Complex Instruments Have Increased Risk and Reduced Performance at Mutual Funds*

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Abstract

We study the allowance and use of derivatives, leverage, and illiquid assets by mutual funds. We observe that an increasing number of funds are granted access to these complex instruments over our sample period. 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 mutual funds that are allowed to use derivatives. We also find that mutual funds underperform when they actually use complex instruments. Overall, our results suggest caution in allowing funds to use these complex instruments.

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

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Since 2000, there has been a rise in the complexity of mutual funds as more funds have been given the authority to use derivatives, leverage, and illiquid assets. The increase in the allowance of these *complex instruments* raises the question of whether this trend has helped or hurt mutual fund investors.[1] On the one hand, Almazan, Brown, Carlson, and Chapman (2004, henceforth ABCC) examine complex instrument allowance and find that it has 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 and prevent misuse of the instruments. Other research shows that complex instruments can reduce fund transaction costs (Deli and Varma, 2002) and systematic risk (Natter et al., 2016), and have a neutral or positive effect on fund performance (e.g., Koski and Pontiff, 1999; Chen et al., 2013; Cici and Palacios, 2015; Natter et al., 2016).

On the other hand, practitioners and regulators have raised concerns that allowing funds to use these instruments may expose investors to severe losses or risks. Anecdotal evidence supports this concern. For example, some funds that were exposed to complex instruments suffered huge losses during the 2008 subprime mortgage crisis, and a mutual fund purchase in the futures market may have contributed to the May 2010 "flash crash."[2] In response to these concerns and after public debate, the Securities and Exchange Commission (SEC) adopted new rules in 2020 aimed at improving the transparency and risk management practices of funds as they pursue complex portfolio strategies.[3]

Given the increase in complex instrument allowance, the goal of this paper is to contribute to this debate by examining the effects of the allowance and use of these instruments on mutual fund performance and risk. An

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[1] We use the term *complex instruments* to describe a variety of complicated investment strategies (derivatives, leverage, 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; and "The Mutual Fund in the Flash Crash" The Wall Street Journal, October 6, 2010. For more recent examples, see "Behind the Mysterious Demise of a $1.7 Billion Mutual Fund" The Wall Street Journal, April 20, 2021, and footnote 3 in https://www.sec.gov/news/public-statement/crenshaw-derivatives-2020-10-28.

[3] These rules (https://www.sec.gov/news/press-release/2020-269) include adopting a derivatives risk management program and complying with a limit on the amount of leverage-related risk that the fund may obtain based on value-at-risk. An SEC commissioner (see https://www.sec.gov/news/public-statement/crenshaw-derivatives-2020-10-28) criticized the new rules for failing "to provide a meaningful limit on registered funds' ability to take on leverage."

important consideration is the market condition during the period in which complex instrument allowance is studied. Specifically, complex instruments allow investors to take leveraged positions, which work best during bull markets. As explained by Warren Buffett, “When leverage works, it magnifies your gains. Your spouse thinks you're clever, and your neighbors get envious,” but “You only learn who has been swimming naked when the tide goes out.”[4] ABCC’s sample, which spans the period from 1995 to 2001, was a relatively strong market period with an annualized return of 15.9% on the S&P 500 index. Consequently, their results may be influenced by a small sample effect (e.g., Flavin, 1983), which could misrepresent the returns earned using 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 focus on actively managed domestic equity funds and extract information from SEC filings on the allowance of six complex instruments: borrowing, margin, short selling, options, futures, and restricted securities. This information is included in Form N-SAR, a semi-annual report that mutual funds are required to file with the SEC. We use this information to compute an aggregate measure of complex instrument allowance, and find that there has been an increase in complex instrument allowance over our sample period. For example, the percentage of funds that are allowed to use all six instruments increased from 8% to 21% (from 26% to 60% if we exclude margin). We also examine the determinants of complex instrument allowance, and find that funds that are larger, are members of larger fund families, are younger, and those with higher levels of institutional ownership and weaker fund flows are granted more allowance to complex instruments.

We next examine the relation between allowance and performance. Using portfolio and OLS regression approaches, we find that funds with more allowance underperform those with less allowance. In particular, being

[4] The first quote is from http://www.berkshirehathaway.com/letters/2010ltr.pdf, and the second quote is from http://www.berkshirehathaway.com/letters/2007ltr.pdf.

[5] Our main sample begins in 2000, rather than 1994, due to availability of daily mutual fund net-return data, which we use to compute our performance and risk measures. In Section 6.5 we replicate our main results in a larger sample that includes ABCC’s period and find that the main results are robust.

allowed to use all six instruments is associated with 1.34% lower annual excess returns and 0.89% 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 caused by nonlinearity and asymmetry likely to be present in the returns for funds that use complex instruments.

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 whether 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 is positively related to the fund's standard deviation and beta exposure, 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 whether the market excess return is positive or negative, and find that allowance is associated with large losses during market downturns, which is consistent with our prediction.

Complex instrument allowance is set internally, which raises endogeneity concerns. For this concern to affect our results, funds must anticipate future returns and adjust allowance accordingly. It is unclear whether these conditions are met given the unpredictable nature of returns, and because allowance is governed by fund bylaws, which change infrequently. Nevertheless, for robustness, we conduct three additional sets of analyses to address this concern. 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. Second, we 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 that do not share the same investment style as the fund of interest. 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, and a positive relation with respect to risk. Third, we use a matched sample technique to examine fund performance and risk in the period immediately following an increase in the fund's complex instrument allowance. We find that funds that experience an increase in allowance have lower four-factor alpha, higher standard deviation, and higher beta exposure relative to a control group of funds that do not experience an allowance increase.

The complex instruments that we examine are distinct in nature and can be used by funds for different purposes. To understand the contribution each instrument makes to our results, we partition our measure of allowance into three categories (derivatives, leverage, and illiquid assets) and consider their individual effects on fund performance. We find that the allowance of derivatives, arguably the most complex of the instruments, is associated with significant underperformance and higher standard deviation and beta exposure. Unsurprisingly, we find that the allowance of leverage is associated with higher levels of fund risk, but we 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.

There are at least two channels through which the allowance of complex instruments may affect performance and risk. First, there may be a direct effect on fund performance and risk, when mutual funds that are allowed to use these instruments actually use them. To capture this effect, we create a measure of complex instrument use, Use Score, which is defined as the proportion of the six complex instruments that a fund uses in a given period. Our results show that, like fund allowance, fund use is associated with lower performance. This result is robust to a specification that includes fund fixed effects and a specification that is estimated using 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 instrument allowance and fund performance being driven, at least in part, by their actual use.

Second, there may be an indirect effect where mutual funds that are allowed to use complex instruments change their behavior, which in turn affects fund performance and risk. In particular, risk-compensation theory (Peltzman, 1975; see Section 1 for more details) describes how individuals increase their risk-taking behavior in the presence of insurance and other safety mechanisms. In the context of mutual funds, we predict that complex instrument allowance may alter managerial investment behavior toward riskier positions, given the insurance-like properties embedded in some of the complex instruments (e.g., derivatives).

To better understand the extent to which direct and indirect effects drive our results, we distinguish between funds that are allowed to use each instrument but do not actually use them (non-use), and funds that do use the instruments. We also compute a measure of fund risk based on the underlying equity holdings of the funds. These results show that the non-use of derivatives is associated with lower fund returns, higher fund risk, and higher fund equity risk. This test provides evidence in support of the risk compensation theory given the insurance-like properties of derivatives. We also examine leverage and illiquid assets using this framework. While we do not find an association between leverage non-use and performance, we do find that the use of leverage is negatively associated with performance. Interestingly, we find evidence that both leverage use and non-use are positively associated with fund standard deviation and equity standard deviation. The latter result is inconsistent with the prediction of Frazzini and Pedersen (2014) that unconstrained funds would invest in lower-risk stocks.

In the last part of the paper, we expand our data set to include both our and ABCC's sample periods. We then replicate our main specifications in ABCC's sample, and, consistent with their findings, do not observe a significant relation between complex instrument allowance and performance. To test whether the lack of significance is related to the limited sample period, we also estimate the specification in a larger combined sample that includes both sample periods, and find a significant negative relation between allowance and fund performance. We also find that allowance in down markets is associated with significantly lower returns than allowance in up markets in both ABCC's and the combined samples.

Our paper makes several contributions to the literature that examines the effect of complex investment strategies on mutual fund performance. First, our paper provides out-of-sample evidence on ABCC's results. Using a more recent and larger sample, we document a loosening of investment constraints which is negatively associated with fund performance. We also highlight the role of market conditions in the relation between complex instruments and fund performance. Second, recent literature has found that complex instruments neither harm fund performance (i.e., are neutral or positive) nor lead to increased fund risk (e.g., Koski and Pontiff, 1999; Chen et al., 2013; Cici and Palacios, 2015; Natter et al., 2016).[6] Our results provide new evidence that these instruments can be harmful to fund shareholders. We also contribute to this literature by examining a broad set of complex instruments, whereas nearly all of the existing literature has examined the use of a single instrument such as derivatives or short sales. We argue that it is important to focus on a broad set of instruments, as a significant number of funds have been simultaneously given access to multiple instruments. For example, the average fund in our sample has access to 4.8 of the 6 instruments, and 17% (49%) of funds in our sample have access to all 6 instruments (all except margin). Third, we rely on risk-compensation theory to address how access to complex instruments, even without actual use, can affect fund performance and risk. Despite the importance of risk in finance and the potential for the theory to explain risk-taking behavior, it has received limited attention in the finance literature.

[6] Koski and Pontiff (1999) document that mutual funds that use derivatives have risk exposure and return performance that are similar to non-users. Other papers investigate the use of derivatives by mutual funds in international settings with similar results (Fletcher et al., 2002; Johnson and Yu, 2004; Pinnuck, 2004).

1. Motivation

The existing literature highlights several potential positive and negative effects that complex instruments may have 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), costs associated with fund flows, and the opportunity cost of holding cash (Deli and Varma, 2002).

There are several potential mechanisms through which complex instrument use can harm fund performance. Mutual fund managers may 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, which are typically active users of complex instruments, and are considered among the most sophisticated institutional investors (e.g., Akbas et al., 2015; Calluzzo et al., 2019). Similarly, portfolio insurance demands may create overpricing in the markets for some of these instruments that reduce returns (Bollen and Whaley, 2004). It is also possible that transactions in these instruments generate high administrative and trading costs (e.g., Koski and Pontiff, 1999), which negatively impact fund performance.

Complex instrument use may also affect fund risk. 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). Access to complex instruments may also enable managers to alter the risk-return distributions of their portfolios for opportunistic reasons that may harm shareholders (e.g., Brown et al., 1996; Chevalier and Ellison, 1997).

The mere allowance of complex instruments (without use) may also affect funds. We posit that managers may change their investment behavior due to risk compensation (also known as the Peltzman, 1975, effect). This theory predicts that individuals change their risk-taking behavior in the presence of insurance or safety mechanisms.[7] For example, Peterson et al. (1995) find that drivers of airbag-equipped cars are more aggressive, which offsets the safety benefits of this feature. More recently, infection rates of COVID-19 spike in the days immediately following receipt of the first dose of the vaccine (before immunity builds) as people lower their adherence to safety measures (Trogen and Caplan, 2021). Given the insurance-like properties of complex instruments, their allowance may cause managers to feel more protected and to take more risk in their equity positions. This effect may indirectly impact fund performance, given the documented low risk-adjusted returns of high-beta stocks (Black, 1972; Frazzini and Petersen, 2014 and 2020). If this channel affects funds, we expect it to be concentrated in derivative allowance, as these instruments exhibit stronger insurance-like properties, compared to the other complex instruments.

In our paper we examine both the allowance and use of complex instruments. However, we put more focus on allowance for several reasons. First, the endogeneity concern is more severe for the use of complex instruments. Unlike allowance, which is under the control of fund shareholders (through bylaws) and regulators, 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

[7] Although this theory is frequently cited in the organizational behavior literature, there are also some citations in the finance literature (e.g., Lo, 2013).

make it challenging to measure their contribution to fund performance.[8] Third, knowing how allowance is related to fund performance is important for shareholders and regulators as they consider changes in allowance. Fourth, by focusing on allowance, we more closely align our results with ABCC. 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.

2. 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, albeit with some regulatory limitations.[9] We extract data on mutual funds' investment practices from the SEC's Form N-SAR, which 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 (reproduced in Appendix Figure 1) asks whether a mutual fund had the authorization to use different complex instruments during the reporting period. We follow ABCC and 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. Questions 70O, 70Q, 70R, 70B, 70F, and 70J

[8] The SEC recently reformed mutual fund disclosure on complex instruments with the introduction of Form N-PORT that requires funds to disclose detailed terms of derivative contracts, among other things. Filing Form N-PORT through the EDGAR system started in April 2019 (see https://www.sec.gov/rules/interim/2019/ic-33384.pdf).

[9] Open-end funds that use leverage (including uncovered written options, futures, and short selling) must maintain asset coverage of at least 300%. Starting in 2019, mutual funds can only invest up to 15% of their assets in illiquid assets (see https://www.sec.gov/divisions/investment/guidance/secg-liquidity.htm).

identify borrowing, margin purchases, short selling, writing or investing in options on equities, writing or investing in stock index futures, and investments in restricted securities, respectively.[10]

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 the 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 derivatives, leverage, 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. Each of our measures of allowance is equal to one minus the corresponding ABCC measure, because they constructed the measure in terms of restrictions. We prefer to frame the measures in terms of allowance, given the trend toward 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.[11] Because of the semi-annual reporting requirement of Form N-SAR, our dataset is structured at the semi-annual (semester) fund level. We drop filings if they are filed more than 90 days after the end of the reporting period or if balance sheet items are not reported at the fund level. There are 101,074 filings remaining

[10] We follow ABCC and categorize restricted securities as complex instruments 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 an ABCC score that does not include restricted securities, as well as a score that includes questions 70G and 70H in the definition of options.

[11] There are two N-SAR forms. 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. If the fiscal year end does not align with these months, we use data from the most recent filing. Our main results are unaffected by the different reporting periods.

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 active 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.[12] 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.[13] 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 fund risk (e.g., Busse 1999 and 2001). Furthermore, obtaining risk and performance measures 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 fund outcomes, and allows us to control for other factors that may affect fund performance and risk. 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.[14]

2.1 Univariate Statistics

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

[12] 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).

[13] 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.

[14] The MPPM can be interpreted as the annualized geometric excess return certainty equivalent of a particular fund. This 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).

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. Table 1 Panel A reports 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), margin (from 0.11 to 0.27), and futures (from 0.73 to 0.88).[15] The average allowance in our sample is also considerably higher than the allowance documented in the earlier ABCC sample: 0.86 vs. 0.78 for borrowing; 0.22 vs. 0.09 for margin; 0.61 vs. 0.31 for short selling; 0.91 vs. 0.75 for options; 0.85 vs. 0.65 for futures; and 0.94 vs. 0.82 for restricted stocks.[16] Appendix Table 1 presents patterns in allowance of funds by their inception date. We observe that the trend of higher allowance over time is present across funds with different inception dates. This result implies that at least part of the increase is driven by funds being granted additional allowance, rather than new funds simply being granted more allowance at inception.

Table 1 Panel B presents statistics on each style's average allowance of each individual instrument and ABCC Score. We use each fund's four-digit CRSP Objective Code to classify the domestic equity funds in our sample into seven categories: sector funds (style codes beginning with EDS); large- and mid-cap funds (EDCL and EDCM); small-cap funds (EDCS); micro-cap funds (EDCI); growth style funds (EDYG); growth and income style funds (EDYB); income style funds (EDYI); and hedged and short style funds (EDYH and EDYS). We present summary statistics on fund characteristics based on these classifications. These statistics show that hedged and short style funds have the highest average ABCC Score (0.92 vs. 0.84 average across all funds). With respect to the individual instruments, they have substantially greater margin (0.40 vs. 0.22 average across all funds) and

[15] As explained by Chen et al. (2013), the SEC has progressively relaxed restrictions on short selling over time. 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.
[16] The numbers from ABCC's sample are computed from Table 1 Panel A of their paper. We convert their statistics, which are presented as restrictions, as: Allowance = 1 – Restriction.

short sales (0.97 vs. 0.61 average across all funds) allowance. Sector style funds have the next highest average ABCC Score (0.90) and the highest option allowance (0.97). Growth and income funds have the lowest ABCC Score (0.81). We include fund style × time fixed effects in our regression analysis to control for potential factors related to fund style that may affect our results.

Table 2 Panel A 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 toward 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 – the number of years since the fund's inception as reported by CRSP; Institutional Ownership – the proportion of the fund's AUM composed of institutional share classes as reported by CRSP; and Fund Flows – the proportional change in the fund's AUM, adjusted for the return of the fund, as in Chevalier and Ellison (1997). Table 2 Panel B provides characteristics of the domestic equity funds included in our sample by fund style.

3. Determinants of Complex Instrument Allowance

We next explore determinants of complex instrument allowance. ABCC posit that investment restrictions can act as a monitoring mechanism that can reduce fund agency costs. They find that substitution effects exist between fund characteristics associated with monitoring and complex instrument restrictions. We build on their analysis by examining the determinants of complex instrument allowance in our longer and more recent sample period. Specifically, we estimate an OLS regression model where the fund's ABCC score is the dependent variable. Among our variables of interest are measures associated with monitoring quality, such as institutional fund ownership and family size. Given the trend of increasing allowance over time, newer funds may be less constrained than older funds, and we also consider fund age as an explanatory variable. Furthermore, given the potential benefit of complex instruments in managing fund flows (Deli and Varma, 2002), we also include fund flows as an explanatory variable.[17] The results of the model are reported in the first column of Table 3. Consistent with the findings of ABCC, the variables associated with monitoring quality are positively related to allowance. We also find that fund size is positively related to allowance, and that fund age and fund flows are negatively related to allowance.

Given the distinct nature of each complex instrument, we also consider the determinants of allowance of the individual instruments. We follow ABCC and categorize the six instruments into three groups: leverage (borrowing, margin, and short selling); derivatives (options and futures); and restricted securities. Within each group, we construct a variable that measures the proportion of individual instruments that the fund is allowed to use. We then re-estimate the deterministic model using these variables as the dependent variable. The results of these specifications are reported in columns 2 through 4 of Table 3. Despite the distinct nature of each complex instrument, we find that the same factors that drive higher ABCC allowance scores at funds also drive the allowance of the individual instrument types. That is, funds that are larger, are members of larger fund families, are younger, and those with higher levels of institutional ownership (except leverage) and weaker fund flows are granted more allowance to the individual complex instrument types.

4. Complex Instrument Allowance and Fund Performance

4.1 Univariate Performance Analysis

In this section we examine the relation between complex instrument allowance and fund performance, and we begin by presenting evidence using 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

[17] In untabulated tests, we obtain data on board independence through 2011 from Calluzzo and Dong (2014), and include it as an explanatory variable. We find that it is positively related to ABCC score.

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.[18] The excess return reported in Table 4 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.[19]

Table 4 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 −0.81% 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 its allowance less weight (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

[18] In an untabulated analysis, we found that this result is robust to using monthly (instead of daily) data, and to using terciles (instead of two groups).
[19] 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.

fund's age, the level of institutional ownership, and fund flows.[20] Additionally, we include fund style-time interactive fixed effects, which control for observable and unobservable factors related to the fund's style each quarter that affect performance. Fund style is identified using four-digit CRSP Objective Codes. We estimate the regression

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

where *i* indicates the fund and *t* refers to time measured by semester.

The first row of Table 5 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 performance. 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 of a negative relation between allowance and fund performance 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 small-sample inference 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. In this section, we present tests that examine

[20] We exclude expense ratio and turnover ratio from our set of control variables given that they are both channels (via fees and transaction costs) through which complex instruments can affect fund performance. In unreported tests, we find that our main results are robust to the inclusion of each variable.

the relation between allowance and risk, and then examine the effect of allowance on fund performance in up and down markets.

5.1 Complex Instrument Allowance and Fund Risk

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 the fund's idiosyncratic risk computed as the standard deviation of the residuals from the four-factor model. Table 6 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 beta exposure, but not to idiosyncratic volatility. This result is consistent with two non-mutually exclusive explanations: Complex instruments provide leverage and/or mutual funds that are allowed to use complex instruments invest in risky equity securities consistent with risk compensation effects. Section 6.4 below provides analyses to distinguish between these two explanations.

5.2 Complex Instrument Allowance and Market Conditions

High risk is not necessarily bad for fund investors. Fund investors may prefer higher-risk funds if they deliver better performance, especially during a bull market, and if they do not suffer disproportionately during a bear market. To understand whether these dynamics are present in our sample, we present tests that separately examine the effect of allowance in different market conditions. We define an Up (Down) Market as a semester in which excess return of the market is positive (negative). 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 7 show that allowance is associated with positive returns in good markets, but negative returns during poor market conditions. The difference between the coefficients in up and down markets is statistically significant in all three specifications. 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 1.28 (0.33) [0.95], and is much lower in absolute terms than the coefficient on Down Market × ABCC Score, which is −5.50 (−2.82) [−6.56]. 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 (65% of semesters) than down markets in our sample period.

The concentration of the negative association between ABCC Score and fund performance in down markets raises the concern that the results are being driven by an extreme and rare market event, notably the financial crisis. We take two steps to address this concern. First, we replicate Table 5, excluding the two semesters in 2008 that experienced extreme negative returns associated with the financial crisis. These results, presented in Appendix Table 2 Panel A, continue to show a significant negative relation between ABCC Score and fund performance excluding the financial crisis. Next, we further partition semesters into moderate and extreme up and down market periods based on 25% annualized return thresholds. These results are presented in Appendix Table 2 Panel B. While we find that allowance in extreme down markets is associated with negative fund performance of a substantial magnitude, we also find that moderate down markets are significantly negatively associated with fund performance. We also continue to find asymmetry in the magnitude of the effects in up and down markets. The absolute value of the magnitude of coefficients on moderate (extreme) down markets is between 2.5 and 4.6 (6.3 and 11.1) times greater than the magnitude of the coefficients in moderate (extreme) up markets. We find that the patterns are qualitatively similar if we use alternate cutoffs (e.g., 15%) for moderate and extreme markets.

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.[21] 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. Furthermore, omitted variable concerns driven by unmodeled fund characteristics may also bias our results. In this section, we present three sets of analyses aimed at addressing these concerns.

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. Fund fixed effects also control for the possibility that the choice to include or exclude complex instruments at a fund's inception may be related to unobservable fund characteristics. 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). Columns 1 through 3 of Table 8 report 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. We also use the fixed-effects setting to assess the impact of within-fund changes in the ABCC Score on fund risk. The results are presented in columns 4 through 6 of Table 8 and continue to show a significant positive relation between ABCC Score and fund risk.

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

[21] At inception, funds in our sample have access to 4.42 of the 6 instruments. We find that 36.0% of funds experience an increase in their complex instrument allowance at some point, and that the number of instruments each fund is allowed to use changes once every eight years.

concern by employing a two-stage instrumental variable approach. For each fund, we identify other funds within the same fund family that have different style classifications as the fund of interest. We focus on funds with different style classifications to mitigate the concern that funds within a family have high correlated returns (Elton et al., 2007). We then compute our instrument, *Family ABCC Score*, as the mean ABCC Score of these funds. 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 in the family are granted 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

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

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

Other control variables include those used in our main tests. The first column of Table 9 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 2 through 4, 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 columns 5 through 7, we use the instrumental variable approach to examine the relation between allowance and fund risk and continue to find a positive association between the two.

Last, we also examine fund outcomes in the period immediately following increases to the fund's complex instrument allowance using a nearest-neighbor matched sample technique that estimates average treatment effects (Abadie and Imbens, 2006). The treatment group is identified as funds that experience an increase in their allowance, while the control group for each treatment fund is identified as other funds in the same fund style and semester as the treated fund, but that do not experience an allowance increase. For each fund in each group, we select the "nearest neighbor" from the other group based on the fund's characteristics (our control variables, the level of allowance, and lags of the dependent variable). We then compare fund performance across the two groups in the four semesters following the increase in complex instrument allowance. These results are presented in Appendix Table 3 and provide some evidence of worse performance after allowance increases (significantly lower four-factor alpha, and negative but statistically insignificant estimates on excess return and the MPPM measure). The limited significance of this result is unsurprising, given the noisiness of the return-generating process, which is observed over a short window and among a limited number of funds experiencing an allowance increase. We expect fund risk levels to be relatively less noisy than returns, and consistent with our earlier results, we find that allowance increases are associated with higher fund standard deviations and beta levels.

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

The individual complex instruments are distinct in nature. ABCC addresses their distinctness by categorizing them into three groups: derivatives, leverage, 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 derivatives, leverage, 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 10). For excess return (four-factor alpha) [MPPM], the coefficient is −1.43 (−0.53) [−1.71] and is statistically significant. In contrast, we do not observe a significant relation between leverage or illiquid security allowance and fund performance.

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 10. We find that derivatives are associated with significantly higher fund risk as measured by standard deviation and beta exposure. However, derivatives are associated with significantly lower idiosyncratic volatility. The derivatives category includes investments in stock index futures, which have little, if any, idiosyncratic volatility. Their presence may explain the negative relation between derivative allowance and idiosyncratic volatility. As expected, we also find that leverage allowance is associated with higher fund risk across our three risk measures. We find no relation between illiquid asset allowance and our three risk measures.

6.3 Complex Instrument Use

We next consider the effect of complex instrument use on fund returns to examine 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.[22] 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 specification. Appendix Table 4 provides summary statistics on the use of the individual instruments and the Use Score over our sample period. In contrast to the increasing trend for allowance, complex instrument use has been relatively stable over the sample period. For example, the proportion of funds that use at least one complex instrument each semester was 0.35 in 2000 and 0.37 in 2015.

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

Table 11 presents the results of the regression analysis. The first row replicates our baseline analysis, which was presented in Table 5. The coefficient estimates show that the Use Score is associated with significantly negative excess return (−1.79%), four-factor alpha (−1.14%), and MPPM (−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 performance being worse within each fund 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. As our instrument, we select the mean Use Score of other funds with different style classifications within the same mutual fund family. In unreported first-stage results, we find that the instrument is a strong predictor of complex instrument use to a similar degree as the instrument in the allowance regression (Table 9). The third row of Table 11 reports the coefficient estimates for predicted Use Score. The coefficients are statistically and economically significant for Excess Return, but statistically insignificant for the four-factor alpha and MPPM regressions.

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. Furthermore, the coefficient on the down market interaction is significantly less than the coefficient on up market interaction, and is also substantially larger in (absolute) magnitude. This result provides additional evidence that the negative returns associated with complex instruments are driven by the "tide going out" in bad markets.

6.4 Risk Compensation

Complex instruments, especially derivatives, can be used by fund managers to hedge the risk of their investments. One concern is that their insurance properties can lead to risk compensation behavior by the fund. For example, a fund manager may be less worried about the risk of her equity investments, given that she could use complex instruments to reduce portfolio risk. In this section, we present analyses to better understand the extent to which risk compensation may drive our results.

First, we construct dummy variables that identify funds that are allowed to use the instruments but do not actually use them in a given semester. We then estimate equation (1) with the inclusion of these "non-use" variables, as well as the use dummy variables for each instrument type. The results presented in the first three columns of Table 12 consider the relation between these variables and fund performance. In contrast to the existing literature (e.g., Koski and Pontiff 1999; Cici and Palacios, 2015; Natter et al., 2016), we find a negative relation between derivatives and fund performance. Specifically, we find that both the derivative use and the derivative non-use variables are associated with negative excess returns and MPPM. As derivatives have strong insurance-like properties, this result is consistent with risk compensation at least partially explaining our results. We do not find that derivative use is significantly associated with four-factor alpha. This result is consistent with potential biases in the four-factor alpha in the presence of nonlinearity and asymmetry in the returns associated with the use of derivatives (Goetzmann et al., 2007). By contrast, leverage and illiquid assets do not possess insurance-like properties. It is therefore not surprising that we do not observe a negative relation between the non-use of these instruments and fund performance. We do, however, find a negative relation between leverage use and fund performance, highlighting potential concerns of granting funds leverage allowance.

Next, we consider the relation between use and non-use on fund risk. Risk compensation predicts that funds will change the risk characteristics of their non-complex instrument holdings in the presence of instruments with insurance-like properties. To test whether this is the case, we consider a new dependent variable that measures the standard deviation of the fund's underlying equity holdings. This measure is computed using daily returns for the semester from the fund's holdings disclosed just prior to the beginning of the semester (the holdings are aggregated at the fund level first using lagged value as weight), and we examine it alongside our variable that measures the realized standard deviation of fund returns in the semester.

The results of the risk analysis are presented in columns 4 and 5 of Table 12, and show that derivative non-use is associated with higher levels of fund risk and fund equity risk.[23] This result is consistent with the risk compensation framework, as derivatives can provide funds with insurance, and may contribute to underperformance, given the evidence that high-risk stocks deliver lower risk-adjusted returns (e.g., Black 1972; Frazzini and Petersen, 2014 and 2020). We find derivative use is not associated with higher fund risk, but continues to be associated with higher risk in the underlying equity holdings. This result provides evidence that derivatives are, at least to some extent, used as insurance, as funds appear to use them to lower the risk of their underlying holdings (the standard deviation goes down from 0.38% to 0.12% for users, whereas it remains at the same level for non-users).[24]

As expected, for leverage, we find that use is associated with elevated levels of fund risk. Surprisingly, we find that leverage non-use is also associated with elevated levels of fund risk, and that both leverage use and non-use are associated with elevated levels of risk in the underlying equity holdings. This result is counter to the betting-against-beta hypothesis of Frazzini and Petersen (2014), which argues that leverage-unconstrained

[23] In unreported results we also measure the risk of the underlying equity holdings using beta exposure and find similar results.
[24] Short sales also possess insurance-like qualities but are classified as leverage. In untabulated tests, we create a new classification "Insurance-Like Instruments" which includes short sales, derivatives, and futures, and find that the non-use of these instruments is associated with worse performance and higher risk.

investors will invest in low-beta securities. Instead, our results suggest a doubling-down effect, where users of leverage also invest in riskier equity securities. We do not find any relation between illiquid asset use or non-use and fund returns or fund risk, suggesting that they are not as impactful on fund outcomes as leverage or derivatives.

It is difficult to distinguish between speculative and hedging motives based on the binary allowance and use variables (described by question 70 of the N-SAR forms). We therefore also conduct analysis that considers the association between option positions and fund performance and risk. This analysis relies on options data from the CRSP Mutual Fund database, which are available from 2009. Given that there is no identifier for options, we identify option positions using the security name field in the database. Once we identify the options, we match the underlying equity position to a ticker that is typically provided in the security name field of the database, and we check whether a fund has a long or short position in the underlying security. Using these data, we categorize the different option positions into three categories: hedged, unhedged, and income strategies. A hedged strategy is defined as a long option position with an offsetting position in the underlying security. For example, a fund holding (shorting) IBM stock along with a put (call) option in IBM would be considered a hedged equity position. An unhedged strategy is defined as an option position (long or written) with no offsetting position in the underlying security. An income strategy is defined as a covered call or a covered put, which are both written option positions with offsetting positions in the underlying security, such as a fund writing a call (put) option on IBM while holding (shorting) IBM stock.

The results of this analysis are shown in Appendix Table 5. The first three columns present results on returns and show that hedged option strategies are associated with significantly lower excess return and MPPM, but not four-factor alpha, which is more likely to be biased for derivatives users. These results show that complex instruments that reduce risk are associated with negative returns, which complement the results presented in Table 12 on risk compensation. We also find evidence that income strategies are detrimental to fund performance, as their use is associated with significantly lower excess return and MPPM. In contrast, we observe no significant relation between unhedged option strategies and fund performance.

The results with respect to risk, presented in columns 4 through 6, show that all three option strategies are associated with significantly lower fund standard deviation and beta exposure. As expected, the magnitude of the effect is largest for hedged option strategies. There is also significant negative relation between hedged option strategies and idiosyncratic volatility, and a significant positive relation between unhedged strategies and idiosyncratic volatility.

6.5 Comparison with ABCC Sample

In this section, we present tests that help verify the assertion that ABCC's results reflect the nature of their sample period. To do so, we acquire data for ABCC's sample period and replicate our main result on the relation of complex instrument allowance and returns in their sample. We then extend the tests to a longer sample that includes both their and our sample periods.

Compiling the data and conducting this analysis required multiple steps. First, we acquired information on the funds in ABCC analysis thanks to the generosity of the authors who provided us with their original data. The identifier used by ABCC was based on an old version of the CRSP Mutual Fund database which is no longer available. However, they did have a CIK (SEC EDGAR identifier), which we were able to match to our dataset and to the current CRSP Mutual Fund Database. Using the CIK, fund name, and report date, we are able to link 91.7% of the fund-semester observations in their sample to observations in our sample. Second, our sample identifies funds using the CRSP Class Group variable, which allows us to aggregate share classes of the same fund. This variable is not available in ABCC's sample period. We therefore use an alternate fund identifier, WFICN, which is common across both periods.[25] Another challenge is that in our main results, we compute fund

[25] In the main analysis we use the CRSP Class Group fund identifier as it is better populated (see Zhu 2020).

returns from daily mutual fund data. Fund return data are available only on a monthly basis in ABCC's sample period. We therefore create two new measures of fund performance based on monthly returns. The monthly excess return is computed as the return of the funds minus the risk-free rate each month. We also compute a monthly four-factor alpha. Specifically, we compute the four-factor loadings of funds using the funds' returns for the previous 36 months (with a minimum of 24 months), and then compute the alpha for the funds in the current month by subtracting the product of the funds' factor loadings and returns of each factor from the funds' excess return. We also exclude the funds' institutional ownership from our set of control variables as it is not available in the ABCC's sample period.

Using this fund-month level dataset, we replicate our regression model that examines the relation between allowance and fund performance. The results of this analysis are presented in Table 13. The first two columns present results using ABCC's sample. Consistent with their results, we find no significant relation between complex instrument allowance and excess return or four-factor alpha.[26] These results suggest that the differences between our main result and ABCC's is not driven by differences in methodology. We next conduct the analysis using the combined sample that spans the full sample period (2000 to 2015). These results are presented in columns 3 and 4 of Table 13, and show that consistent with our main results, complex instrument allowance is negatively associated with fund performance measured using both monthly excess return and monthly four-factor alpha.

We also use this framework to examine the association between complex instrument allowance and fund performance in Up and Down markets using the ABCC and combined samples. The results of the analysis are presented in Appendix Table 6 Panel A and show that in the ABCC sample, allowance is associated with positive performance in up markets (significant for excess return but not four-factor alpha), and negative performance in

[26] We do not consider the MPPM measure due to challenges in computing the measure using monthly (rather than daily) return data, and the fact ABCC do not include the measure in their original analysis.

down markets (again, significant for excess return but not four-factor alpha). The differences between the up and down markets are statistically significant, and we continue to observe the same pattern in the combined sample. Panel B further divides the up and down markets using 5% monthly return cutoffs, and shows that (with the exception of column 2, which examines four-factor alphas in ABCC's original sample), allowance in more extreme market conditions is associated with more extreme returns. Taken together, these results provide additional support that it is important to study the implications of complex instrument allowance at funds over a long sample that includes up and down market periods that are representative of the historic time series of market returns.

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 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 helps or hurts 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 derivatives, leverage, and illiquid assets.

Our results suggest that the concerns are justified. Allowance is associated with lower performance and higher risk. The negative effects are magnified during market downturns. Warren Buffett once called derivatives "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.

[27] See www.berkshirehathaway.com/letters/2002pdf.pdf.

These findings raise the question of why there has been a trend toward more complexity in the mutual fund industry if these instruments are associated with poor performance. One potential explanation is that these funds cater to an investor bias for complexity. Hsu and West (2016) argue that while simplicity leads to better investor outcomes, complex strategies support higher fees and cater to investors' perception that navigating a complicated investment landscape requires complicated solutions. Another possibility is that mutual fund investors do not realize that complex instruments can be harmful to their interests. The results of ABCC suggest that the allowance of these instruments is benign. In this regard, the contrasting results of our paper provide useful information to investors and policy makers. Our paper also highlights the potential for complex instruments to give fund managers a false sense of security, which can lead to risk compensation behavior. In light of the potential harmful effects of complex instruments highlighted by our paper, their allowance should be granted with caution.

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Figure 1
Complex Instrument Allowance over Time

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

Interpretation: This figure shows the increase in complex instrument allowance at funds over our sample period.

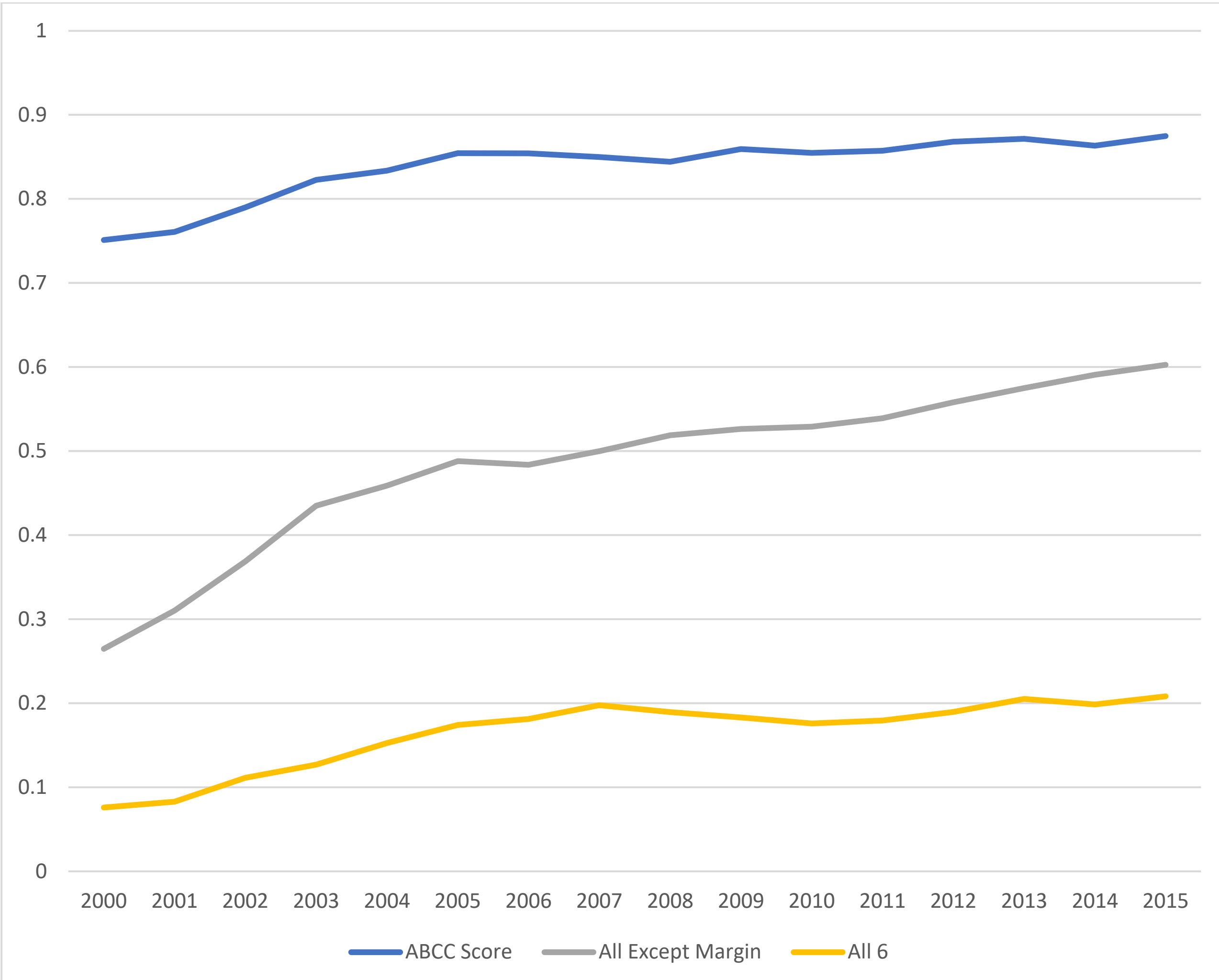

Table 1
Allowance of the Individual Complex Instruments

Description: This table reports statistics on the frequency of complex instrument allowance in funds by year (Panel A) and by the fund's style (Panel B) in a sample that spans the period from 2000 to 2015. It presents data on the allowance for each of the six individual complex instruments and for the ABCC Score. N is the number of fund-semester observations. We use each fund's four-digit CRSP Objective Codes to classify the domestic equity funds in our sample into seven categories: large- and mid-cap funds (EDCL and EDCM); small-cap funds (EDCS); micro-cap funds (EDCI); growth style funds (EDYG); income style funds (EDYI); growth and income style funds (EDYB); sector funds (style codes beginning with EDS); and hedged and short style funds (EDYH and EDYS).

Interpretation: The allowance of all six instruments increased over our sample period, with the largest increases occurring in short sales, margin, and futures. Hedged and short style funds have the highest overall level of allowance, followed by sector funds.

Panel A: Allowance by year

Year	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
2000	2,988	0.813	0.109	0.367	0.819	0.732	0.889	0.751
2001	3,233	0.819	0.112	0.412	0.844	0.756	0.908	0.761
2002	3,489	0.847	0.139	0.466	0.871	0.805	0.922	0.790
2003	3,554	0.846	0.163	0.539	0.886	0.835	0.939	0.823
2004	3,622	0.851	0.185	0.564	0.891	0.842	0.941	0.833
2005	3,641	0.845	0.211	0.603	0.905	0.852	0.945	0.854
2006	3,879	0.848	0.222	0.601	0.914	0.859	0.949	0.854
2007	3,997	0.848	0.236	0.616	0.913	0.863	0.946	0.850
2008	4,071	0.856	0.234	0.633	0.921	0.871	0.946	0.844
2009	5,139	0.849	0.230	0.644	0.925	0.884	0.948	0.859
2010	4,974	0.853	0.226	0.649	0.924	0.875	0.948	0.855
2011	4,859	0.860	0.238	0.665	0.921	0.873	0.946	0.857
2012	4,682	0.867	0.259	0.674	0.928	0.874	0.949	0.868
2013	4,636	0.890	0.275	0.685	0.930	0.872	0.952	0.871
2014	4,605	0.896	0.263	0.700	0.926	0.873	0.953	0.863
2015	3,448	0.901	0.275	0.713	0.932	0.876	0.962	0.875
Total	64,817	0.857	0.217	0.607	0.907	0.852	0.942	0.842

Panel B: Allowance by fund style

Fund Style	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
Large and Mid Cap	7,729	0.853	0.235	0.632	0.930	0.888	0.964	0.864
Small Cap	11,788	0.846	0.212	0.574	0.916	0.859	0.950	0.842
Micro Cap	990	0.904	0.308	0.642	0.840	0.777	0.942	0.828
Growth	24,501	0.863	0.201	0.608	0.894	0.836	0.935	0.836
Income	2,785	0.822	0.185	0.515	0.926	0.856	0.926	0.823
Growth and Income	10,262	0.845	0.232	0.537	0.870	0.819	0.907	0.809
Sector	5,633	0.883	0.205	0.732	0.972	0.913	0.992	0.899
Hedged and Short	1,129	0.904	0.399	0.965	0.941	0.913	0.970	0.923
Total	64,817	0.857	0.217	0.607	0.907	0.852	0.942	0.842

Table 2
Summary Statistics

Description: This table reports descriptive statistics of our complex instrument measures, fund returns, fund risk, and fund characteristics in a sample that spans the period from 2000 to 2015. Returns are 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. Characteristics include fund size (AUM in millions), family size (AUM in millions), fund's age (years), the percentage of AUM in the institutional share classes, and fund flows (%). Panel A presents statistics for our full sample. Panel B presents mean levels of our fund characteristics by fund style.

Panel A: Summary statistics for the full sample

Variable Name	N	Mean	Std. Dev.	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 and Risk						
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
Standard Deviation	64,817	18.46	7.86	12.72	16.25	21.85
Beta Exposure	64,817	0.98	0.23	0.88	0.99	1.09
Idiosyncratic Volatility	64,817	5.23	3.57	2.87	4.12	6.36
Fund Characteristics						
Fund Size	64,796	1,260	4,611	64	231	837
Family Size	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

Panel B: Summary statistics by fund style

Fund Style	N	Fund Size	Fund Family Size	Age	Institutional Fund Ownership	Fund Flows
Large and Mid Cap	7,729	967	72,333	11.35	35.27	0.41
Small Cap	11,788	772	54,749	11.26	34.59	0.29
Micro Cap	990	232	6,602	10.64	26.10	−0.09
Growth	24,501	1,420	69,488	11.47	28.53	0.32
Income	2,785	1,847	70,387	12.32	31.40	0.83
Growth and Income	10,262	1,924	73,313	13.86	29.21	−0.13
Sector	5,633	638	118,225	12.21	7.02	0.50
Hedged and Short	1,129	680	22,180	6.09	48.41	1.34
Total	64,817	1,248	70,228	11.76	29.07	0.31

Table 3
Determinants of Complex Instrument Allowance

Description: This table reports tests on the determinants of complex instrument allowance in a sample that spans the period from 2000 to 2015. We estimate panel regressions of fund complex instrument allowance score on a set of explanatory variables, which include the proportion of fund shares owned by institutional shareholders, the log of the AUM of the fund's family, the log of the fund's AUM, the log of the fund's age, and fund flows. All the explanatory variables are observed six months before the dependent variable. Additionally, we include time × 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.

Interpretation: Institutional fund ownership, fund family size, and fund size are positively related to complex instrument allowance, while fund age and fund flows are negatively related to allowance.

	ABCC Score	Leverage	Derivatives	Restricted Securities
	(1)	(2)	(3)	(4)
Institutional Fund Ownership (t−1)	0.03	0.01	0.06	0.03
	(0.000)	(0.658)	(0.000)	(0.000)
Log(Fund Family Size) (t−1)	2.33	0.98	3.05	2.10
	(0.000)	(0.000)	(0.000)	(0.000)
Log(Fund Size) (t−1)	0.73	1.11	0.56	0.80
	(0.001)	(0.001)	(0.099)	(0.002)
Log(Fund Age) (t−1)	−4.72	−5.22	−5.18	−3.51
	(0.000)	(0.000)	(0.000)	(0.000)
Fund Flows (t−1)	−0.24	−0.12	−0.32	−0.19
	(0.000)	(0.039)	(0.000)	(0.000)
N	50,097	50,097	50,097	50,097
R^2	0.153	0.076	0.109	0.083

Table 4
Performance of Constrained vs. Unconstrained Funds

Description: This table presents the performance of portfolios of funds sorted according to the ABCC Scores in a sample that spans the period from 2000 to 2015. 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.

Interpretation: The least constrained funds (i.e., those with highest allowance) underperform the most constrained funds.

Panel A: ABCC Score

	Excess Return	Four-Factor Alpha	MPPM
Most constrained	4.75	−0.55	0.11
	(0.293)	(0.536)	(0.502)
Least constrained	3.94	−1.35	−2.92
	(0.401)	(0.162)	(0.400)
Least constrained − Most constrained	−0.80	−0.81	−3.02
	(0.018)	(0.002)	(0.000)
N	3,877	3,877	3,877

Panel B: ABCC Score (Equal weighted)

	Excess Return	Four-Factor Alpha	MPPM
Most constrained	4.75	−0.56	0.12
	(0.292)	(0.530)	(0.502)
Least constrained	3.96	−1.35	−2.90
	(0.400)	(0.162)	(0.400)
Least constrained − Most constrained	−0.80	−0.80	−3.03
	(0.023)	(0.003)	(0.001)
N	3,877	3,877	3,877

Table 5
Fund Performance and Complex Instrument Allowance

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls in a sample that spans the period from 2000 to 2015. 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 × 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.

Interpretation: Complex instrument allowance is negatively associated with fund performance after controlling for factors that affect performance.

	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	50,097	50,097	50,097
R^2	0.813	0.410	0.829

Table 6
Fund Risk and Complex Instrument Allowance

Description: This table reports results from panel regressions of fund risk on complex instrument allowance score and a set of controls in a sample that spans the period from 2000 to 2015. 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 × 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.

Interpretation: Complex instrument allowance is positively associated with fund risk, and this relation is driven by beta (systematic risk) exposure.

	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	50,097	50,097	50,097
R^2	0.854	0.500	0.728

Table 7

Fund Performance and Complex Instrument Allowance in Up and Down Markets

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score conditional on the market environment, and a set of controls in a sample that spans the period from 2000 to 2015. Our variables of interest are the interactions of the ABCC Score with dummy variables that indicate whether the market is in an up or down state. An up (down) market is defined as a semester in which excess return of the market portfolio 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 × 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.

Interpretation: The negative relation between complex instrument allowance and fund performance is concentrated in down markets.

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Up market × ABCC Score (a)	1.28	0.33	0.95
	(0.000)	(0.190)	(0.002)
Down market × ABCC Score (b)	−5.50	−2.82	−6.56
	(0.000)	(0.000)	(0.000)
N	50,097	50,097	50,097
R^2	0.814	0.410	0.830
p-value for difference between (a) and (b)	0.000	0.000	0.000

Table 8
Fund Performance and Complex Instrument Allowance with Fund Fixed Effects

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls in a sample that spans the period from 2000 to 2015. 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). 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 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 × 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.

Interpretation: This table uses fund fixed effects to assess the impact of within-fund changes in the ABCC Score on fund performance and risk. The results continue to show that complex instrument allowance is negatively associated with fund performance and positively associated with fund risk.

	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(5)	(5)	(6)
ABCC Score	−2.80	−1.27	−3.33	0.81	0.04	0.21
	(0.002)	(0.018)	(0.001)	(0.000)	(0.000)	(0.072)
Log(Fund Size) (t−1)	−3.07	−1.91	−3.39	0.42	0.02	0.10
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Fund Family Size) (t−1)	−0.53	−0.33	−0.59	0.06	0.00	−0.01
	(0.000)	(0.000)	(0.000)	(0.134)	(0.092)	(0.813)
Log(Fund Age) (t−1)	1.15	1.18	1.43	−0.36	−0.01	−0.13
	(0.014)	(0.000)	(0.007)	(0.007)	(0.066)	(0.071)
Institutional Fund Ownership (t−1)	0.02	0.01	0.02	0.00	0.00	0.00
	(0.002)	(0.005)	(0.002)	(0.100)	(0.403)	(0.152)
Fund Flows (t−1)	−0.25	−0.10	−0.26	0.01	0.00	0.01
	(0.000)	(0.000)	(0.000)	(0.207)	(0.465)	(0.034)
N	49,867	49,867	49,867	49,867	49,867	49,867
R^2	0.855	0.540	0.873	0.937	0.800	0.907

Table 9
Fund Performance and Instrumented Complex Instrument Allowance

Description: This table shows the results of a two-stage least squares regression in a sample that spans the period from 2000 to 2015. 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 (but with different style) and control variables. In the second stage (columns 2 through 7), we regress fund performance and risk 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). 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 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 × 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.
Interpretation: This table uses an instrumental variable approach to address the endogeneity concerns. The results continue to show that complex instrument allowance is negatively associated with fund performance and positively associated with fund risk.

	First Stage	Second Stage					
	ABCC Score	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family ABCC Score	0.771 (0.000)						
Predicted ABCC Score		−1.89 (0.009)	−1.29 (0.015)	−2.81 (0.001)	1.56 (0.000)	0.09 (0.000)	0.23 (0.272)
Log(Fund Size) (t−1)	0.005 (0.000)	−0.31 (0.000)	−0.07 (0.079)	−0.29 (0.000)	−0.07 (0.014)	0.00 (0.008)	−0.06 (0.000)
Log(Fund Family Size) (t−1)	0.003 (0.006)	0.23 (0.000)	0.12 (0.001)	0.22 (0.000)	0.01 (0.524)	0.00 (0.017)	−0.07 (0.000)
Log(Fund Age) (t−1)	−0.019 (0.000)	0.31 (0.020)	0.09 (0.342)	0.30 (0.047)	0.09 (0.147)	0.01 (0.001)	−0.03 (0.451)
Fund Institutional Ownership (t−1)	0.000 (0.737)	0.00 (0.053)	0.00 (0.002)	0.00 (0.054)	0.00 (0.834)	0.00 (0.009)	−0.01 (0.000)
Fund Flows (t−1)	−0.001 (0.002)	−0.06 (0.003)	0.03 (0.018)	−0.05 (0.014)	−0.02 (0.019)	0.00 (0.000)	0.01 (0.118)
N	44,607	44,607	44,607	44,607	44,607	44,607	44,607
R^2	0.525	0.824	0.431	0.839	0.867	0.529	0.747

Table 10
Individual Complex Instrument Classifications

Description: 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 in a sample that spans the period from 2000 to 2015. We consider three different types: derivatives, leverage, 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 × 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.

Interpretation: This table shows that the negative relation between complex instrument allowance and fund performance is predominantly driven by derivative allowance, while the positive relation between allowance and total fund risk is driven by derivative and leverage allowance.

	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
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)
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)
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	50,097	50,097	50,097	50,097	50,097	50,097
R^2	0.813	0.410	0.829	0.854	0.500	0.729

Table 11
Complex Instrument Use

Description: This table reports results from panel regressions of fund performance on complex instrument use score and a set of controls in a sample that spans the period from 2000 to 2015. 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 5. The second specification is the regression with fund fixed effects used in Table 8. The third specification is the instrumental variable regression used in Table 9. The fourth specification is the regression that includes the up and down market interactions used in Table 7. 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 × 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.
Interpretation: Complex instrument use is also associated with negative fund performance, and this relation is also concentrated in down markets.

Specification	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Use Score (Base)	−1.79	−1.14	−1.61
	(0.020)	(0.060)	(0.072)
N	50,097	50,097	50,097
R^2	0.813	0.41	0.829
Use Score (Fixed Effects)	−1.61	−1.91	−1.96
	(0.057)	(0.001)	(0.039)
N	49,867	49,867	49,867
R^2	0.855	0.54	0.873
Use Score (Instrumental Variable)	−4.51	−1.34	−4.15
	(0.057)	(0.456)	(0.135)
N	44,607	44,607	44,607
R^2	0.823	0.43	0.839
Up Market Interaction (a)	0.79	1.48	1.02
	(0.189)	(0.001)	(0.064)
Down market Interaction (b)	−6.15	−5.58	−6.07
	(0.001)	(0.000)	(0.006)
N	50,097	50,097	50,097
R^2	0.813	0.411	0.829
Difference between (a) and (b)	0.000	0.000	0.002

Table 12
Risk Compensation and Complex Instrument Allowance

Description: This table reports results from panel regressions of fund performance and risk of funds that are allowed to use each of the different types of complex instruments but do not actually use them (Non-Use), and those that do actually use them (Use) in the specified semester in a sample that spans the period from 2000 to 2015. We construct Use and Non-Use dummy variables for the three different types of complex instruments: derivatives, leverage, 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 net returns and the standard deviation of the equity securities. All measures are computed from daily 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 × 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.

Interpretation: Derivatives non-use is negatively associated with fund performance and positively associated with the risk of the fund's underlying equity holdings, which is consistent with risk compensation theory.

	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Equity Standard Deviation
	(1)	(2)	(3)	(4)	(5)
Derivatives Use	−1.45	−0.29	−1.55	0.12	0.38
	(0.000)	(0.331)	(0.000)	(0.507)	(0.044)
Derivatives Non-Use	−1.18	−0.44	−1.51	0.57	0.58
	(0.001)	(0.100)	(0.000)	(0.001)	(0.001)
Leverage Use	−0.56	−0.82	−0.90	0.39	0.76
	(0.179)	(0.011)	(0.060)	(0.042)	(0.000)
Leverage Non-Use	0.27	0.09	0.09	0.28	0.28
	(0.398)	(0.705)	(0.815)	(0.038)	(0.037)
Illiquid Assets Use	0.21	0.08	0.21	0.05	0.23
	(0.636)	(0.807)	(0.684)	(0.819)	(0.348)
Illiquid Assets Non-Use	0.07	0.02	0.06	0.14	−0.21
	(0.856)	(0.940)	(0.896)	(0.478)	(0.365)
N	50,097	50,097	50,097	50,097	41,819
R^2	0.813	0.410	0.829	0.855	0.890

Table 13
Comparison with ABCC Sample

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls at the month-fund level. We consider two different samples. The ABCC Sample period includes fund-months that appeared in ABCC's original sample (1994 to 2001), whereas the combined sample includes fund-months in both our and ABCC's sample (1994 to 2015). The variable of interest is the ABCC Score. All the control variables are observed in the most recent December or June before the dependent variable is realized. Fund performance is measured using the monthly excess returns and monthly four-factor alphas computed using factor loadings from the previous 36 months. 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, and fund flows. Additionally, we include time × 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.

Interpretation: This table shows that there is no relation between complex instrument allowance and fund performance in the ABCC sample using our methodological approach. It also shows that the negative relation between allowance and fund performance is present in the combined sample.

	ABCC Sample		Combined Sample	
	Excess Return	Four-Factor Alpha	Excess Return	Four-Factor Alpha
	(1)	(2)	(3)	(4)
ABCC Score	−0.46	0.21	−1.17	−0.69
	(0.723)	(0.872)	(0.000)	(0.019)
Log(Fund Size) (t−1)	0.21	0.44	0.15	0.24
	(0.303)	(0.026)	(0.001)	(0.000)
Log(Fund Family Size) (t−1)	−0.24	−0.04	0.03	0.00
	(0.201)	(0.783)	(0.446)	(0.956)
Log(Fund Age) (t−1)	−0.81	−1.58	−0.20	−0.48
	(0.078)	(0.001)	(0.064)	(0.000)
Fund Flows (t−1)	0.19	0.15	0.13	0.08
	(0.000)	(0.000)	(0.000)	(0.000)
N	24,154	24,154	286,667	286,667
R^2	0.607	0.181	0.825	0.290

Internet Appendix

to accompany

Complex Instruments Have Increased Risk and Reduced Performance at Mutual Funds

Appendix Figure 1
N-SAR Question 70

70. ☐ Investment practices.
Answer "Y" (Yes) or "N" (No) to the following:

Activity	Permitted by Investment Policies? Y/N	If permitted by investment policies, engaged in during the reporting period? Y/N
A. Writing or investing in repurchase agreements		
B. Writing or investing in options on equities		
C. Writing or investing in options on debt securities		
D. Writing or investing in options on stock indices		
E. Writing or investing in interest rate futures		
F. Writing or investing in stock index futures		
G. Writing or investing in options on futures		
H. Writing or investing in options on stock index futures		
I. Writing or investing in other commodity futures		
J. Investments in restricted securities		
K. Investments in shares of other investment companies		
L. Investments in securities of foreign issuers		
M. Currency exchange transactions		
N. Loaning portfolio securities		
O. Borrowing of money		
P. Purchases/sales by certain exempted affiliated persons		
Q. Margin purchases		
R. Short selling		

Appendix Table 1
Allowance of Complex Instruments by Inception Date

Description: This table reports statistics on the frequency of complex instrument allowance in funds by year based on the fund's inception date in a sample that spans the period from 2000 to 2015. Specifically, the four panels present data on funds with inception dates before 1980 (Panel A), between 1980 and 1989 (Panel B), between 1990 and 1999, (Panel C), and after 1999 (Panel D). The table presents data on the allowance for each of the six individual complex instruments and for the ABCC Score.

Interpretation: The trend of higher allowance over time is present across funds with different inception dates.

Panel A: Inception before 1980

Year	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
2000	176	0.830	0.080	0.318	0.750	0.665	0.830	0.704
2001	179	0.827	0.101	0.369	0.771	0.704	0.860	0.719
2002	179	0.804	0.089	0.397	0.821	0.721	0.866	0.728
2003	186	0.742	0.108	0.478	0.801	0.737	0.844	0.733
2004	177	0.746	0.119	0.469	0.819	0.763	0.870	0.752
2005	174	0.695	0.115	0.511	0.845	0.805	0.874	0.773
2006	188	0.718	0.165	0.532	0.846	0.819	0.915	0.791
2007	175	0.754	0.189	0.566	0.851	0.823	0.909	0.795
2008	164	0.787	0.189	0.604	0.884	0.835	0.927	0.807
2009	166	0.777	0.181	0.590	0.880	0.843	0.934	0.818
2010	156	0.808	0.167	0.583	0.891	0.853	0.923	0.820
2011	136	0.831	0.191	0.566	0.897	0.860	0.912	0.824
2012	134	0.843	0.254	0.575	0.910	0.881	0.881	0.831
2013	122	0.844	0.279	0.631	0.926	0.877	0.902	0.844
2014	118	0.822	0.271	0.619	0.924	0.839	0.915	0.822
2015	89	0.831	0.247	0.607	0.933	0.843	0.944	0.835
Total	2,519	0.786	0.162	0.516	0.852	0.797	0.891	0.781

Panel B: Inception from 1980 to 1989

Year	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
2000	524	0.786	0.084	0.374	0.811	0.672	0.865	0.723
2001	535	0.784	0.090	0.387	0.834	0.698	0.881	0.728
2002	526	0.828	0.106	0.441	0.843	0.752	0.894	0.757
2003	526	0.829	0.112	0.487	0.850	0.780	0.922	0.788
2004	528	0.847	0.127	0.532	0.850	0.803	0.943	0.813
2005	539	0.826	0.135	0.532	0.865	0.816	0.935	0.825
2006	554	0.821	0.159	0.518	0.883	0.829	0.930	0.821
2007	534	0.830	0.167	0.549	0.890	0.837	0.931	0.823
2008	519	0.873	0.171	0.593	0.904	0.840	0.942	0.830
2009	612	0.873	0.188	0.621	0.904	0.835	0.946	0.843
2010	584	0.889	0.180	0.630	0.911	0.824	0.949	0.843
2011	546	0.886	0.187	0.647	0.907	0.824	0.945	0.844
2012	522	0.887	0.203	0.655	0.935	0.839	0.950	0.861
2013	509	0.900	0.222	0.654	0.941	0.835	0.949	0.859
2014	496	0.897	0.216	0.651	0.933	0.839	0.962	0.851
2015	377	0.910	0.196	0.653	0.936	0.854	0.966	0.862
Total	8,431	0.853	0.158	0.557	0.886	0.804	0.931	0.816

Panel C: Inception from 1990 to 1999

Year	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
2000	2,209	0.833	0.117	0.373	0.830	0.755	0.900	0.766
2001	2,288	0.839	0.116	0.417	0.848	0.765	0.914	0.769
2002	2,255	0.863	0.132	0.466	0.869	0.808	0.927	0.794
2003	2,176	0.860	0.154	0.549	0.889	0.837	0.945	0.829
2004	2,134	0.859	0.182	0.568	0.894	0.842	0.941	0.836
2005	2,018	0.858	0.212	0.618	0.908	0.852	0.952	0.861
2006	1,990	0.855	0.225	0.611	0.914	0.855	0.955	0.857
2007	1,857	0.852	0.238	0.613	0.911	0.857	0.947	0.849
2008	1,770	0.857	0.244	0.628	0.919	0.872	0.947	0.844
2009	2,245	0.852	0.241	0.638	0.932	0.895	0.958	0.866
2010	2,132	0.852	0.239	0.640	0.932	0.888	0.961	0.862
2011	2,033	0.860	0.254	0.655	0.931	0.886	0.965	0.867
2012	1,899	0.864	0.268	0.655	0.936	0.882	0.964	0.873
2013	1,806	0.893	0.277	0.659	0.935	0.878	0.961	0.874
2014	1,739	0.902	0.263	0.679	0.933	0.877	0.961	0.866
2015	1,271	0.905	0.268	0.692	0.932	0.867	0.965	0.871
Total	31,822	0.861	0.210	0.584	0.905	0.849	0.946	0.840

Panel D: Inception after 1999

Year	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
2000	152	0.829	0.138	0.408	0.816	0.803	0.928	0.789
2001	473	0.821	0.150	0.497	0.880	0.844	0.924	0.806
2002	757	0.855	0.194	0.531	0.922	0.885	0.953	0.838
2003	882	0.873	0.215	0.568	0.913	0.893	0.964	0.857
2004	985	0.883	0.226	0.590	0.908	0.880	0.956	0.859
2005	1111	0.869	0.259	0.643	0.927	0.879	0.956	0.876
2006	1329	0.882	0.249	0.644	0.939	0.886	0.960	0.879
2007	1589	0.868	0.262	0.653	0.931	0.884	0.958	0.869
2008	1750	0.862	0.246	0.660	0.936	0.885	0.949	0.855
2009	2316	0.847	0.235	0.670	0.934	0.895	0.941	0.864
2010	2299	0.849	0.235	0.674	0.929	0.886	0.939	0.858
2011	2336	0.855	0.240	0.681	0.922	0.879	0.934	0.856
2012	2307	0.867	0.263	0.696	0.922	0.878	0.944	0.869
2013	2355	0.887	0.284	0.712	0.923	0.875	0.950	0.873
2014	2391	0.895	0.269	0.729	0.918	0.878	0.949	0.866
2015	1814	0.901	0.293	0.746	0.932	0.888	0.960	0.882
Total	24846	0.869	0.250	0.669	0.924	0.882	0.948	0.864

Appendix Table 2

Fund Performance and Complex Instrument Allowance and Extreme Market Conditions

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score and a set of controls in a sample that spans the period from 2000 to 2015. Our variable of interest is the ABCC Score or the interaction of the ABCC Score with dummy variables that indicate if the market is in an up or down state. Panel A replicates the specification presented in Table 5 after excluding observations in 2008. Panel B defines four market periods, semesters with annualized excess returns greater (less) than 25% (−25%), and semesters with annualized excess returns less (greater) than 25% (−25%) but greater (less) than 0%. 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 × 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.

Interpretation: This table shows that the negative relation between complex instrument allowance and fund performance is robust to excluding the down market period associated with the financial crisis. It also shows that the negative relation between allowance and fund performance is present in both moderate and extreme down markets.

Panel A: Without 2008

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
ABCC Score	−1.27	−0.84	−1.89
	(0.005)	(0.010)	(0.000)
N	46,503	46,503	46,503
R^2	0.776	0.372	0.782

Panel B: Moderate and extreme market events

	Excess Return	Four-Factor Alpha	MPPM
	(1)	(2)	(3)
Up market > 25% × ABCC Score (a)	1.62	−0.74	1.19
	(0.004)	(0.049)	(0.017)
Up market <25% × ABCC Score (b)	1.14	0.82	0.85
	(0.000)	(0.002)	(0.009)
Down market > −25% × ABCC Score (c)	−3.05	−2.08	−3.90
	(0.000)	(0.001)	(0.000)
Down market < −25% × ABCC Score (d)	−11.59	−4.66	−13.18
	(0.000)	(0.000)	(0.000)
N	50,097	50,097	50,097
R^2	0.814	0.411	0.830
p-value for difference between (a) and (d)	0.000	0.000	0.000
p-value for difference between (b) and (c)	0.000	0.000	0.000

Appendix Table 3
Nearest-Neighbor Approach

Description: This table reports results from a nearest-neighbor matched sample technique that estimates average treatment effects to return and risk following increases to a fund's complex instrument allowance in a sample that spans the period from 2000 to 2013. The treatment (control) group is identified as funds that (do not) experience an increase in their allowance in a given semester. The technique finds a match for each fund in each group using a two-step approach. First, it identifies a set of potential matches based on funds in the same style and semester. Among those potential matches it selects one "nearest neighbor" based on our set of control variables (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), lagged allowance, and the one- and two-semester lags of the dependent variable. It then estimates the average treatment effect by comparing the difference in the dependent variable over the subsequent four quarters between the matched pairs in the two groups. *p-values* are reported below the average treatment estimates in parentheses.

Interpretation: This table provides some evidence that funds experience worse performance and higher risk after allowance increases, compared to a matched sample that does not experience an allowance increase.

	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
ABCC Score Increase	−0.30	−0.36	−0.45	0.27	0.013	0.02
	(0.264)	(0.089)	(0.126)	(0.015)	(0.018)	(0.753)
N	30,700	30,700	30,700	30,700	30,700	30,700

Appendix Table 4
Use of the Individual Complex Instruments

Description: This table reports statistics on the frequency of complex instrument use by funds by year (Panel A) and by the fund's style (Panel B) in a sample that spans the period from 2000 to 2015. The table presents data on the use of six individual complex instruments and for the Use Score.

Interpretation: Complex instrument use has been relatively stable over our sample period.

Panel A: Use by year

Year	N	Borrow Use	Margin Use	Short Sales Use	Options Use	Futures Use	Restricted Use	Use Score
2000	2,988	0.096	0.001	0.026	0.069	0.115	0.154	0.077
2001	3,233	0.090	0.001	0.038	0.080	0.125	0.159	0.082
2002	3,489	0.086	0.002	0.040	0.084	0.122	0.148	0.080
2003	3,554	0.080	0.002	0.042	0.102	0.109	0.154	0.081
2004	3,622	0.073	0.002	0.038	0.084	0.098	0.157	0.075
2005	3,641	0.081	0.002	0.030	0.078	0.095	0.160	0.074
2006	3,879	0.090	0.002	0.038	0.075	0.097	0.163	0.078
2007	3,997	0.099	0.003	0.041	0.085	0.109	0.160	0.083
2008	4,071	0.099	0.006	0.048	0.090	0.116	0.170	0.088
2009	5,139	0.086	0.004	0.039	0.085	0.126	0.160	0.083
2010	4,974	0.090	0.005	0.039	0.081	0.126	0.166	0.085
2011	4,859	0.081	0.005	0.040	0.079	0.125	0.170	0.083
2012	4,682	0.082	0.004	0.040	0.076	0.125	0.171	0.083
2013	4,636	0.079	0.003	0.045	0.071	0.128	0.159	0.081
2014	4,605	0.077	0.006	0.048	0.066	0.126	0.163	0.081
2015	3,448	0.082	0.005	0.047	0.062	0.122	0.158	0.079
Total	64,817	0.086	0.003	0.040	0.079	0.117	0.161	0.081

Panel B: Use by fund style

Fund Style	N	Borrow	Margin	Short Sales	Options	Futures	Restricted	ABCC Score
Large and Mid Cap	7,729	0.082	0.001	0.010	0.056	0.102	0.161	0.069
Small Cap	11,788	0.072	0.001	0.012	0.042	0.138	0.160	0.071
Micro Cap	990	0.137	0.000	0.036	0.067	0.025	0.284	0.092
Growth	24,501	0.087	0.003	0.036	0.084	0.116	0.141	0.078
Income	2,785	0.054	0.008	0.011	0.109	0.095	0.181	0.076
Growth and Income	10,262	0.078	0.001	0.023	0.081	0.166	0.130	0.080
Sector	5,633	0.116	0.002	0.044	0.122	0.022	0.285	0.099
Hedged and Short	1,129	0.174	0.075	0.863	0.221	0.205	0.121	0.277
Total	64,817	0.086	0.003	0.040	0.079	0.117	0.161	0.081

Appendix Table 5
Hedged and Unhedged Option Strategies

Description: This table reports results from panel regressions of fund performance and risk for funds that use various option strategies in a sample that spans the period from 2008 to 2015. We use dummy variables to categorize option positions into three strategies: hedged strategies are defined as long option positions with an offsetting position in the underlying security; unhedged strategies are defined as option positions (long or written) with no offsetting position in the underlying security; and income strategies are defined as a covered call or put, which is a written option position with an offsetting position in the underlying security. 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. The sample period is from 2009 to 2015. Additionally, we include time × 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.
Interpretation: This table shows that complex instruments that reduce risk are associated with negative returns. It also provides evidence that income strategies are detrimental to fund performance.

	Excess Return	Four-Factor Alpha	MPPM	Standard Deviation	Beta Exposure	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Hedged Strategies	−2.67	−0.43	−1.70	−2.23	−0.10	−0.95
	(0.006)	(0.486)	(0.046)	(0.005)	(0.055)	(0.000)
Unhedged Strategies	0.01	−0.30	0.18	−0.37	−0.04	0.39
	(0.985)	(0.377)	(0.650)	(0.086)	(0.009)	(0.004)
Income Strategies	−1.65	0.30	−1.44	−0.70	−0.06	0.09
	(0.001)	(0.447)	(0.004)	(0.018)	(0.004)	(0.535)
N	23,355	23,355	23,355	23,355	23,355	23,355
R^2	0.894	0.446	0.916	0.917	0.586	0.794

Appendix Table 6

Fund Performance and Complex Instrument Allowance in Up and Down Markets

Description: This table reports results from panel regressions of fund performance on complex instrument allowance score conditional on the market environment, and a set of controls at the month-fund level. We consider two different samples. The ABCC Sample period includes fund-months that appeared in ABCC's original sample (1994 to 2001), whereas the combined sample includes fund-months in both our and ABCC's sample (1994 to 2015). In Panel A, an up (down) market is defined as a month in which excess return of the market portfolio is positive (negative). Panel B defines four market conditions, semesters with monthly excess returns greater (less) than 5% (−5%), and semesters with monthly excess returns less (greater) than 5% (−5%) but greater (less) than 0%. The variable of interest is the ABCC Score interacted with the up and down market dummies. All the control variables are observed in the most recent December or June before the dependent variable is realized. Fund performance is measured using monthly excess returns and monthly four-factor alphas computed using factor loadings from the previous 36 months. 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, and fund flows. Additionally, we include time × 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.

Interpretation: The negative relation between complex instrument allowance and fund performance during down market periods is present in both the ABCC and combined samples.

Panel A: Up and down markets

	ABCC Sample		Combined Sample	
	Excess Return	Four-Factor Alpha	Excess Return	Four-Factor Alpha
	(1)	(2)	(3)	(4)
Up market × ABCC Score (a)	12.82	1.74	3.62	0.10
	(0.000)	(0.313)	(0.000)	(0.780)
Down market × ABCC Score (b)	−16.41	−1.57	−8.07	−1.84
	(0.000)	(0.283)	(0.000)	(0.000)
N	24,232	24,232	270,242	270,242
R^2	0.609	0.181	0.824	0.290
p-value for difference between (a) and (b)	0.0000	0.0942	0.0000	0.0007

Panel B: Moderate and extreme up/down markets

	ABCC Sample		Combined Sample	
	Excess Return	Four-Factor Alpha	Excess Return	Four-Factor Alpha
	(1)	(2)	(3)	(4)
Up market > 5% × ABCC Score (a)	5.16	0.15	4.52	−0.79
	(0.147)	(0.963)	(0.008)	(0.429)
Up market < 5% × ABCC Score (b)	15.81	2.36	3.36	0.35
	(0.000)	(0.166)	(0.000)	(0.309)
Down market > −5% × ABCC Score (c)	−10.21	−1.69	−4.46	−1.26
	(0.000)	(0.211)	(0.000)	(0.006)
Down market < −5% × ABCC Score (d)	−30.78	−1.29	−15.30	−3.00
	(0.000)	(0.650)	(0.000)	(0.001)
N	24,232	24,232	270,242	270,242
R^2	0.609	0.181	0.824	0.290
p-value for difference between (a) and (d)	0.000	0.719	0.000	0.143
p-value for difference between (b) and (c)	0.000	0.038	0.000	0.001