotal evidence supports this concern, for example, the use of derivatives resulted in some funds suffering large losses during the 2008 subprime mortgage crisis.[2] In response to these concerns, the Securities and Exchange Commission (SEC) has proposed new rules designed to limit the amount of risk that funds can take as they pursue increasingly complex portfolio strategies.[3]

The goal of this paper is to reconcile the divergent views of the academic and practitioner/regulatory communities by examining the effect of complex instrument allowance on mutual fund performance. An important consideration is the market condition in the period in which complex instrument allowance is studied. Specifically, complex instruments allow investors to take leveraged positions, which work best during up markets, and as explained by Warren Buffet, "When leverage works, it magnifies your gains. Your spouse thinks you're clever, and your

[1] We use the term *complex instruments* to describe a variety of complicated investment strategies (leverage, derivatives, and illiquid assets) that mutual funds may adopt. The list is not exhaustive, but it is consistent with the list used by Almazan et al. (2004).
[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

neighbors get envious." "You only learn who has been swimming naked when the tide goes out."[4] ABCC's sample, which spans from 1995 to 2001, was a relatively strong market period during which the S&P 500 index earned an annualized return of 15.9%. Consequently, their results may be influenced by a small sample effect or "Peso Problem" (e.g., Krasker, 1980) which could misrepresent the returns earned from complex investment strategies. Our sample period, which spans from 2000 to 2015, is longer than ABCC's and includes both bull and bear markets, and is therefore less susceptible to these issues.[5]

We extract information on the allowance of leverage, derivatives, and illiquid securities at domestic equity funds from SEC filings (Form N-SAR).[6] We use this information to compute two measures of complex instrument allowance, which are equivalent to ABCC's measures and capture whether a fund is allowed to use these instruments. We first focus on the relation between allowance and performance. Using portfolio and OLS regression approaches, we find that less constrained funds underperform more restricted funds. In particular, being allowed to use these instruments is associated with 1.26% lower annual excess returns and 0.84% lower Carhart (1997) four-factor alphas. We also find a negative relation between complex instrument allowance and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). This measure is robust to potential biases created by nonlinearity and asymmetry likely to be present in the returns for funds that use complex instruments.

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[4] The first quote is from the Chairman's Letter in the 2010 Berkshire Hathaway Annual Report (http://www.berkshirehathaway.com/letters/2010ltr.pdf). The second quote is from the Chairman's Letter in the 2010 Berkshire Hathaway Annual Report (http://www.berkshirehathaway.com/letters/2007ltr.pdf).

[5] Our sample begins in 2000, rather than 1994, due to availability of daily mutual fund net-return data (available only from the end of 1999), which we use to compute our performance and risk measures.

[6] Form N-SAR is a semi-annual report that mutual funds are required to file with the SEC. The form is available at https://www.sec.gov/about/forms/formn-sar.pdf.

We next present results that shed light on what drives this underperformance and, at the same time, attempt to reconcile our findings with those of ABCC. We consider the concerns raised by practitioners and regulators that complex instrument allowance can encourage risk taking, and that higher levels of risk can expose funds to large losses during market downturns. To test if this is the case, we first examine the relation between complex instrument allowance and fund risk. We measure risk along three dimensions, the fund's standard deviation, beta exposure, and idiosyncratic risk. We find that allowance and risk are positively related, which provides support for the concerns raised about complex instruments. Next, we analyze the impact of market downturns on the allowance-performance relation. Investors who take large risks are likely to be penalized during market downturns. We condition our results on up and down markets and find that allowance is associated with large losses during market downturns, which is consistent with our prediction. We do find some evidence of more positive returns during good market conditions among funds that are allowed to use complex instruments. However, the magnitude of the effect is much smaller than the effect observed during downturns, suggesting that the overall negative relation we observe is driven by large losses during market downturns.

Complex instrument allowance may change in response to or in anticipation of fund performance, which raises endogeneity concerns. The fact that allowance is governed by fund bylaws, which are usually set at the fund's inception and change infrequently, mitigates these concerns. Nevertheless, for robustness, we conduct two additional sets of analyses. First, we estimate a model with the inclusion of fund fixed effects. This specification allows us to isolate within fund "before-and-after" effects of changes in complex instrument allowance. For example, if our results are driven by poorly performing funds being granted allowance, we should observe no relation between allowance and performance after the inclusion of fund fixed effects. We find that our performance and risk results persist after including fund fixed effects.

Fund fixed effects do not control for the possibility that fund allowance changes in anticipation of future performance. Although we are skeptical of this explanation, especially given the unpredictability of returns, we also implement an instrumental variable methodology to isolate the causal nature of the allowance-performance relation. For our instrument, we use the mean allowance score of other funds in the same fund family. We expect that this instrument is related to the likelihood that a fund uses complex instruments, but not to the fund's performance. Using this approach, we continue to find a negative relation between allowance and fund performance, which further mitigates the endogeneity concern.

We conduct two additional sets of tests to better understand the mechanisms that drive our results. First, we partition our measure of allowance into the individual components of leverage, derivatives, and illiquid assets and consider their individual effects on fund returns. We find that the allowance of derivatives, arguably the most complex of the instruments, is associated with significant underperformance and increased fund risk. Unsurprisingly, we find that the allowance of leverage is associated with higher levels of fund risk, but do not observe a significant effect on fund performance. We do not observe significant relations between the allowance of illiquid assets and fund performance or risk.

Second, we consider the relation between fund monitoring and complex instrument allowance. The negative relation between allowance and fund performance is inconsistent with the optimal contracting equilibrium, posited by ABCC, existing in our sample period. However, it is unclear if allowance and monitoring remain substitutes. We conduct two tests to address if this is the case. First, we estimate a deterministic model of complex instrument allowance using proxies for fund monitoring quality as our independent variables of interest: institutional fund ownership, board independence, and fund family size. Consistent with ABCC's finding that allowance and monitoring are substitutes, we find that monitoring quality is positively related to allowance. Second, we estimate a regression model where we interact our proxies of fund monitoring quality with our measure of complex instrument allowance. The results indicate that the negative impact of complex instrument allowance on fund performance is mitigated in the presence of strong monitoring, which we interpret as being consistent with substitution.

Last, we consider the effect of complex instrument use on fund performance. We create a measure of complex instrument use, the Use Score, which is defined as the proportion of the six complex instruments that a fund uses in a given semester. Our results show that, like fund allowance, fund use is associated with lower returns. This result is robust to a specification that includes fund fixed effects and a specification that is estimated with an instrumental variable approach. Furthermore, we find that the negative association between complex instrument use and performance is also concentrated in down markets. These results are consistent with the negative relation between complex instruments and fund performance being, at least partially, driven by the actual use of these instruments. However, we also find that funds that are allowed but that do not use complex instruments underperform, which suggests that other indirect factors may be at play.

Our paper makes two contributions to the literature that examines the effect of complex investment strategies on mutual fund performance (e.g., Koski and Pontiff, 1999, Chen et al., 2013, Cici and Palacios, 2015, and Natter et al., 2016).[7] This strand of literature has found that complex

[7] Koski and Pontiff (1999) were the first to study the use of derivatives by equity mutual funds. They document that derivative users have risk exposure and return performance that are similar to non-users. 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).

instruments have either a neutral or a positive effect on fund performance. Our results provide new evidence that access to these instruments can actually be harmful to fund shareholders. We also contribute to this literature by examining a broad set of complex instruments, whereas nearly all the existing literature has examined the use of individual instruments such as derivatives or short sales. We argue that focusing on a broad set allows for a more comprehensive analysis as a large portion of funds have been given access to multiple instruments. For example, we find that 94% of funds in our sample have access to restricted assets, 91% to options, 87% to borrowing, 85% to futures, 61% to short sales, and 22% to margin.

Several factors motivate our focus on allowance rather than use. First, there is an endogeneity concern. The use of complex instruments is a choice actively and frequently made by the fund manager and may be driven by fund performance. For example, the theory on tournament incentives (e.g., Brown et al. 1996) suggests that managers may use the instruments in response to fund performance. These incentives limit our ability to make causal inferences on the relation between use and fund performance. Second, complex instrument use may be associated with window dressing (Agarwal et al., 2014), and the limited data on complex instrument holdings makes it challenging to measure their contribution to fund performance.[8] Third, allowance is under the control of fund shareholders (through bylaws) and regulators, whereas use is at the discretion of the fund managers. Therefore, knowing how allowance is related to fund performance is important for shareholders and regulators as they consider changes in allowance. Fourth, examining allowance captures not only the direct impact of use on performance, but also indirect channels through which complex instruments affect the fund. For example, as we elaborate on in

[8] The SEC is in the process of reforming mutual fund disclosure on complex instruments with the introduction of Form N-PORT that will require funds to disclose detailed terms of derivative contracts, among other things. Filing Form N-PORT through the EDGAR system will begin in April 2019 for larger fund groups and in April 2020 for smaller fund groups. For more information, see https://www.sec.gov/rules/interim/2019/ic-33384.pdf.

the next section, some managers may take more risk (e.g., increase the exposure to high-beta securities) when they feel safer by having access to instruments that provide insurance.

2. Motivation

The existing literature highlights several potential positive and negative effects that complex instruments may exert on fund performance. Among the benefits, investors may use complex instruments to efficiently exploit superior information and take advantage of market inefficiencies. These instruments allow investors to increase risk exposure through implicit or explicit leverage. Short sales, options, and futures also allow investors to execute bearish bets, which are difficult to access and can be highly profitable (Drechsler and Drechsler, 2014). Furthermore, investors can use these instruments to reduce transaction costs (Merton, 1995), and costs associated with fund flows and the opportunity cost of holding cash (Deli and Varma, 2002). All of these effects predict that access to these instruments will improve fund performance.

Complex instruments also have the potential to harm fund performance. Liu (2015) examines the optimal use of investment constraints in delegated portfolio management using a theoretical framework. In the model, fund managers are exposed to noise-induced compensation risk, which deters long-term information acquisition, and imposing investment restrictions can mitigate these effects. A corollary of this prediction is that the removal of complex instrument restrictions decreases incentives to acquire long-term information and thus harm investors.

Complex instruments may also harm fund investors if managers do not fully understand the effects of complex instruments on the return distribution or if they are competing against more skilled counterparties. For example, they may trade against hedge funds who are typically active users of complex instruments and who are considered among the most sophisticated institutional investors (e.g., Akbas et al., 2015, and Calluzzo et al., 2019). Similarly, portfolio insurance demands may create overpricing in the markets for some of these instruments that would reduce returns (Bollen and Whaley, 2004). It is also possible that trades in these instruments generate high administrative and transaction costs (e.g., Koski and Pontiff, 1999), which negatively impact fund performance.

Complex instruments may also affect fund risk and exacerbate agency costs. The leverage embedded in many of the instruments makes it easier for managers to speculate. These instruments may thus aggravate the moral hazard problem identified in the delegated portfolio management literature, as fund managers may increase fund risk exposure when the risk is borne by fund shareholders (e.g., Palomino and Prat, 2003). Also, Brown et al. (1996) and Chevalier and Ellison (1997) show that tournament incentives may cause poorly (well) performing funds to increase (decrease) fund risk.[9] Access to complex instruments may also enable opportunistic managers to alter the risk-return distributions of their portfolios in ways that are detrimental to shareholders.

Many of the complex instruments also have insurance-like properties. On the one hand, buying these instruments may reduce risk if funds use the instruments to hedge (e.g., buying a put option on a stock the fund owns). On the other hand, risk compensation or offsetting behavior theory predicts that the insurance-like properties of these instruments will cause managers to take more risk when they feel protected (e.g., Peltzman, 1975). For example, Peterson et al. (1995) find that drivers of airbag-equipped cars are more aggressive, which offsets the safety benefits of this feature. It is an empirical question, which we address in this paper, of whether risk compensation effects outweigh risk-reduction benefits.

[9] The literature has considered other factors that may influence risk shifting. For example, Taylor (2003) formulates a model where winning funds are more likely to gamble than losing funds because of strategic interactions between the funds. Kempf et al. (2009) show that poorly performing funds will not increase fund risk if they face employment risk.

ABCC report no difference in performance between funds that are restricted and unrestricted in their access to complex instruments. They interpret this finding as evidence that an optimal contract exists between investors and managers, and that in equilibrium investment restrictions substitute for monitoring (i.e., poorly monitored funds are restricted). We revisit this question using a larger and more recent sample. We also extend their empirical contribution by examining the effect of allowance on fund risk.

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. We extract data on mutual funds' investment practices from the SEC's Form N-SAR that registered investment companies must file on a semi-annual basis. Throughout the paper, we refer to each semi-annual period as a semester. We download these filings from the SEC's EDGAR FTP server and extract data on investment practices. In particular, Question 70 asks whether a mutual fund had the authorization to use different complex instruments during the reporting period.[10] We focus on the following complex instruments: leverage (grouping together borrowing, margin, and short selling), derivatives (grouping together options on equities and stock index futures), and illiquid assets.[11,12]

[10] The Investment Company Act imposes restrictions beyond the voluntary investment restrictions that mutual funds can adopt. 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, futures, and short selling are regulated as forms of leverage. Open-end funds that use leverage must maintain asset coverage of at least 300%.

[11] Borrowing is identified using Question 70O and does 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. Question 70Q, 70R, 70B, 70F, 70J identify margin purchases, short selling, writing or investing in options on equities, writing or investing in stock index futures, and investments in restricted securities, respectively.

[12] We follow ABCC and do not include questions 70G (options on futures) and 70H (options on stock index futures) when we construct our allowance score. Our results are robust to their inclusion.

We first calculate an aggregate score measure equivalent to ABCC (see footnote 3 in their paper), which we call the ABCC Score. The measure is computed in two steps. First, we construct a dummy variable for each instrument's allowance. We then aggregate these dummy variables, using as weights the percentage of funds that actually used a given complex instrument in the semester. Data on complex instrument use in a semester are also disclosed in Question 70 of Form N-SAR. We also construct a second allowance measure that is equivalent to the primary allowance measure used by ABCC, which we call the ABCC Score (Equal weighted). To compute this measure we assign equal weights to leverage, derivatives, and illiquid assets, rather than weighting by their actual use. Specifically, we assign a one-ninth weight to each of three leverage instruments, a one-sixth weight to each of the two derivative instruments, and a one-third weight to the illiquidity instrument. We acknowledge the somewhat arbitrary nature of both of these measures, but think it is important to be consistent with the measures employed by ABCC. By construction, both scores lie between zero and one and a higher score indicates a less constrained fund. In this way our allowance score is different from ABCC's who constructed their measure in terms of restrictions. Each of our measures of allowance is equal to one minus the corresponding ABCC measure of restriction. We prefer to frame the measures in terms of allowance given the trend towards increasing allowance that has been present in the mutual fund industry.

Our sample includes N-SAR forms filed from January 2000 through December 2015 for a total of 104,849 individual filings.[13] Because of the semi-annual reporting requirement of Form N-SAR, our dataset is structured at the semi-annual fund level. We drop filings if they are filed more than 90 days after the end of the reporting period and if balance sheet items are not reported

[13] There are two N-SAR forms. The N-SAR-A is usually filed in June and covers the first half of the reporting year. N-SAR-B is usually filed in December and covers the full reporting year. However, in the case of a fiscal year end that does not align with these months, we use data from the most recent filing preceding either June or December. In unreported tests, we find that the results are unaffected by the different reporting periods.

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 ensure 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), and funds that have more than 50% of their net assets at the end of the current period invested in the securities of issuers engaged primarily in the production or distribution of precious metals (Question 68.A), or in the securities of issuers located primarily in countries other than the United States (Question 68.B). We also exclude index funds (Question 69). We further check the fund names and drop funds 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. 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 to obtain additional fund characteristics such as net returns. Given that there is no common identifier between N-SAR and CRSP, the matching is done using tickers and 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 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.[14] The final sample includes 4,793 funds for 61,980 fund-semester observations. This is significantly larger than the sample used by ABCC, which consists of 4,800 fund-year observations.

We use daily net mutual fund returns from CRSP to compute performance and risk measures.[15] Given the semi-annual frequency of the filings, we compute the performance and risk measures every six months requiring a minimum of 100 daily observations. Using data at the daily frequency is important to obtain more precise estimates of the fund risk measures (e.g., Busse 1999 and 2001). Furthermore, obtaining the measure every semester allows us to use panel data regressions, which are able to capture the time-series variation in the relation between complex instrument allowance and outcomes, and allows us to control for other factors that may affect fund performance. We compute three measures of fund performance based on daily net returns: excess return defined as the net fund return minus the risk free rate, the fund's Carhart (1997) four-factor alpha, and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). The MPPM is more difficult to manipulate and addresses the concern that the nonlinearity and asymmetry in the returns associated with complex instruments could create a bias in the four-factor alphas.[16]

[14] 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).

[15] 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.

[16] 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 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).

Figure 1 reports time-series trends in the allowance of complex instruments by funds. Over our 16-year sample period, there has been an increase in the ABCC Score, from 0.75 in 2000 to 0.87 in 2015. Because of the difficulty of interpreting the ABCC Score, we also compute the proportion of funds allowed to use all six instruments. The proportion of these funds increased from 0.08 in 2000 to 0.21 in 2015. Few funds are allowed to use margin. If we exclude margin we see that the proportion of funds allowed to use all of the other five instruments increased from 0.26 to 0.60. Taken together these figures indicate that funds have increasingly been given access to complex instruments. In unreported statistics, we also examine the change in the allowance of the six individual instruments. We find that the allowance of all six instruments increased over our sample period, with the largest increases occurring in short sales (from 0.37 to 0.71),[17] margin (from 0.11 to 0.27), and futures (from 0.73 to 0.88). In unreported results, we also examine trends in complex instrument use over time. We find that complex instrument use has been relatively stable over the sample period. For example, the proportion of funds that use at least one complex instrument was 0.35 in 2000 and 0.37 in 2015.

Table 1 presents summary statistics for the variables that we use in the empirical analyses. We report a mean ABCC Score (Equal Weighted) of 0.79, which is larger than the corresponding 0.64 mean allowance score reported by ABCC (Table 1, Panel A of their paper), and consistent with the trend towards increased allowance. Our fund characteristics are defined as follows: Fund Size – assets under management (AUM), as reported in Question 74N in Form N-SAR; Fund Family Size – the aggregate fund size within the fund's family as classified by CRSP; Fund Age

[17] 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.

– the number of years since the fund's inception as reported by CRSP; Institutional Ownership – the proportion of fund's AUM composed of institutional share classes as reported by CRSP; Fund Flows – the proportional change in the fund's AUM adjusted for the return of the fund as in Chevalier and Ellison (1997); and Board Independence – the proportion of a fund board's directors that are independent.[18]

4. Complex Instrument Allowance and Fund Performance

4.1 Univariate Performance Analysis

We first examine the relation between complex instrument allowance and fund performance. In this section, we present results for portfolio sorts. Every semester we sort funds based on their ABCC Score. Similar to ABCC, we consider two portfolios according to the median score. Funds with a score below (above) the median are classified as the most (least) constrained funds. At the end of each semester, we weight each fund in the portfolio proportional to the distance between the fund's score and the median, and use these weights to compute daily excess returns over the following semester.[19] The excess return reported in Table 2 is the annualized time series average of each portfolio. We also use the daily time series to compute four-factor alphas and the MPPM measure for the two portfolios.[20]

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[18] Our measure of board independence is obtained from Calluzzo and Dong (2014). They define a director as being independent if she is not listed in the Capital IQ database as being a fund employee, and if she is not listed in the 10-K form of an investment company as an officer of that company. This definition is slightly different from the SEC definition of independence, which identifies an independent director as one who does not "currently have, or at any time during the previous two years have had, a significant business relationship with the fund's adviser, principal underwriter (distributor), or affiliates. An independent director also cannot own any stock of the investment adviser or certain related entities, such as parent companies or subsidiaries." Their dataset only covers a sample period through 2011, which restricts the sample size of this analysis. We do not include board independence as a control variable in our regressions because of this restriction.

[19] In an untabulated analysis, we tried to use monthly data instead of daily data. We also tried to use terciles instead of two groups based on the median. Both cases deliver similar results for the spread portfolio that goes long in the least constrained funds and short in the most constrained funds.

[20] Given that the MPPM measure is the log of an average we cannot use a t-test to compute p-values, and therefore use bootstrapping.

Table 2 presents the results. We find that the least constrained funds underperform the most constrained funds. The difference in performance is statistically significant and is approximately -0.80% per year considering excess return and four-factor alpha. The larger estimate when using MPPM (-3.02%) is consistent with potential bias in the four-factor alpha in the presence of nonlinearity and asymmetry in the returns associated with complex instruments. We also compute the returns using the ABCC Score (Equal weighted), which we report in Panel B, and find very similar results. Hereafter, we only report results for the use-weighted ABCC Score. We prefer to use the use-weighted measure so as not to assign a sizeable weight to instruments that are rarely used. For example, given how infrequently margin is used (0.34% of observations) relative to borrowing (8.56% of observations), its allowance will likely be less impactful than the allowance of borrowing, and it is therefore sensible to assign less weight to its allowance (as the use-weighted ABCC Score does). Nevertheless, all of our subsequent results are robust to using either measure.

4.2 Multivariate Performance Analysis

Next, we estimate panel regressions to further analyze the relation between allowance and fund performance. The panel regression allows us to control for other factors that may affect fund performance. Our dependent variables are the three measures of fund performance computed from daily net returns: excess returns, four-factor alphas, and MPPM. Our independent variable of interest is the ABCC Score. Our control variables are lagged one semester and 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. The regressions take the following form where i indicates the fund and t refers to the semester:

[21] We exclude expense ratio and turnover ratio from our set of control variables. The rationale behind this decision is that these ratios are channels through which allowance affects performance, as ceteris paribus higher fees and more transactions will harm firm performance. Consistent with this prediction, in unreported tests we show that the ABCC

$$Fund\ Performance_{i,t} = \beta_0 + \beta_1 ABCC\ Score_{i,t} + \sum_{k=2}^{1+K} \beta_k \cdot Controls_{i,k,t-1} + FE_{Fund\ Style*Time} + \varepsilon_{i,t} \quad (1)$$

The first row of Table 3 presents our coefficient estimates for the ABCC Score. Consistent with the univariate results, the coefficient estimates show that complex instrument allowance is associated with significantly negative excess returns. Specifically, an ABCC Score of one – which corresponds to a fund being allowed to use all six complex instruments – is associated with an economically significant reduction of 1.34% (0.89%) [1.96%] per year in excess return (four-factor alpha) [MPPM].

5. Complex Instrument Allowance, Risk, and Market Conditions

Our findings contrast with those of ABCC. In this section, we present tests that shed light on why this is the case. We posit that the disparity may be driven by a "Peso Problem" in ABCC's sample. Specifically, their sample period mostly spans a bull market. If complex instrument allowance encourages risk taking, the negative effects associated with higher risk may have been masked by ABCC's sample period. In contrast, our sample includes both bull and bear markets and is likely more representative of the overall distribution of returns. We first present tests that examine the relation between allowance and risk. We then examine the effect of allowance on fund performance in up and down markets.

5.1 Complex Instrument Allowance and Fund Risk

Score is positively associated with each ratio. We also find that our main results are robust (although as expected the magnitudes of our estimates are smaller), when we include each ratio in the regression.

To test the relation between complex instrument allowance and fund risk, we use the same regression framework of equation (1) but replace the dependent variable with 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 computed as the standard deviation of the residuals from the four-factor model. Table 4 presents the results of our analysis. Consistent with allowance increasing fund risk, we find a positive and statistically significant relation between the ABCC Score and the fund's standard deviation. Furthermore, we find that the increase in total risk is driven by an increase in systematic risk as allowance is significantly related to fund beta, but not to idiosyncratic volatility. This result is consistent with two, non-mutually exclusive, explanations: that complex instruments provide leverage and/or that they lead to risk compensation effects at mutual funds.

5.2 Complex Instrument Allowance and Market Conditions

We next present tests that separately examine the effect of allowance in different market conditions. We define an Up (Down) Market as a semester where the average mutual fund in our sample had positive (negative) excess returns. We then estimate equation (1), replacing the ABCC Score with its interaction with Up Market and Down Market dummies. The Up Market and Down Market dummies are subsumed by the time-fixed effects, and are therefore not included in the regression. Consistent with higher risk amplifying returns, the results presented in Table 5 show that allowance is associated with positive returns in good markets, but negative returns during poor market conditions. However, the magnitude of the effect under the two market regimes is not symmetrical. For excess returns (four-factor alpha) [MPPM] the coefficient on Up Market*ABCC Score is 1.27 (0.32) [0.94] and is much lower in absolute value than the coefficient on Down Market*ABCC Score, which is -5.24 (-2.69) [-6.28]. This result suggests that the benefit of complex instruments in up markets is not sufficient to compensate funds for the losses they incur during down markets, even after considering the fact that up markets are more common (62% of semesters) than down markets in our sample period.

6. Additional Tests

6.1 Endogeneity Concerns

Fund bylaws that govern complex instrument allowance are set at the fund's inception, change infrequently, and are not directly controlled by the fund manager.[22] These institutional features limit concerns about endogeneity, nevertheless, we cannot completely rule out the concern. For example, the decision to grant complex instrument allowance may be driven by past fund performance or expectations about future performance. In this section, we present two sets of analyses aimed at addressing the endogeneity concern.

6.1.1 Fund Fixed Effects

First, we estimate the model with the inclusion of fund fixed effects. This specification allows us to assess the impact of within-fund changes in the ABCC Score on fund performance. If unobservable fund characteristics, rather than complex instrument allowance, drive our results, then we should observe poor performance both when a fund's ABCC Score is low and when it is high. In contrast, if allowance drives our results, we should observe that funds perform worse (better) when their allowance score is higher (lower). Table 6 reports the results of this analysis. Consistent with a causal relation between complex instrument allowance and fund performance, we find that the coefficient on the ABCC Score is negative and statistically significant. Furthermore, in unreported tests we find that our other results − the positive relation between

[22] We find that ABCC Score (Equal weighted) for a fund changes, on average, once every eight years. Our fund fixed effects analysis in the next subsection implicitly examines how these changes affect fund performance.

allowance and fund risk and the concentration of poor performance in down markets − are also robust to the inclusion of fund fixed effects.

6.1.2 Instrumental Variable Approach

The fund fixed effect specification does not address the concern that allowance is related to expectations of future fund performance. There is not a strong case for why fund families would grant allowance when they anticipate poor fund returns, or if they are even able to anticipate poor returns. Nevertheless, we address this concern by employing a two-stage instrumental variable approach. We select the mean ABCC Score of other funds within the mutual fund's family to serve as our instrument. This instrument is a good predictor of complex instrument allowance given that funds within a family are likely to share trading desks. When other funds have allowance, the facilities to trade the instruments will be in place and the marginal cost of other funds accessing the instruments will decrease (see Koski and Pontiff, 1999). 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 allowance. In the first stage, we regress a fund's complex instrument allowance in a semester on the mean ABCC Score of the other funds in its family and control variables:

$$ABCC\ Score_{i,t} = \alpha_0 + \alpha_1\ Family\ ABCC\ Score_{i,t}$$

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

In the second stage, we replace ABCC Score with the value instrumented by the family ABCC Score:

$$Fund\ Performance_{i,t} = \beta_0 + \beta_1 \cdot Predicted\ ABCC\ Score_{i,t}$$

$$+\sum_{k=2}^{1+K}\beta_k \cdot Controls_{i,k,t-1} + FE_{Fund\ Style*Time} + \varepsilon_{i,t} \quad (3)$$

Control variables include those used in our main tests. The first column of Table 7 presents the results for the first stage of the regression. As anticipated, we find that the family's ABCC Score is a strong (and positive) predictor of the fund's ABCC Score. In columns two through four, we examine the relation between predicted allowance and fund performance. Consistent with our main results, we find a negative relation. Taken together with the earlier analysis, these results suggest that allowance contributes to poor fund performance, which is detrimental to fund shareholders. In unreported tests, we also use the instrumental variable approach to examine the relation between allowance and fund risk and continue to find that the two are positively associated.[23]

6.2 The Individual Effects of Leverage, Derivatives, and Illiquid Asset Allowance

The individual complex instruments are distinct in nature. The ABCC Score addresses their distinctness by categorizing them into three groups: leverage, derivatives, and illiquid assets. In this section, we consider the impact of the allowance of each category on fund performance. To do so we estimate the model in equation (1), replacing ABCC Score with variables for leverage, derivatives, and illiquid assets. The variables are defined as the proportion of the instruments within each category the fund is allowed to use. We find a negative relation between derivative allowance and performance (see Table 8). For excess return (four-factor alpha) [MPPM] the coefficient is -1.43 (-0.53) [-1.71] and statistically significant. In contrast, we do not observe a significant relation between leverage and illiquid security allowance and fund performance. In

[23] In additional unreported tests, we instrument for allowance using the mean ABCC Score of other funds in the same style class. Our results also hold in this specification.

unreported tests, we also examine the relation between the six individual instruments and fund performance. The results show that the two instruments classified as derivatives (options and futures) are both associated with negative performance. The relation between the other four instruments and performance is statistically insignificant. It is an outstanding question of why derivative allowance is associated with lower performance than the other instruments. We leave it to future research to disentangle the mechanisms that drive this result.

We also examine the relation between the individual categories and fund risk. The results of this analysis are presented in the last three columns of Table 8. Unsurprisingly, we find that the leverage allowance is associated with higher fund risk across our three risk measures. We also find that derivatives are associated with significantly more fund risk when measured by standard deviation and beta exposure. However, we find that derivatives are associated with significantly lower idiosyncratic volatility. This result is also unsurprising given that stock index futures, which should have very little idiosyncratic volatility, are included in the derivatives category. We find no relation between illiquid securities and our three risk measures.[24]

6.3 Complex Instrument Allowance and Monitoring Quality

Our results do not support the optimal contracting equilibrium postulated by ABCC in which monitoring quality and investment restrictions are perfect substitutes. Nevertheless, it is possible that the two are substitutes, albeit imperfectly. In this section, we examine if this is the case by exploring the relation between complex instrument allowance and monitoring quality.

[24] In additional unreported tests, we replicate the up and down market results with the individual classifications, and find that derivative allowance also drives the down market result. Although leverage allowance is associated with more risk, we find that the magnitude of the coefficients on leverage in up and down markets are of similar scale and smaller than the coefficients for derivatives.

First, we explore the determinants of complex instrument allowance. If investment restrictions and monitoring quality are substitutes, we expect to find a positive relation between a fund's monitoring quality and ABCC Score. To do so, we estimate an OLS regression model where the fund's ABCC Score is the dependent variable, and the independent variables of interest are proxies for fund monitoring quality.[25] We use three measures to proxy for fund monitoring quality: (1) the proportion of fund shares owned by institutional shareholders; (2) the log of the AUM of the fund's family; and (3) the proportion of the fund's directors who are independent. Evans and Fahlenbrach (2012) highlight the monitoring role of institutional investors at mutual funds, and their ability to reduce agency costs. Furthermore, several papers, including ABCC, have used fund family size and board independence to gauge fund monitoring quality. We also include our controls and fixed effects from equation (1). The results of the model are reported in Table 9 and support the substitution hypothesis. Specifically, we find that all three measures of fund monitoring quality are positively and significantly related to allowance.

Next, we consider if fund monitoring quality affects the relation between allowance and fund performance. The substitution hypothesis implies that well monitored funds are allowed to use the instruments because the monitoring mechanism will prevent them from abusing the instruments. The flip side of this prediction is that if poorly monitored funds are granted allowance they may abuse them, and that we should observe cross-sectional differences in the allowance-performance relation when we condition on monitoring quality. To test this prediction, we estimate equation (1) including the interaction of the three monitoring variables with the fund's ABCC Score.

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[25] Given ABCC Score is bounded between 0 and 1, we also estimate a Tobit regression model and find that our results are robust.

The first row of Table 10 presents the coefficient estimates for the interaction of institutional fund ownership and ABCC Allowance Score. The coefficient on the interaction variable is positive and statistically significant across all three performance measures. We find similar results, albeit with weaker significance, when we examine the effect of board independence (second row of Table 10), and fund family size (third row of Table 10). The magnitude of this effect is such that there is no negative effect (rather than a positive effect) associated with complex instrument use in well governed funds. The finding that the negative association between allowance and performance is most acute in poorly monitored funds and mitigated in well monitored funds provides some support for ABCC's substitution hypothesis. However, the fact that we find a negative relation between allowance and performance in the full sample suggests the substitution effect is imperfect.

7. Complex Instrument Use

In this section we consider the effect of complex instrument use on fund returns to see whether the underperformance of funds allowed to use complex instruments is driven by funds actually using these instruments. We construct a new variable, Use Score, which measures the proportion of the six complex instruments that are actually used in a given semester.[26] We extract information on fund use of the instruments each semester from Question 70 of Form N-SAR. We then replicate our main results, replacing the ABCC Score with the Use Score in each regression.

Table 11 presents the results of this analysis. The first row replicates our baseline analysis which was presented in Table 3. The coefficient estimates show that the Use Score is associated with significantly negative excess return (-1.79%), four-factor alpha (-1.14%), and MPPM (-

[26] Ideally, we would prefer to use the magnitude of use for each instrument as weights, but the data are not readily available.

1.61%). These results suggest that the actual use of complex instruments is associated with negative fund performance. In the second row of Table 11, we replicate our specification that includes fund fixed effects. We continue to find that the Use Score is associated with underperformance. Furthermore, the magnitude and statistical significance of the results increase with respect to the four-factor alpha and MPPM specifications. This result can be interpreted as, within each fund, performance is worse when the managers use complex instruments than when they do not use them.

Because mutual fund managers actively choose to use these instruments, it is difficult to disentangle whether the use of these instruments is the cause or a symptom of poor performance. As discussed in the introduction, this concern partially drives our decision to focus most of the analysis of the paper on complex instrument allowance, which is not directly controlled by fund managers. As we do earlier in the paper for allowance, we use a two-stage instrumental variable approach to address the endogeneity concerns. We select the mean Use Score of other funds within the mutual fund family to serve as our instrument. In unreported first-stage results, we find that the instrument is a strong predictor of complex instrument use. The third row of Table 11 reports the coefficient estimates for predicted Use Score. The coefficients are statistically and economically significant for Excess Return and MPPM, but statistically insignificant for the four-factor alpha regression.

The last two rows of Table 11 report results for the up and down market interactions with the Use Score. As with the coefficient estimates for the ABCC Score interactions, the estimates for the interaction of Use Score and down market are negative and statistically significant at the one percent level for all three return measures, and substantially larger in magnitude than the positive coefficients on the up market interactions. This result provides additional evidence that the negative returns associated with complex instruments are driven by the "tide going out" in bad markets.

In untabulated tests, we also consider whether funds that are allowed to use complex instruments but that do not actually use them also underperform. Specifically, we split the ABCC Allowance Score into two components. One component captures the score of mutual funds that are allowed but that do not use complex instruments, while the other component captures the score of mutual funds that use complex instruments in a given semester. The results suggest that funds that are allowed but that do not use complex instruments also underperform. For example, in the base case regression, both components are statistically significant with an alpha of -0.84% for the non-users and -0.95% for the users. This finding is consistent with the underperformance also being driven by indirect channels.

8. 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 of higher risk. This negative potential has raised concerns at the SEC, which has considered reforms designed to limit access to complex instruments in an effort to protect the investors in these funds. Whether the allowance of complex instruments help or harm fund shareholders is ultimately an empirical question that we address in this paper using a comprehensive dataset of mutual funds that are given access to leverage, derivatives, and illiquid assets.

Our results suggest that the concerns are justified. Allowance is associated with lower performance and greater risk taking. The negative effects are magnified during market downturns and when the funds are poorly monitored. Warren Buffet is famously quoted as stating:

"derivatives are financial weapons of mass destruction."[27] The poor shareholder outcomes associated with complex instrument allowance provide ammunition for this claim, and it appears mutual fund investors are better off choosing simplicity.

These findings raise the question of why there has been a trend towards more complexity in the mutual fund industry if these instruments are associated with poor performance. One explanation is that these funds cater to an investor bias for 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. Another explanation is that mutual fund investors do not realize that complex instruments can be harmful to their interests. In this regard, the results of our paper provide useful information to investors. One possible solution to this problem, as implied by our results and ABCC, is to constrain access to complex instruments in poorly governed funds.

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

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Figure 1
Complex Instrument Allowance over Time

This figure reports the average ABCC Score, the average ABCC Score (Equal weighted), the proportion of funds allowed to use all six instruments, and all instruments excluding margin over the sample period.

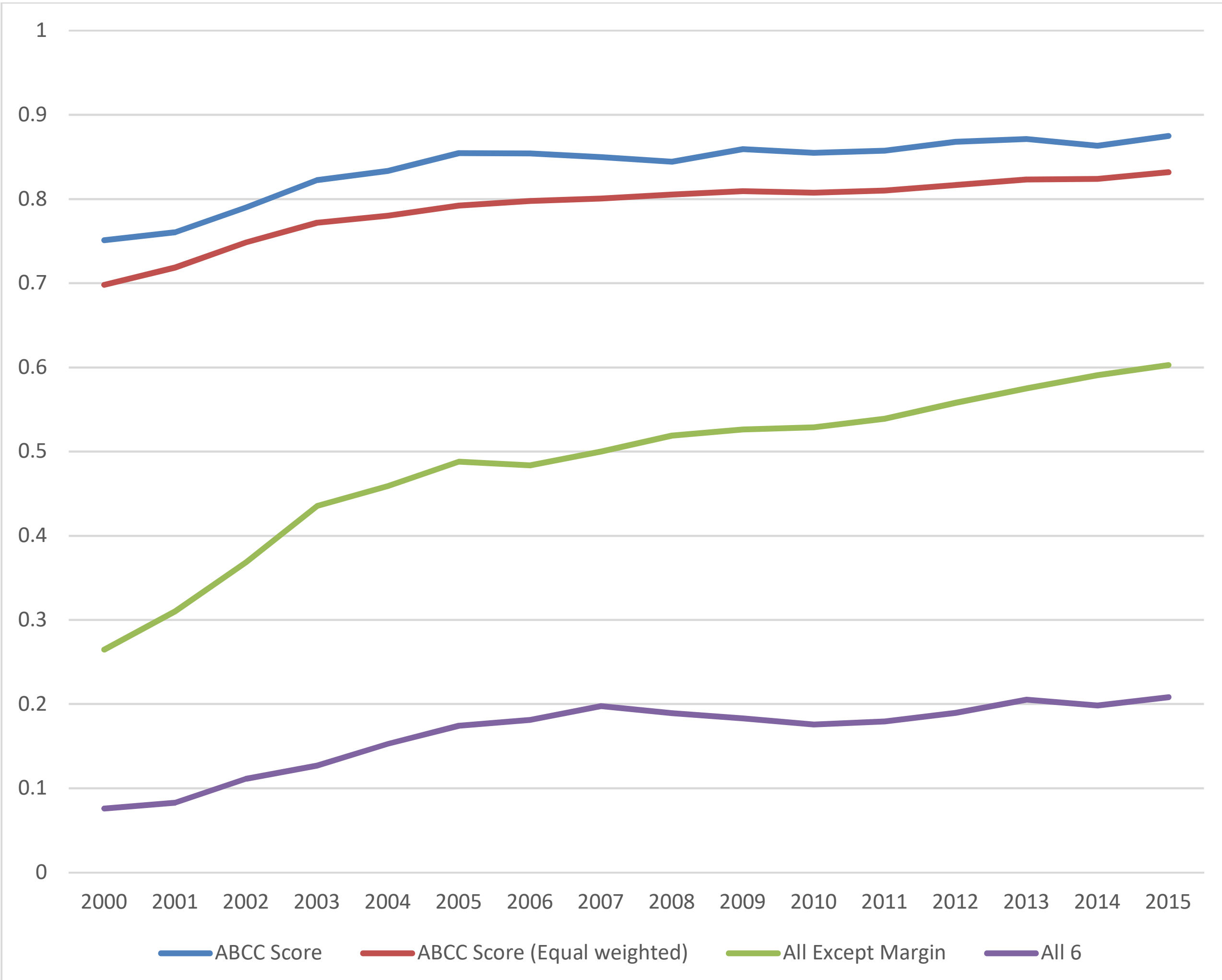

Table 1
Summary Statistics

This table reports descriptive statistics of our complex instrument measures, fund returns and characteristics. Fund performance is measured using excess returns, four-factor alphas, and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). Fund characteristics include fund size (log of the fund's AUM), family size (the log of the fund family's AUM), the log of the fund's age, the proportion of AUM in the institutional share classes, fund flows, and the proportion of a fund board's director that are independent.

Variable name	N	Mean	Std	25th	Median	75th
Complex Instruments						
ABCC Score	64,817	0.84	0.20	0.80	0.90	0.98
ABCC Score (Equal weighted)	64,817	0.79	0.20	0.78	0.89	0.89
Fund Return						
Excess Return	64,817	5.94	25.27	-6.13	8.93	20.39
Four-Factor Alpha	64,817	-2.52	10.72	-6.13	-1.40	2.60
MPPM	64,817	-0.07	28.32	-13.42	5.25	16.38
Fund Characteristics						
Fund Size (millions)	64,796	1,260	4,611	64	231	837
Family Size (millions)	64,817	71,193	131,994	1,187	7,442	41,540
Fund age	62,886	11.75	8.48	5.33	10.08	16.00
Institutional Fund Ownership	57,095	29.27	38.86	0.00	3.64	62.87
Fund Flows	64,550	0.30	3.59	-1.41	-0.42	1.04
Fund Board Independence	44,624	0.70	0.23	0.59	0.73	0.85

Table 2

Performance of Constrained vs. Unconstrained Funds

This table presents the performance of portfolios of funds sorted according the ABCC Scores. We form two portfolios based on the median ABCC Score in Panel A and on the median ABCC Score (Equal weighted) in Panel B. The weights of the funds in each portfolio are proportional to the distance of a fund's score value from the median. Fund performance is measured using excess returns, four-factor alphas, and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All performance measures are computed from daily fund net return data observed during a six-month period after portfolio formation, reported on an annualized basis and expressed in percentages. *p-values* are reported in parentheses.

Panel A: ABCC Score	Excess Return	Four-Factor Alpha	MPPM
Most constrained	4.746	-0.546	0.106
	(0.293)	(0.536)	(0.502)
Least constrained	3.943	-1.352	-2.915
	(0.401)	(0.162)	(0.400)
Least constrained - Most constrained	-0.803	-0.806	-3.022
	(0.018)	(0.002)	(0.000)

Panel B: ABCC Score (Equal weighted)	Excess Return	Four-Factor Alpha	MPPM
Most constrained	4.752	-0.555	0.123
	(0.292)	(0.530)	(0.502)
Least constrained	3.956	-1.352	-2.904
	(0.400)	(0.162)	(0.400)
Least constrained - Most constrained	-0.796	-0.797	-3.027
	(0.023)	(0.003)	(0.001)

Table 3
Fund Performance and Complex Instrument Allowance

This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls. The variable of interest is the ABCC Score. All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All performance 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 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)
ABCC Score	-1.34	-0.89	-1.96
	(0.002)	(0.008)	(0.000)
Log(Fund Size) (t-1)	-0.31	-0.06	-0.28
	(0.000)	(0.129)	(0.000)
Log(Fund Family Size) (t-1)	0.19	0.08	0.16
	(0.000)	(0.007)	(0.000)
Log(Fund Age) (t-1)	0.30	0.14	0.31
	(0.014)	(0.140)	(0.027)
Institutional Fund Ownership (t-1)	0.00	0.00	0.00
	(0.084)	(0.004)	(0.123)
Fund Flows (t-1)	-0.05	0.04	-0.05
	(0.003)	(0.001)	(0.027)
N	50097	50097	50097
R-sq	0.813	0.410	0.829

Table 4
Fund Risk and Complex Instrument Allowance

This table reports results from panel regressions of fund risk on complex instrument allowance score and a set of controls. The variable of interest is the ABCC Score. All the control variables are observed six months before the dependent variable. Risk is measured using the standard deviation of returns (1), CAPM beta (2), and idiosyncratic volatility (3) as computed from the four-factor model. The returns used to compute the risk measures are the fund's daily net returns observed during a six-month period, reported on an annualized basis and expressed in percentages. Our controls 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. 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	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)
ABCC Score	1.10	0.06	0.14
	(0.000)	(0.000)	(0.305)
Log(Fund Size) (t-1)	-0.09	-0.01	-0.05
	(0.001)	(0.000)	(0.003)
Log(Fund Family Size) (t-1)	0.06	0.01	-0.09
	(0.008)	(0.000)	(0.000)
Log(Fund Age) (t-1)	0.06	0.01	-0.05
	(0.310)	(0.003)	(0.171)
Institutional Fund Ownership (t-1)	0.00	0.00	-0.01
	(0.378)	(0.000)	(0.000)
Fund Flows (t-1)	-0.02	0.00	0.00
	(0.000)	(0.000)	(0.210)
N	50097	50097	50097
R-sq	0.854	0.500	0.728

Table 5

Fund Performance and Complex Instrument Allowance in Up and Down Markets

This table reports results from panel regressions of fund performance on complex instrument allowance score, market environment, and a set of controls. Our variable of interest is the interaction of the ABCC Score with dummy variables that indicate if the market is in an up or down state. An up (down) market is defined as a semester in which the average mutual fund excess return in our sample is positive (negative). All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas, 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. 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)
Up market*ABCC Score	1.27	0.32	0.94
	(0.000)	(0.213)	(0.003)
Down market*ABCC Score	-5.24	-2.69	-6.28
	(0.000)	(0.000)	(0.000)
N	50097	50097	50097
R-sq	0.814	0.410	0.830

Table 6
Fund Performance and Complex Instrument Allowance with Fund Fixed Effects

This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls. The variable of interest is the ABCC Score. All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas 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 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 fund and 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)
ABCC Score	-2.80	-1.27	-3.33
	(0.002)	(0.018)	(0.001)
Log(Fund Size) (t-1)	-3.07	-1.91	-3.39
	(0.000)	(0.000)	(0.000)
Log(Fund Family Size) (t-1)	-0.53	-0.33	-0.59
	(0.000)	(0.000)	(0.000)
Log(Fund Age) (t-1)	1.15	1.18	1.43
	(0.014)	(0.000)	(0.007)
Institutional Fund Ownership (t-1)	0.02	0.01	0.02
	(0.002)	(0.005)	(0.002)
Fund Flows (t-1)	-0.25	-0.10	-0.26
	(0.000)	(0.000)	(0.000)
N	49867	49867	49867
R-sq	0.855	0.54	0.873

Table 7
Fund Performance and Instrumented Complex Instrument Allowance

This table shows the results of a two-stage least squares regression. In the first stage (Column 1) we regress fund ABCC Score in a semester on the average ABCC Score of other funds in the family and control variables. In the second stage (Column 2-4), we regress fund performance on the predicted ABCC Score from the first stage and control variables. Fund performance is measured using excess returns, four-factor alphas, and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). Our controls 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.

	First Stage	Second Stage		
	ABCC	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)	(4)
Family ABCC Score	0.81			
	(0.000)			
Predicted ABCC Score		-1.62	-0.93	-2.34
		(0.011)	(0.057)	(0.001)
Log(Fund Size) (t-1)	0.00	-0.31	-0.07	-0.29
	(0.002)	(0.000)	(0.073)	(0.000)
Log(Fund Family Size) (t-1)	0.00	0.22	0.12	0.21
	(0.006)	(0.000)	(0.001)	(0.000)
Log(Fund Age) (t-1)	-0.02	0.29	0.09	0.27
	(0.000)	(0.024)	(0.363)	(0.063)
Fund Institutional Ownership (t-1)	0.00	0.00	0.00	0.00
	(0.978)	(0.075)	(0.001)	(0.080)
Fund Flows (t-1)	0.00	-0.06	0.04	-0.05
	(0.009)	(0.003)	(0.006)	(0.015)
N	45,693	45693	45693	45693
R-sq	0.573	0.823	0.431	0.839

Table 8
Individual Complex Instrument Classifications

This table reports results from panel regressions of fund performance and risk on the allowance of the different types of complex instruments and a set of controls. We consider three different types: leverage, derivatives, and illiquid assets. Leverage includes borrowing, margin, and short selling. Derivatives include options on equities and stock index futures. Illiquid assets include investments in restricted securities. All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas, and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). Risk is measured using the standard deviation of returns, CAPM beta, and idiosyncratic volatility as computed from the four-factor model. 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. 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	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage	0.30	-0.32	0.00	0.45	0.02	0.31
	(0.249)	(0.118)	(0.991)	(0.001)	(0.012)	(0.000)
Derivatives	-1.43	-0.53	-1.71	0.51	0.04	-0.23
	(0.000)	(0.031)	(0.000)	(0.001)	(0.000)	(0.012)
Illiquid Assets	0.16	0.14	0.19	0.04	0.00	0.12
	(0.687)	(0.647)	(0.680)	(0.816)	(0.959)	(0.333)
N	50097	50097	50097	50097	50097	50097
R-sq	0.813	0.410	0.829	0.854	0.500	0.729

Table 9
Determinants of Complex Instrument Allowance

This table reports tests on the determinants of complex instrument allowance. We estimate panel regressions of fund complex instrument allowance score on a set of explanatory variables, which include proxies for fund monitoring quality, log of the fund's AUM, log of the fund's age, and fund flows. We use three measures to proxy for fund monitoring quality: (1) the proportion of fund shares owned by institutional shareholders; (2) the log of the AUM of the fund's family; and (3) the proportion of the fund's directors who are independent. All the explanatory variables are observed six months before the dependent variable. 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.

	ABCC Score x 100	
	(1)	(2)
Institutional Fund Ownership (t-1)	0.030	0.030
	(0.000)	(0.000)
Log(Fund Family Size) (t-1)	2.330	2.400
	(0.000)	(0.000)
Board Independence (t-1)		0.030
		(0.017)
Log(Fund Size) (t-1)	0.730	0.820
	(0.001)	(0.001)
Log(Fund Age) (t-1)	-4.720	-5.250
	(0.000)	(0.000)
Fund Flows (t-1)	-0.240	-0.260
	(0.000)	(0.000)
N	50097	36731
R-sq	0.153	0.152

Table 10

Monitoring Quality and Performance Associated with Complex Instrument Allowance

This table reports how different monitoring environments affect the relation between complex instrument allowance and fund performance. We estimate panel regressions of fund performance on complex instrument allowance, fund monitoring quality, and a set of controls. Our independent variables of interest are the interaction of the ABCC Score with three measures of fund monitoring quality. All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas, 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. 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 Ownership*ABCC Score	2.62	1.42	2.74
	(0.017)	(0.065)	(0.028)
Board Independence*ABCC Score	3.60	2.75	3.75
	(0.162)	(0.130)	(0.258)
Log Fund Family Size*ABCC Score	0.32	0.06	0.23
	(0.034)	(0.560)	(0.184)

Table 11
Complex Instrument Use

This table reports results from panel regressions of fund performance on complex instrument use score and a set of controls. The variable of interest is the Use Score, which measures the proportion of the six complex instruments that are actually used in a given semester. We consider four different specifications. The first specification is the base case regression used in Table 3. The second specification is the regression with fund fixed effects used in Table 6. The third specification is the instrumental variable regression used in Table 7. The fourth specification is the regression that includes the up and down market interactions used in Table 5. All the control variables are observed six months before the dependent variable. Fund performance is measured using excess returns, four-factor alphas and the manipulation-proof performance measure (MPPM) derived by Goetzmann et al. (2007). All performance 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 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.

Specification	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Base	-1.79	-1.14	-1.61
	(0.020)	(0.060)	(0.072)
with Fixed Effects	-1.61	-1.91	-1.96
	(0.057)	(0.001)	(0.039)
Instrumental Variable	-4.86	-1.90	-4.77
	(0.026)	(0.251)	(0.062)
Up Market Interaction	0.87	1.56	1.10
	(0.158)	(0.000)	(0.051)
Down Market Interaction	-5.91	-5.34	-5.82
	(0.001)	(0.000)	(0.005)