

# Unmasking Mutual Fund Derivative Use

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## Abstract

Using new SEC data, we study fund derivative use and its impact on performance. Despite small portfolio weights, derivatives contribute largely to fund returns. Contrary to prior research, we find most employ derivatives to amplify, not hedge, equity returns. Using machine learning to classify funds' derivative strategies reveals high specializations linked to information-related trading, liquidity management, gaining exposure, or hedging motives. Long index derivative users drive the amplification. During the COVID-19 crisis, they significantly increased derivative use more than others and shifted strategies, but initially lost on existing positions and then on newly opened short positions when markets unexpectedly rebounded.

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# 1 Introduction

Over thirty percent of mutual funds hold derivatives, and holding them is permitted by most funds. Yet, there is little evidence to date of a direct relation between fund performance and derivative use. Progress in evaluating fundamental hypotheses in this regard, such as whether funds use derivatives to hedge or amplify positions, has been hindered by the lack of appropriate data. A central limitation of data used in prior work attempting to tackle this topic is that it did not enable recovering reasonable estimates for funds' derivative positions and derivative portfolio returns, since the data typically provided only flags identifying derivative use at a semiannual frequency. This is especially limiting when trying to understand dynamic relations between derivative and equity positions. The most direct evidence so far comes from a survey of mutual funds by Koski and Pontiff (1999), which suggests most mutual fund managers use derivatives for hedging, and only a small minority use them for amplification and speculation.

Using a novel dataset extracted from SEC's Form N-PORT, which became available only in September 2019, we infer the performance of fund derivative positions, evaluate the impact of derivatives on fund returns, and empirically test whether derivatives are used for hedging or amplification among US domestic active equity mutual funds.<sup>1</sup> We show that, contrary to the common belief that derivatives are used for hedging, most (59%) of the derivative-using funds use derivatives to amplify their equity returns.

Prior research has discussed the potential benefits of using derivatives. Hypothesized benefits include better use of information, lower transaction cost, lower cost of liquidity-motivated trading, and more efficient means of maintaining a certain risk exposure (Koski and Pontiff (1999)), Deli and Varma (2002), Almazan, Brown, Carlson, and Chapman (2004), Frino, Lepone, and Wong (2009)). Despite potential performance enhancement through derivatives, we find no evidence that funds using derivatives to amplify their equity returns outperform nonusers.

Our central contributions are fourfold. First, we compare Form N-PORT and the commonly used CRSP database in terms of mutual funds' derivative coverage and point out several key limitations of CRSP. Second, we evaluate the primary objective of derivative use by mutual funds, debunking the prevailing hypothesis that funds mostly use derivatives to hedge and revealing most funds use derivatives to amplify equity returns. Specifically, the majority of derivative users solely use long equity index

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<sup>1</sup>Throughout the paper, we generally use the term funds to refer to active equity mutual funds.

derivatives, the return of which positively correlates with the rest of the portfolio, with an average correlation of 0.67. This analysis provides evidence consistent with the preponderance of an amplification motive. Third, we challenge prior conclusions in the literature regarding the insignificant impact of derivatives on fund performance and risk exposure by providing evidence that derivatives contribute substantially to fund returns. Lastly, we analyze how the extent of derivative use, associated strategies, and contribution to fund returns change at times of crisis. This analysis also enables us to consider and more carefully evaluate the mechanism driving the changes, in part revealing differential salience of the crisis across managers plays an important role in shaping derivative strategies.

In comparing the new Form N-PORT data with the established CRSP Mutual Fund Database, we highlight the latter’s limitations in covering mutual funds’ derivative holdings. CRSP, which has provided derivative holdings since 2010 after partnering with Lipper, offers a more extensive historical dataset but falls short in several crucial aspects. Notably, N-PORT data offers monthly data on fund-level realized and unrealized Profit and Loss (PnL) from derivative positions—unique metrics not available in other datasets that facilitate assessing a fund’s derivative performance. Additionally, unlike CRSP data, N-PORT includes the notional amounts of derivatives, which is crucial for assessing a fund’s derivative exposure relative to its size. CRSP also misses a substantial amount of derivative positions that N-PORT captures, as it often lumps various positions into a general category that may include derivatives. Furthermore, CRSP sometimes confuses derivatives’ notional amounts with their market values, leading to inaccurate calculations of portfolio weights of these derivative positions.

Utilizing our dataset from N-PORT, we first provide some stylized facts on fund derivative use in our sample. Derivative users represent a substantial proportion of active equity funds in our sample, 35% in terms of the number of funds and 36% in terms of total net assets. Examining detailed derivative holding, we find substantial cross-sectional variation and high persistence in the extent of derivative usage, which can explain differences in fund returns and risk exposure. We measure the extent of derivative use by gross notional exposure, which is the notional amount of all derivative contracts scaled by the fund’s total net assets. Among derivative users, 50% are *token* users, which have a gross notional exposure of less than 2% and perform similarly to nonusers. The prevalence of *token* users helps explain why prior work that predominantly relied on flags identifying derivative use without identifying the extent

of use concluded that derivative users have similar performance and risk exposure as nonusers (see for example, Koski and Pontiff (1999), Fong, Gallagher, and Ng (2005), and Cao, Ghysels, and Hatheway (2011)). In contrast, the other 50% of derivative users (*non-token* users), which represent 17% of total net assets among all active equity funds, invest substantial amounts in derivatives, with a median gross notional exposure of 15%. Furthermore, prior work on derivative use by funds focuses almost exclusively on options and futures, but has overlooked an important derivative class: swaps. The omission was due to the fact that Form N-SAR, the main data source used in these papers to identify users, asks whether the fund uses options and futures, but does not ask about other derivatives.<sup>2</sup> We find that swap users have higher notional exposure, and their derivative positions contribute more to fund returns than any other derivative users. As a result, failing to account for swap users will significantly underestimate the impact of derivatives on fund portfolio allocation and performance.

Our paper introduces a novel approach by being the first to empirically measure the performance of funds' derivatives and use these insights to investigate how derivatives contribute to fund returns. Prior studies attempting to answer this question find suggestive evidence of hedging motives by derivative users, but they were forced to tackle the question indirectly since their data could not facilitate estimating derivative performance.<sup>3</sup> Surprisingly, we find that most derivative-using funds use derivatives to amplify exposure. The data we use is unique in providing fund-level PnL on derivative positions, allowing us to accurately estimate the component of fund returns stemming from derivative positions, and to directly calculate the correlation between derivative and non-derivative components of fund returns. In our sample, 59% of derivative users have a positive correlation between these components, with a median correlation of 0.17.

To delve into the mechanism behind funds' amplification motives and to facilitate a more refined analysis, we examine in detail how derivatives are used by looking into their allocation of derivatives'

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<sup>2</sup>Koski and Pontiff (1999), Deli and Varma (2002), Almazan et al. (2004) study options and futures; Frino et al. (2009) study index futures; Cici and Palacios (2015) and Natter, Rohleder, Schulte, and Wilkens (2016) focus on options alone. An exception is Cao et al. (2011) that considers total derivative use, but does not consider swaps separately. Recent studies have also examined derivative use in bond funds. For example, Aragon, Li, and Qian (2019) and Jiang, Ou, and Zhu (2021) study credit-default swaps, and Sialm and Zhu (2020) study foreign exchange forwards.

<sup>3</sup>For example, Koski and Pontiff (1999) use survey data and find only a very small number of managers claiming that they use derivatives for amplification. Cao et al. (2011) find hedging evidence by comparing return distribution between users and nonusers. Cici and Palacios (2015) and Natter et al. (2016) also find that the use of options by mutual funds is consistent with hedging motives.



underlying assets. Specifically, we employ a data-driven approach and use the machine learning K-Means Clustering analysis to categorize derivative users based on the allocation of underlying assets from their derivative positions. This analysis focuses on the proportion of notional amounts across various asset categories (equity, interest rate, foreign exchange, commodity, and others) as reported by Form N-PORT. Additionally, we subdivide the equity category into equity index and individual stock categories, considering both long and short positions across these categories, resulting in 12 distinct categories in total.

Our clustering analysis uncovers significant patterned use of derivatives among funds. We identify five distinct derivative strategies, each specializing in a specific asset category and direction (long or short). Meanwhile, the strategy employed by a fund is highly persistent over time. Specifically, 41.4% of derivative users adopt a “long index” derivative strategy, heavily investing in derivatives with long positions on equity indices, where a staggering 96.4% of their derivative underlying assets are in this category. The average return correlation between their derivative and equity strategies is highly positive at 0.67, indicating a primary use of derivatives to amplify equity exposure, contrary to the hedging motive suggested in prior literature. Next, there are three other equity-based derivative strategies: “long stock”, “short stock”, and “short index”. These strategies allocate 95%, 84%, and 82% of their derivatives to long individual stocks, short individual stocks, and short equity indices, respectively, and collectively represent 32.5% of all derivative users. The final strategy, “non-equity derivatives”, primarily focuses on interest rate and currency derivatives, and comprises 26% of all derivative users, with an average allocation of 82% to non-equity derivatives.

More importantly, our data-driven classification uncovers patterns of funds’ derivative use, which align closely with theoretical motivations. Long index users use derivatives to gain equity exposure and amplify fund returns, as well as to manage liquidity and flows, and are the drivers of the identified amplification. To further substantiate the purpose for which they use derivatives, we utilize textual analysis on funds’ derivative-related discussions in the prospectus. We find that they are much more likely to mention amplification-related keywords, such as *enhance returns* and *gain exposure*, than other users. Meanwhile, they are also likely to mention cash management-related keywords, such as *equitize cash* and *manage cash flows*. Long and short stock users hold the majority of their derivative positions on individual

stocks, and mostly use derivatives to exploit firm-specific signals. Consistent with this conjecture, they frequently mention individual stock-specific keywords, such as *company-specific* and *specific investment opportunities*, in their derivative discussions, which is rare among other users. On the contrary, short index users do not trade on firm-specific information. Rather, they hold short index derivatives to hedge against systematic risks. Lastly, non-equity users trade heavily on interest rates and currency derivatives, and they frequently mention keywords related to alternative assets, consistent with using derivatives to gain exposure to alternative asset classes and hedge non-equity risks.

To further shed light on long index users' amplification channel, we next examine their cash and equity exposure management. Compared to nonusers, long index users hold 3% more cash and 4% less equity. Despite holding a smaller share of equity than nonusers, long index users have a similar CAPM beta to nonusers, around 0.95, because their derivative positions are predominantly tied to equity indices and amplify their equity returns. This finding contrasts with other equity-based derivative strategies like short index and short stock users, whose derivatives returns are, on average, negatively correlated with the rest of the portfolio. As a result, their CAPM beta, 0.52, is substantially lower than nonusers, which cannot be solely explained by the difference in equity and cash holdings. Lastly, non-equity derivative users have 0.35 lower CAPM beta than nonusers, and they hold 19% less equity, which explains a substantial portion of the difference in their CAPM beta. Because their derivative positions are primarily on interest rates and currencies, the return correlation is slightly negative and close to zero, -0.06.

Moreover, the cash management strategies of long index users reveal their unique responses to capital flows. Unlike nonusers and other derivative strategies which show a positive correlation between changes in excess cash holdings and contemporaneous flows (An, Huang, Lou, and Shi (2021)), long index users show a striking negative correlation. On the other hand, they show a positive correlation between change in equity holding and contemporaneous flows. The results suggest that long index users are more aggressive in allocating capital flows to their equity holdings. That is, for every dollar capital flow they receive, they allocate a larger fraction of it into equity holding than their existing overall equity allocation ratio. Such an aggressive investment strategy is consistent with the fact that they use equity derivatives to leverage up and amplify fund returns.

Our sample also features two special episodes: the COVID-19 pandemic-induced market crash in early

2020 and a ten-month bear market induced by the Fed rate hike in 2022. We utilize the two episodes to identify changes in derivative trading behavior and the associated contribution of derivative positions and trading to fund performance that would otherwise be difficult to identify in normal times, both in the time series and the cross-section. Both episodes feature large price drops and excessive volatility, yet they are very distinct in nature. The COVID-19 pandemic started as a healthcare crisis, which provided an exogenous shock to the financial markets.<sup>4</sup> In contrast, the Fed rate hike induced bear market is endogenous and stemmed from deteriorating economic conditions, and the announcements of rate hikes were likely anticipated.

We find that entering the COVID-19 crisis, the long index users tried to exploit the market crash by significantly shorting equity indices through derivative strategies in an attempt to enhance their fund performance. In fact, they doubled the gross notional exposure of derivative positions during the crisis, all coming from short equity index derivatives with a notional amount equivalent to 10% of fund total net assets, while their notional exposure from long equity index derivatives remained unchanged. However, they suffered a double whammy from their aggressive derivative trading, which did not position them to outperform nonusers throughout the crisis. First, their long derivative positions incurred large losses during the outbreak. Second, although they increased short notional exposure, we find they were slow to do so, and the market rebounded sharply after the unexpected Fed’s announcement on a series of market interventions on March 23, 2020. As a result, they also suffered losses from their newly opened short derivative positions.

During the Fed rate hikes episode, consistent with their late response during the COVID-19 episode, long index users increased their derivative notional exposure one quarter after the first rate hike. Because most FOMC members projected rate increases in the December 2021 FOMC meeting, the rate hikes in 2022 were likely anticipated. As a result, the magnitude of the increase in notional exposure, about 3.4%, is much smaller than the previous episode. Similar to the COVID-19 episode, long index users failed to outperform nonusers in response to the prolonged macroeconomic shock.

Since Form N-PORT only started in late 2019, our sample is fairly short to enable reliable estimation

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<sup>4</sup>Other papers that utilize the pandemic to improve understanding of fund behavior include Pástor and Vorsatz (2020), which study sustainability and fund performance, and Falato, Goldstein, and Hortaçsu (2021) that focus on financial fragility in corporate bond funds.

of derivative users' performance and flows throughout market cycles, which typically requires at least a decade of data. Therefore, we rely on the imperfect CRSP data since 2010 to test the performance and flows of derivative users. We find that, consistent with the two episodes of market crashes in our sample, long index users underperform nonusers in the extended sample, but somehow receive abnormally high flows from institutional investors. This raises the natural question: why do institutional investors allocate extra capital to these funds despite their underperformance in normal times and failure to outperform in bad times? To answer these questions, we propose two potential channels. The first is through a risk-shifting channel, in which derivative use attracts flows. Specifically, institutional investors who provide extra flows can, ex-ante, identify funds that will use derivatives to increase their risk-taking and deviate from benchmarks, which is a necessary but not sufficient condition for outperformance in a crisis period. Alternatively, there could be a reverse causality explanation through a flow-management channel, where these long index users receive extra flows for some unobserved characteristics that are uncorrelated with performance and hold long equity index futures or swaps as a cash-equitization tool. Our evidence supports the risk-shifting channel, as funds that substantially increased their tracking error during the COVID period received abnormally high flows from institutional investors in normal times, prior to the crisis. Moreover, these funds indeed shifted their strategies by betting on short derivative positions during the crisis. While consistent with the risk-shifting channel, such a shift in strategy did not yield superior performance on the realized price path due to the quick and unexpected Fed intervention announcement and the sharp market rebound that followed it.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 provides an overview of derivative use. Section 4 studies different derivative strategies employed by funds. Section 5 analyzes the change in funds' trading behavior during the COVID-19 pandemic and Fed rate hikes, and studies how derivatives impact fund returns and risks. Section 6 examines derivative users' performance and flows in an extended sample from CRSP. Finally, section 7 concludes.

## 2 Data

### 2.1 An overview of derivative data from Form N-PORT

Our study utilizes a newly available dataset from the SEC’s Form N-PORT, which contains detailed derivative holdings at the quarterly frequency, and (un)realized Profit-and-loss (henceforth, PnL) of derivatives by instrument at the monthly frequency. Following the Investment Company Reporting Modernization reforms adopted in October 2016 and revised in January 2019, mutual funds other than money market funds and small business investment companies are required to file the form. Funds belonging to fund families with net assets of \$1 billion or more were required to start reporting from June 1, 2019. Others were required to start reporting on March 1, 2020. Most (89%) funds started to report in 2019. Although funds report filings monthly, the holding parts of the reports are available to the public only at a quarterly frequency, corresponding to fiscal quarter-ends.

We extract the following information at monthly and quarterly levels from N-PORT. The monthly-level data include realized and unrealized PnL of each derivative instrument; information that has not been recorded in other data sources and is crucial to test how derivatives contribute to fund strategy and performance. We further hand-collect individual security-level daily returns for each derivative position reported in N-PORT by manually matching security names with Yahoo Finance and Bloomberg, which allows us to study derivative returns at a more granular level.

The quarterly-level data include funds’ total net assets and portfolio holdings. The holding data cover not only equity and debt positions, but also detailed descriptions of over-the-counter and exchange-traded derivative positions. We extract derivative instruments, names of underlying assets, portfolio weight, notional amount, expiration date, and unrealized appreciation or depreciation for each derivative position.<sup>5</sup> The value of these derivative positions is marked to market as they are reported. The derivative instrument not only includes forwards/futures and options, which are indicated by flags in N-SAR, but also covers swaps, swaptions, warrants, and foreign exchange contracts, all of which have not been documented in prior studies.<sup>6</sup> Due to the small fraction of swaptions and warrants and their similarities to options,

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<sup>5</sup>Form N-PORT reports notional amount for all derivative positions, except for options. The notional amount of options is proxied by the number of contracted shares multiplied by the stock price.

<sup>6</sup>In N-SAR, the identification of derivative usage is derived from item 70. With respect to futures, only the use of index and commodity futures is reported. Item 74 reports basic balance sheet information on options (74G) and options on futures

we consolidate swaptions and warrants into the options category. For swaps, we further identify each leg of the swap and upfront payments. For futures and forwards, we further identify the payoff profile (long/short). For options, we further identify the exercise price, whether it is a call or put, and whether the fund writes or purchases the option.

After merging with CRSP, we have 3106 active domestic equity funds, representing 92% of unique names in CRSP and 96% of total net assets. We use Morningstar Direct to obtain funds’ reported benchmark. For each fund, we also download and extract the “Principal Investment Strategy” section of its prospectus from Form N-1A. We obtain county-level COVID-19 statistics from the New York Times.

## 2.2 Limitation of CRSP holding data on derivative positions

In this section, we explore the scope and limitations of derivative position data within the CRSP Mutual Fund Database relative to the N-PORT data. The inclusion of derivative holdings in CRSP began in late 2010, when CRSP switched to Lipper as the data vendor. Derivative holdings, along with stock and bond holdings, are reported on a quarterly basis. However, unlike stocks and bonds, which can be readily identified using CUSIP or Ticker symbols, derivative positions require inference based on security names (for a detailed description of this process, please refer to the Appendix). In addition to security names, CRSP also provides information on security weight, market value, and the number of shares for derivative positions.

Researchers aiming to study funds’ derivative use using CRSP data encounter several notable limitations when compared to Form N-PORT. First, Form N-PORT stands out as the sole source providing monthly data on fund-level realized and unrealized Profit and Loss (PnL) related to derivative positions. This information serves as a direct measure of a fund’s derivative performance, a metric unattainable from holdings data alone, which facilitates computing the contribution of derivatives to fund returns and the correlations between derivative and non-derivative contributions to fund returns.

Second, Form N-PORT offers a more comprehensive dataset concerning funds’ derivative positions compared to CRSP holdings. While CRSP provides portfolio weight of derivative positions, it may not accurately reflect a fund’s derivative exposure, as many derivative contracts, such as swaps and futures, initially have zero portfolio value despite substantial notional amounts. As a result, using portfolio weight

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(74H) but not on other derivatives.

alone can underestimate a fund’s derivative exposure. N-PORT data can address this issue. In addition to the information available in CRSP, N-PORT provides valuable details such as notional amounts, maturity dates, comprehensive descriptions of underlying assets, and even counterparty names for each derivative position. Furthermore, N-PORT also provides unrealized PnL for each existing holding position at quarter end. This is a snapshot that can be used to check whether the existing position is profitable and is different from the fund-level PnL that is reported at monthly frequency.

Third, CRSP fails to capture a noteworthy portion of derivative positions that are available in Form N-PORT. CRSP relies on a catch-all category, typically labeled as ”other assets” or ”other assets less liabilities,” which may encompass derivative positions. To illustrate, the Guggenheim Style-Plus Large Core Fund reported a swap position on the S&P 500 index with Wells Fargo as the counterparty and a portfolio weight of 3.7% in N-PORT. However, this specific position is absent in CRSP holdings and is instead grouped under ”other assets less liabilities.” In many instances, derivative positions are entirely omitted in CRSP. Specifically, among the sample of derivative users identified using Form N-PORT, CRSP data fail to capture any equity derivative positions in 39% of fund-quarter observations. In the remaining 61% of fund-quarter observations where both sources list equity derivatives, CRSP omits some derivatives in 36% of cases compared to N-PORT. Consequently, CRSP tends to underestimate the extent of derivative use. Moreover, CRSP occasionally mistakes the notional amount of derivatives for the market value. For instance, in Q1/2020, the Invesco V.I. Managed Volatility Fund held a short position in S&P index futures. CRSP erroneously used the notional amount as the portfolio value, resulting in a -40% weight recorded in CRSP, whereas N-PORT reported only a -1.78% weight for the same position.

While CRSP does provide a longer time period in covering derivative positions than Form N-PORT, it falls short in providing the level of detail and accuracy of Form N-PORT. Researchers seeking comprehensive and timely information on funds’ derivative use, including performance metrics and detailed position characteristics, will find Form N-PORT to be the superior resource.

### **3 Overview of derivative use**

Previous studies on fund derivative use have almost exclusively relied on Form N-SAR. While N-SAR contains yes-no questions on whether a fund held options or futures, it fails to cover other important

derivative categories, especially swaps, which turn out to be a major component of derivative positions. Importantly, it also lacks information as to what extent derivatives are used. Consequently, N-SAR data does not facilitate a detailed analysis of how, or how much, derivative positions contribute to fund returns or risks. Specifically, it has limited use for testing whether funds use derivatives to hedge or amplify returns, an important part of our analysis. This section addresses these unanswered questions.

In Section 3.1, we show there is a large cross-sectional variation in the extent of derivative use. Section 3.2 provides the first evidence in the literature on how much derivatives contribute to fund returns, focusing both on the question of the magnitude of the contribution and on evaluating whether their central role is to amplify or hedge the rest of the fund’s portfolio.

### 3.1 The extent of derivative use

We extract the portfolio weight and notional amount of each derivative position from N-PORT. To proxy for the extent of derivative use, we use two measures. The first, keeping in mind that funds can increase exposure by trading derivatives on both long and short sides, is the sum of *absolute derivative weights* in the portfolio. The second is *gross notional exposure*, which is the sum of the notional amounts of derivative positions scaled by fund size.

The top row of Panel A in Table 1 shows the number of derivative users between September 2019 and December 2022. A fund is classified as a derivative user if it uses derivatives at least once in the sample. Our sample contains 3106 active funds, 1079 (34.7%) of which use derivatives and manage 36% of total assets. The fraction of derivative users has increased by 13.7% from the 21% reported in Koski and Pontiff (1999). Using funds’ most recent N-SAR reports, we find that 82% of funds are permitted to trade derivatives. Among derivative users, 606 funds use futures or forwards, 197 swaps, 585 options, and 269 foreign exchange contracts. By focusing exclusively on options and futures, prior studies have misclassified a nontrivial number of swap users as nonusers. Such a misclassification will underestimate not only the extent of derivative use, but also derivative contribution to fund returns, which we will show in subsequent sections.

The remaining rows of Panel A in Table 1 further break down derivative portfolio composition and highlight the importance of swap contracts. On average, funds have a derivative weight of 2.48%, with



futures (0.93%) being the largest derivative type, closely followed by swaps (0.83%). Options represent only 0.42% of the portfolio. Although a 2.48% portfolio weight seems small in absolute terms, derivatives provide funds ample market exposure because of the embedded leverage. Specifically, the average gross notional exposure is 23.52% relative to a fund’s total net assets. Swaps provide the most gross notional exposure with 11.8%, and futures are close behind with 10.46%. Options, in contrast, provide merely 0.55% gross notional exposure.

One may be concerned that the quarterly snapshot may not correctly reflect funds’ derivative usage, as derivative holdings may have a short duration. We show this is not the case by comparing derivative holding across quarters and providing several stylized facts on funds’ derivative trading. First, funds seldom alter quantities of their derivative positions once they are opened. The probability of modifying a position is about 2% across quarters. Second, our evidence suggests that these derivatives have a fairly long time to maturity. For example, the median time-to-maturity of futures is 81 days, the interquartile range is from 76 days to 89 days, and they are typically rolled over by new positions. Swaps have much longer time-to-maturity, with interquartile ranging from 120 days to over three years.

Moreover, there is substantial cross-sectional variation in the extent of derivative use, with half of the funds using a negligible amount of derivatives, and the remaining half using derivatives heavily. Such a pattern is also documented in Cao et al. (2011) but has received little attention in subsequent studies. Figure 1 visualizes the cross-sectional variations in derivative use. On the one hand, 50% of funds have derivative weights (gross notional exposure) of less than 0.2% (2%). On the other hand, the remaining 50% of funds have a median derivative weight (gross notional exposure) of more than 1.6% (15%). In fact, over 13% (28%) of derivative users have a derivative weight (gross notional exposure) of more than 5% (10%), so that derivatives are a large part of funds’ asset allocation.

To gain deeper insight into how funds use derivative positions, and since, as noted above, a substantial subset of derivative users have minimal derivative exposure, we group derivative users by the extent of usage into two categories: token users and non-token users. Specifically, for each quarter, funds are ranked into two groups by the median of gross notional exposure. *Token users* have below-median gross notional exposure, and *non-token users* have above-median gross notional exposure.

### 3.2 Derivative contribution to fund returns

How derivative positions contribute to fund returns is an open question. Prior studies rely either on survey evidence or comparisons of return distribution between nonusers and users to gauge the impact of derivatives on fund returns. So far, no study has systematically examined the performance of derivative positions. Using monthly-level realized and unrealized PnL from N-PORT between July 2019 and December 2022, we are the first to shed light on funds' derivative performance, compare it with funds' non-derivative performance, and test the central hypothesis of whether derivatives are used for hedging or amplification.

We calculate *derivative induced returns* (henceforth, *DIR*) as the sum of realized PnL and changes in unrealized PnL of all derivatives, scaled by the fund size in the previous month. *DIR* captures the part of fund returns due to derivatives, and is different from the return on fund derivative positions. Non-derivative induced returns (henceforth, *non-DIR*) are the difference between fund returns and *DIR*. We then define *signed derivative relative contribution* as the ratio between *DIR* and *non-DIR*, and *derivative relative contribution* as the absolute value of *signed derivative relative contribution*. *Derivative relative contribution* captures the relative magnitude between derivative and non-derivative returns.

$$DIR_t = \frac{PnL_t^{Realized} + PnL_t^{Unrealized} - PnL_{t-1}^{Unrealized}}{TNA_{t-1}}$$

$$Derivative\ Relative\ Contribution_t = \left| \frac{DIR_t}{non-DIR_t} \right|$$

We find that *DIR* is a large component of overall fund returns. Table 1 shows that the average monthly *DIR* (*non-DIR*) is -6.5 (20.7) bps, with a standard deviation of 78 (531) bps. The fact that non-derivative positions weigh over 40 times more than derivative positions, yet the standard deviation of *non-DIR* is only six times larger than *DIR*, highlights the importance of derivative positions to fund returns.

The blue curves in Panel (c) and (d) of Figure 1 show the CDF of signed derivative relative contribution and derivative relative contribution, respectively. Signed derivative relative contribution is winsorized between -1 and 1 in the figure for ease of presentation. Derivative relative contribution is a non-negative measure and winsorized at 1. Derivatives contribute largely to fund returns: over 30% of the fund-month

observations have a derivative relative contribution of over 0.1, and 10% of observations have a derivative relative contribution of over 0.6. Derivatives play a larger role in fund returns among non-token users, which is shown by the red curves.<sup>7</sup> Within non-token users, over 30% of the fund-month observations have a derivative relative contribution of over 0.17, and 10% of observations have a derivative relative contribution of over 0.75.

In Section 3.1, we documented that the overlooked swaps users tend to use more derivatives. We test whether their derivative positions also contribute more to fund returns. The median derivative relative contribution among swaps users is 0.17, and only 0.005 among non-swaps users. Within swaps users, funds solely using swaps have a median derivative relative contribution of 0.39, whereas funds that use swaps together with other contracts have a median derivative relative contribution of 0.14. A Mood’s Median Test shows differences in the median contribution are all highly significant. We focus on Mood’s Median Test instead of a traditional t-test because the median is not affected when the denominator (*non-DIR*) of the contribution measure is very small. The substantial differences in contributions further buttress the importance of including swaps users when examining funds’ derivative use.

## 4 How are derivative used?

### 4.1 Classification of derivative strategies

To gain a deeper understanding of how funds utilize derivatives, we employ an unsupervised machine learning algorithm called “K-Means Clustering” to categorize derivative users based on the allocation of underlying assets from their derivative positions. This data-driven approach allows us to be agnostic about the set of derivative strategies ex-ante and potentially identify a broad set of strategies. We then map the classification to various economic rationales for using derivatives. These include exploiting firm-specific, industry-wide, and market-wide information signals, liquidity management, gaining exposure to certain asset classes, and hedging. Lastly, we conduct textual analyses on funds’ derivatives-related discussions in the prospectus to gain further insights into how derivatives are used under our classification.

The key input of the classification is the fraction of notional amounts across underlying asset categories, and the algorithm clusters funds with similar allocations of underlying asset categories. How

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<sup>7</sup>To alleviate the concern that our measure of derivative relative contribution may not be stable when the denominator is small, we also require the absolute value of *non-DIR* to be greater than or equal to 10 bps. The conclusions are similar.

do we define categories of underlying assets? For each derivative position, the SEC requires funds to report whether the underlying asset falls into one of the following categories: equity, interest rate, foreign exchange, commodity, and other assets. Because it is very different to trade individual stocks and equity indices, we further break the equity category into equity index category and individual stock category. Therefore, in total, we have six major categories. Furthermore, since the derivative strategy may be very different, depending on whether it is a long or short position, we then break down each major category into long and short positions based on the payoff profiles and detailed derivative description provided by the Form N-PORT, resulting in a total of twelve distinct categories. In the case of derivatives associated with equity index, individual stock, commodity, and other assets, a long position indicates that the derivative’s value increases along with the underlying asset. In contrast, for interest rate derivatives, a long position indicates that the derivative’s value moves inversely to changes in interest rates, while for foreign exchange derivatives, a long position suggests that the derivative’s value rises in conjunction with the value of the US dollar. For each fund in each quarter, we then calculate the fraction of the notional amounts across these twelve categories and denote it as vector  $x = (x_1, \dots, x_{12})$ , so that it sums up to one.

The K-Means algorithm takes the vector  $x$ , the desired number of clusters, and a tolerance parameter, and it groups funds into different clusters. Intuitively, the goal is to minimize intra-cluster distances while maximizing inter-cluster distances. In our case, this translates to clustering funds with similar derivatives allocations based on their underlying assets. For each cluster, the centroids are initialized randomly and redefined in each iteration as the average vector. Convergence is reached when the Euclidean distance between centroids in two consecutive iterations is smaller than the tolerance level. The key parameter to be specified is the number of clusters,  $k$ . We use the standard approach Silhouette Method to determine the optimal number of clusters, which is five in our case. Figure IA1 in the Appendix plots the silhouette coefficients for the number of clusters ranging from 1 to 10. As can be seen, the silhouette coefficient peaks at  $k = 5$ , indicating the optimal number of clusters is five.

More importantly, the clusters are economically meaningful. Panel A of Table 2 reports the average allocations of notional amounts across the twelve categories for each cluster. Notably, 41.4% of derivative users fall within the first cluster, which we identify as the “long index” derivative strategy. Users in

this cluster predominantly invest in derivatives with long positions on equity indices, with a staggering 96.4% of their underlying assets falling into this category. Similarly, other clusters also have dominating categories in terms of derivative allocation, suggesting that our algorithm can successfully group funds that are very similar in derivative strategies. Specifically, “long stock”, “short index”, and “short stock” users allocate 95%, 82%, and 84% of their investments to long individual stocks, short equity indices, and short individual stocks, respectively, collectively representing 32.5% of all derivative users. It is important to note that the first four clusters of funds predominantly use equity derivatives. However, the last cluster, denoted as “non-equity” users, primarily invests in non-equity derivatives, such as interest rate and currency derivatives, and comprises 26% of all derivative users, with an average allocation of 82% to non-equity derivatives. After excluding token users, long index users, other equity users, and non-equity users represent 43%, 26%, and 31% of non-token users, respectively, which implies that long index users represent 62% of equity derivative users, which contrasts with the perception in the literature that funds use derivatives primarily to hedge.

The clustering analysis reveals that derivative users are highly specialized in specific underlying assets and directional positions, as evidenced by the pronounced concentration within these categories. An important question arises concerning whether these asset allocations undergo significant changes across quarters. To demonstrate the persistence of allocation, we calculate two metrics based on the previous quarter’s allocation vector, denoted as  $x_{t-1}$ , and the current quarter’s allocation vector, denoted as  $x_t$ . The first metric computes the Euclidean distance between  $x_{t-1}$  and  $x_t$ , ranging from zero to  $\sqrt{2}$ . The maximum distance occurs when a fund completely shifts its derivative underlying assets from one category to another, while the minimum distance signifies no change in the underlying asset category. The second metric computes the cosine similarity between  $x_{t-1}$  and  $x_t$ , ranging from zero to one, with the maximum value indicating no change in the underlying asset category. Panels (a) and (b) of Figure 2 illustrate the histogram of both measures, revealing a prominent density on the left tail for the Euclidean distance measure and a substantial density on the right tail for the cosine similarity measure. These findings emphasize the significant persistence of the allocation vector across quarters. In addition, for each derivative user, we identify its most frequent user type as its major user group and calculate its probability of deviating from the major user group throughout the sample. The result is shown in Figure

2(c) and suggests that the deviation is unlikely. The probability of a derivative user staying in its major user group ranges from 94% among long index users to 85% among long stock users. Therefore, our findings highlight an important stylized fact that funds' derivative use is highly specialized in certain asset classes and persistent over time.<sup>8</sup>

Panel B of Table 2 reports the average gross notional exposure and its breakdown by derivative instruments for non-token users in each derivative strategy. Keeping in mind that the input of the K-Means algorithm only takes into account the allocation of derivative underlying assets but does not consider the types of derivative instruments, it is interesting to see that the K-means clusters are quite distinct from each other in terms of the use of derivative instruments. Long index users, on average, have a gross notional exposure of 9.55%, where 57.9% (39.2%) of this exposure stems from positions in futures (swaps) contracts. Long stock and short stock users' positions have a substantial gross notional exposure of around 50%, and importantly, most of this exposure comes from swaps contracts, rather than options.<sup>9</sup> Short index users and non-equity users have a gross notional exposure of 22.6% and 28.1%, and the majority come from futures contracts.

In theory, there is a set of rationals for funds to use derivatives. Derivatives can serve as a strategic tool to capitalize on signals, whether they're broad market, industry-specific, or related to individual firms, and these signals can be either positive or negative, as funds can use them to get around short-selling constraints. Alternatively, derivatives can be used to gain exposure to the equity market and amplify fund returns. Derivatives can also be used for liquidity management, because it may be cheaper to trade derivatives than underlying assets, or because funds may use index derivatives to deal with temporary swings in capital flows. Moreover, derivatives can be used for hedging. For example, fund managers can buy put options on the stocks they hold, which provides protection on individual positions. Or they can short certain indices to hedge against systematic risk. Lastly, derivatives offer a versatile means to gain exposure and hedge against risks stemming from non-equity asset categories, including interest rates, currencies, and commodities.

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<sup>8</sup>It is important to note that the clustering analysis is based on quarter-end derivative holdings, which does not capture intra-quarter trading. In later analyses, we also use monthly derivative PnL that captures both inter-quarter and intra-quarter trading to shed light on derivatives' impact on fund returns, as the fund needs to report its realized and unrealized PnL for its entire derivative strategy, and not just their quarter-end holdings.

<sup>9</sup>There are very few single stock futures in the data. OneChicago, the exchange for single stock futures, lost most of its trading volume in 2018 and closed in September 2020.

In practice, funds may discuss how they use derivatives in the Principal Investment Strategy section of Form N-1A.<sup>10</sup> For each fund, we download its Form N-1A from the SEC EDGAR. We use textual analysis to extract the Principal Investment Strategy section for each form. Derivative-related sentences in the section are identified and extracted using keywords: derivative, futures, options, and swaps. We also extract one sentence before and after each identified sentence, as they may discuss derivative-related use without explicitly mentioning these keywords. Lastly, we plot the most frequently mentioned bigrams in derivative-related discussions in Figure 4.<sup>11</sup> The font size of bigrams increases with the frequency, and we manually highlight some representative bigrams in red for each derivative user group.

Our data-driven classification reveals distinct usage patterns that align closely with these economic motivations. Long index users mostly hold long equity index derivatives to gain exposure to the equity market and amplify fund returns. As detailed in Section 5.1, they predominantly hold long index positions in normal times, but also engage in short selling market indices via derivatives as an attempt to capitalize on the market downturn during the market crash. Consistent with them using equity indexes to amplify fund returns, they are likely to mention “equity index”, “market condition”, “equity exposure”, and “gain exposure” when describing their derivative strategies in the prospectus, as shown in Figure 4(a). Another rationale for using equity index derivatives is to help funds manage flows. Correspondingly, we will show in Section 4.2 that their extent of derivative use is positively correlated with fund flows in the previous quarter. To further substantiate the theory that long index users utilize derivatives both to gain market exposure and to manage cash flows, we analyze the probability of funds mentioning specific keywords related to amplification and cash management in their prospectus descriptions of derivative strategies.<sup>12</sup> We find that 42% of long index users refer to amplification-related keywords, compared to only 6% of other derivative users. While only 14% of long index users mention cash management-related terms, this is still notably higher than the mere 2% among others.

One could also argue that funds may use equity index derivatives to time the market. Given that

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<sup>10</sup>Part A of the Form includes information required in the prospectus.

<sup>11</sup>In this analysis, we group other equity-based derivative users together to increase the sample size and because they have similar characteristics in terms of benchmark distributions, fund size and fund expense ratio. Instead of using derivative-related discussions, we also look into the entire section of Principal Investment Strategy, where the distinctions across derivative user groups are much smaller, and the discussions on fund strategies are generic.

<sup>12</sup>Our amplification-related keywords include “increase return”, “enhance return”, “gain exposure”, and “increase exposure”. Cash management related keywords include “equitize cash” and “manage cash flows”.

we classify funds every quarter, it could be that a fund engaging in market timing is classified as a long index user in one quarter and as a short index user in another quarter. However, our previous analysis in Figure 2(c) rules out this explanation. Specifically, among funds whose major user groups are long (short) index users, they only switch to short (long) index users 3% (5%) of the time and stay in their major user group 94% (90%) of the time throughout the sample.

Other equity-based derivative users (long stock, short stock, and short index users) are more like hedge funds, as we will show in Section 4.2 that over 40% of them have a Lipper style of “Long/Short Equity Funds” and they share fairly similar fund characteristics. Despite being similar in many dimensions, they employ derivatives differently. Short index users hold a majority of short index derivatives, so they primarily use derivatives to hedge against systematic risk. Moreover, only 2% of their derivative positions are invested in individual stocks, as can be seen from Panel A of Table 2, suggesting that they rarely trade on firm-specific signals through derivatives. Contrary to short index users, short stock users extensively trade on individual stock derivatives, with over 84% in short positions and 11% in long positions. To distinguish between motives to exploit firm-specific negative information and hedge, we examine whether the stocks underlying these derivative positions are also held in the fund portfolios. We find that, at the security level, only 31% of these are covered positions and are related to hedging existing individual positions, while a significant 69% of their positions are naked positions. At the fund level, 62% of short stock users have over 80% of their derivative positions in naked individual stock derivatives, likely aimed at capitalizing on negative, firm-specific signals, possibly as a means to circumvent short-selling constraints. Similar to short stock users, long stock users use individual stock derivatives to exploit firm-specific but positive signals. We can see from Figure 4(b) that these equity-based derivative users are likely to mention “long short”, “short position”, and “long/short exposure” in their derivative discussions, as they focus on long/short strategies. Moreover, a notable 62% of long and short stock users incorporate individual stock-specific keywords in their derivative discussions, underscoring their emphasis on leveraging firm-specific information.<sup>13</sup> This is in sharp contrast to the 5% usage of such terms by all other derivative users.

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<sup>13</sup>Individual stock specific keywords include “company-specific”, “specific to the company”, “individual company”, “individual stock”, “specific investment opportunities”, and “particular company”. We also searched for hedging or risk-management related keywords, which are generic and commonly used by all types of derivative users, even among long index users who do not hedge and token users who use very few derivatives.



Finally, non-equity users mostly trade on interest rate and currency derivatives. As we will show in Section 4.2, despite being equity funds, they hold a smaller share of equity than nonusers, so interest rate and currency derivatives help them hedge interest rate and currency risk from the non-equity portion of their portfolios. They can also use non-equity derivatives to gain exposure to alternative asset classes. As shown in Figure 4(c), they are likely to mention “fixed income”, “asset class”, “tactical asset”, “currency”, and “interest rate” in their derivative-related discussions, consistent with their observed derivative use.

In summary, using a data-driven machine learning approach, we identify five distinct derivative strategies employed by funds, which are economically meaningful and highly persistent. In our sample, 41% of users hold long equity index derivatives to gain market exposure and manage cash flows, 21% trade individual stock derivatives to exploit signals on individual firms, and 11% short equity index derivatives to hedge against systematic equity risk. The remaining 26% trade on non-equity index derivatives to either gain exposure to alternative asset classes or hedge against non-equity risks.

## 4.2 How do funds differ across derivative strategies?

Next, we delve into the variations in fund characteristics across derivative strategies. Panel A of Table 3 provides summary statistics regarding fund characteristics, along with detailed explanations of variable constructions. When compared to nonusers, who allocate 96.7% of their holdings to equity and 3.3% to cash and its equivalents, long index users hold 4% less equity but maintain 2.9% more cash. One plausible reason for this disparity may be the need for long index users to reserve more cash to meet margin calls and collateral requirements associated with their derivative positions.

Following the methodology introduced by An et al. (2021), we calculate a fund’s excess cash by deducting 20% of the gross notional exposure of their derivative positions (excluding the purchase of call and put options) and short equity positions from their cash and cash equivalents. Consequently, long index users hold 4.4% excess cash, which is 1.1% higher than nonusers, as shown in Panel A of Table 3. Despite holding a smaller share of equity than nonusers, long index users exhibit very similar CAPM beta, primarily because their derivative positions are predominantly tied to equity indices. Compared to nonusers, long index users have larger assets under management, lower expense ratios, and hold more stocks, which might seem to be more passive. However, their equity holdings maintain a similar

concentration level as nonusers, and they even exhibit a higher turnover ratio than nonusers, which suggests a level of similarity in terms of their active investment approach.

In contrast, compared to long index users, long stock, short stock, and short equity users hold substantially less equity and more cash reserves. They are also much smaller, more expensive, and use more derivatives, as evidenced by higher gross notional exposures and absolute derivative weights, than long index users.

Taking advantage of the time-series *DIR* and *non-DIR*, we test whether funds with different derivative strategies use derivatives to hedge or amplify market exposure. We first calculate the correlation between *DIR* and *non-DIR* over the sample period for each fund. Figure 3 shows the histogram of the correlation. Contrary to the commonly perceived notion that funds use derivatives for hedging purposes, this analysis buttresses that the majority of derivative users use derivatives to amplify exposure. The median correlation of 0.17 is large and positive, and 59% of users have a positive correlation. After excluding non-equity users who mostly hold non-equity derivatives, the median correlation jumps to 0.43, and 64% of equity derivative users have a positive correlation.

After documenting that the majority of derivative users, especially equity derivative users, employ derivatives to amplify their equity returns, we then look into the heterogeneity in derivative use across different derivative strategies. Notably, the average correlation between *DIR* and *non-DIR* for long index users is 0.67, as shown in Panel A of Table 3, signifying a strong positive relationship and indicating that they leverage index derivatives to amplify their fund returns. This finding can also be seen in Figure 3, as they dominate the right tail of the distribution. Additionally, the amplification provided by the derivative strategies for long index users is not small, as *DIR* represents a quarter of the magnitude of *non-DIR*, shown by the *derivative relative contribution* in Table 3.

Short index users and a portion of short stock users mainly use derivatives for hedging purposes, as we have discussed in the previous section. Their correlations between *DIR* and *non-DIR* are -0.58 and -0.25, respectively, as shown in Panel A of Table 3, and they dominate the left tail of the correlation distribution in Figure 3. Furthermore, their derivative hedging plays a crucial role in determining overall fund returns, as the derivative relative contributions are 0.56 and 0.78, respectively. Because of their hedging strategies, their CAPM beta and return volatility are significantly lower than long index users

and nonusers.

Long stock users are somewhat in between long index users and short equity users in terms of how derivatives contribute to fund returns, as their average correlation between *DIR* and *non-DIR* is merely 0.12, slightly tilted towards amplifying equity returns rather than hedging. The positive correlation is consistent with them using individual stock derivatives to exploit positive signals from individual firms, and the small magnitude is driven by the fact that over two-thirds of their derivative positions are naked positions. Moreover, they rely heavily on derivatives to contribute to fund returns, as the derivative relative contribution is large, 0.66.

Lastly, non-equity users, who use few equity derivatives and specialize in interest rate and currency derivatives, have a fairly low average correlation of -0.06 between *DIR* and *non-DIR*. They are also uniformly distributed around zero in Figure 3, consistent with the fact they are not using derivatives to either amplify or hedge equity returns, but rather to gain exposure to non-equity asset classes and hedge against non-equity risks.

Overall, our finding suggests that the majority of derivative users amplify their equity returns with derivative holdings rather than use them to hedge. Moreover, as shown in the figure, the amplification channel predominantly stems from long index users. Given that the amplification channel is not well studied in prior literature and that long index users are the archetypal amplifiers, in subsequent analyses, our focus will be on contrasting long index users with all other derivative users.

Panel B of Table 3 examines the distribution of fund benchmarks across derivative strategies. We list the most common 20 benchmark portfolios, and group everything else into the “other benchmark” category. Nonusers, token users, and long index users are very similar in benchmark distribution, although long index users exhibit a slight deviation with fewer S&P 500 benchmarks and a greater reliance on small-cap-based benchmarks. All other derivative users have a very different set of benchmarks than these three, as is clearly visible from the table. In part, the “other benchmark” category represents a significantly higher proportion of their benchmark distribution. One potential explanation is that over 40% of these other equity derivative users have a “Long/Short Equity Funds” Lipper investment style, so they are mutual funds with a hedge fund style, which benchmarks differently from a typical mutual fund and can attract sophisticated investors.

Our analysis then shifts to how a fund’s utilization of derivatives responds to past flows and performance. The results are presented in Table 4. For each category of derivative users, we conduct a separate panel regression where the dependent variable is the change in gross notional exposure from the previous quarter to the current quarter. The independent variables include the fund’s Fama-French four-factor alpha and the flow from the previous quarter. We also control for the fund’s expense ratio, turnover ratio, the natural logarithm of total net assets, and introduce time fixed effects and Lipper style fixed effects for a more focused comparison of flow and performance within peer groups and their effects on derivative use. In general, all types of derivative users exhibit a negative correlation between the change in gross notional exposure and past-quarter performance, with statistical significance observed only for token users and long index users. This negative correlation suggests that derivatives are employed as a means to leverage up during underperformance and deleverage during periods of outperformance in comparison to their peer group. Notably, only long index users display a positive and statistically significant coefficient estimate for flows affecting changes in derivative use. When experiencing excess inflows, they can efficiently and inexpensively amplify their fund returns by investing in equity index derivatives, aligning with their specialization in this area. This result is also consistent with our finding in the previous section that long index users are more likely to mention keywords related to cash flow management in their prospectus when discussing derivative usage.

Given the cash-collateral requirements faced by derivative users, it is interesting to see how they manage cash in response to contemporaneous capital flows. Specifically, for each type of derivative users, we conduct a panel regression, where the dependent variable is the change in excess cash holdings from the previous quarter to the current quarter, and the independent variable is the fund’s contemporaneous flow. We also control for funds’ expense ratio, turnover ratio, the natural logarithm of TNA, time fixed effects, and Lipper style fixed effects. The regression results are shown in Panel A of Table 5. Long index users stand out as the only group with a negative relation between change in excess cash holding and contemporaneous flows. The other categories show a positive relation, although statistically insignificant for long Stock and non-equity users, consistent with An et al. (2021), which also documents a positive relation, especially for long/short equity funds. In our sample, short equity derivative users show the

highest correlation between change in excess cash holding and capital flows.<sup>14</sup>

Why do long index users have a negative relation between change in excess cash holding and contemporaneous flows? To answer this question, we shift the dependent variable to the change in equity holding, and the results are reported in Panel B of Table 5. Long index users show a positive correlation between change in equity holding and contemporaneous flows, suggesting that long index users are more aggressive in allocating capital flows to their equity holdings. However, this doesn't mean the fund invests over a dollar in equity for every dollar flow received by withdrawing cash. In untabulated results, we also regress the percentage change in dollar cash holding on contemporaneous flows for long index users, and find a positive and significant coefficient. Therefore, the results suggest that long index users still allocate a portion of capital flows to cash. It's just that the investment of flows to equity is more aggressive than the fund's existing equity/cash allocation. Such an aggressive strategy is consistent with the fact that they use equity derivatives to lever up and amplify fund returns.

Lastly, we examine the flow-performance sensitivity of derivative users. For funds in each derivative strategy group, we regress the fund's next-month flows on past-year performance, controlling the fund's lagged flows, expense ratio, turnover ratio, the natural logarithm of TNA, and past-year return volatility. We also control Lipper-style fixed effects and time fixed effects. We consider four performance measures: net-of-fee return, CAPM alpha, Fama-French four-factor alpha, and Fama-French five-factor alpha. Table 6 reports the coefficient estimates of past-year performance for each derivative strategy group. Nonusers, long index users, and non-equity users have comparable positive flow-performance sensitivities, as their estimates are not statistically different from each other. On the other hand, long stock and short equity users have a much higher flow-performance sensitivity, consistent with the findings of An et al. (2021) that long/short equity funds have elevated flow-performance sensitivity. These funds are more like hedge funds, so they attract sophisticated investors sensitive to performance.

## 5 Derivative Use in Two Special Episodes

In this segment, we delve into two pivotal episodes within our sample period to analyze how funds' derivative strategies respond to distinct events and their implications on fund returns and risks. Specifi-

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<sup>14</sup>Results are similar when considering the change in cash holdings instead of excess cash holdings.

cally, we scrutinize the COVID-19 pandemic episode from 1/21/2020 to 6/8/2020 and the Fed Rate Hike episode in 2022. Both occurrences precipitated significant market downturns accompanied by heightened volatility. For instance, during the COVID-19 pandemic, the S&P 500 index plummeted by 34%, and the VIX index surged from 15.56 on 02/20/2020 to 82.69 on 03/16/2020. In the Fed Rate Hike episode, the S&P 500 index witnessed a 25% decline, and the VIX index rose to 32 between 1/1/2022 and 10/14/2022. However, it's crucial to note the distinctive nature of the market downturns in these episodes. The COVID-19 pandemic originated as a healthcare crisis, delivering an essentially exogenous and unforeseen shock to financial markets. In contrast, the Fed Rate Hike episode unfolded in a more endogenous manner to the financial markets, characterized by a prolonged period marked by back-and-forth policy discussions before the first rate hike. In fact, the rate hike in 2022 was well anticipated, as indicated by the projected rate increases made by most FOMC members in the December 2021 meeting. These distinct events offer a unique lens to examine how funds' derivative strategies navigated and responded to the varying challenges posed by each episode, ultimately influencing fund returns during these critical periods.

## 5.1 Derivative Use During the COVID-19 Pandemic

One natural question to ask is how funds trade derivatives during the pandemic. On the one hand, they may reduce derivative positions given the extremely volatile market and pool with the majority of nonusers. As derivative positions are highly leveraged, they can generate extreme returns in either direction. Due to the high employment risk during the pandemic, managers may rather forgo the potential upside and seek job security by reducing derivative positions, as these positions tend to be very volatile. Moreover, as the number of COVID-19 cases continued to rise in the US, many states gradually implemented Stay-at-home orders (SAH). In those SAH states, fund managers were restricted to working from home, which may further reduce their trading activity.

On the other hand, derivative positions allow funds to take short positions, which is especially important in downturns because funds' equity holdings are predominantly long positions. Such flexibility provides hedging against market downturns. Moreover, since agents tend to react to salient risks (Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978), and Dessaint and Matray (2017)), and since the

pandemic, implemented Stay-at-home orders, and the prominent associated effects in financial, real and labor markets are likely to increase salience, a natural conjecture is that derivative trading is more likely during the pandemic.

Therefore, it remains an empirical question of whether funds traded more derivatives during the pandemic and for what purposes. In this section, we first study funds' reactions to the COVID-19 pandemic by examining time-series changes in derivative allocation. Second, we study how derivative positions contributed to fund returns during a crisis. Lastly, we analyze how derivative strategies impacted funds' tracking errors.

We use *outbreak period* to denote the period between January 20, 2020, and March 23, 2020; and *recovery period* to denote the period between March 24, 2020, and June 8, 2020. We then use *crisis period* to denote the cycle of the outbreak and recovery periods. For analyses with only monthly frequency available, we denote the outbreak period as February 2020 and March 2020, and the recovery period as the months between April 2020 and June 2020.<sup>15</sup> We choose January 20, 2020, as the outbreak starting date for the following reasons: Both the WHO and Chinese authorities announced the confirmation that human-to-human transmission of the coronavirus had already occurred; The first recorded US COVID-19 case was also reported on January 20, 2020.<sup>16</sup> Both the announcement and report are exogenous to the financial market. We choose March 24, 2020, as the recovery starting date because the Federal Reserve announced extensive new measures to support the economy on March 23, including an expanded quantitative easing program and new emergency lending facilities.<sup>17</sup> We choose June 8, 2020, as the recovery ending date because it is the first time S&P 500 index closed higher than its December 31, 2019 close since the crash.

First, we test whether funds increased derivative use during the crisis. Table 7 examines the gross notional exposure of funds' long and short derivative positions, one quarter prior to and during the COVID-19 outbreak. As the outbreak unfolded, long index users maintained a stable notional exposure in their long derivative positions. Strikingly, they significantly increased notional exposure in short

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<sup>15</sup>Pástor and Vorsatz (2020) define a crash period starting from February 20, the start of the market's rapid descent. Our results are robust to starting the crisis period at this alternative date.

<sup>16</sup>See news source here: <https://www.theguardian.com/world/2020/jan/20/coronavirus-spreads-to-beijing-as-china-confirms-new-cases>, <https://www.nytimes.com/article/coronavirus-timeline.html>

<sup>17</sup>See news source here: <https://www.americanactionforum.org/insight/timeline-the-federal-reserve-responds-to-the-threat-of-coronavirus>.

derivative positions, moving from a very low level of 0.69% to 10.97%. This substantial surge in short derivative positions, coupled with no alteration in long derivative positions, seems to suggest that long index users may have sought to enhance their fund returns by riding on the market crash by shorting the equity index. Although we do not directly observe the exact timing of when long index users initiated their short derivative positions, we can infer that they opened these positions fairly late, as the unrealized PnL of their outstanding short derivative positions was -27 bps on average by the end of March 2020. Given that these short positions were linked to major equity indices, the negative PnL indicates that they entered the market belatedly and incurred losses on their short derivative positions when the Federal Reserve unexpectedly announced quantitative easing, subsequently leading to a market rebound. In fact, for each of the newly opened short derivative positions, we can roughly back out the date when these positions are opened based on the reported unrealized PnL at the end of March 2020.<sup>18</sup> On average, long index users opened short derivative positions only 11 days before March 23, 2020, when the Fed announced the market intervention, and the interquartile ranges between 5 days and 15 days before the announcement. Other derivative users, on the other hand, had a mild increase in derivative use in both long and short positions with a similar magnitude entering the crisis, as their derivative positions were already well-balanced prior to the crisis.

We also take advantage of the differential salience of the severity of the pandemic to shed light on the role of salience in impacting fund managers' derivative allocation decisions. In Section IA.2 of the Internet Appendix, we explore three potential channels of variation in risk related to the pandemic. The first, staggered Stay-at-home orders implemented at the state level. The second, pre-crisis concentration in funds' industry holdings and differential exposure of industries to the pandemic crisis. For example, the airline industry was more severely hit by COVID-19 disruptions than the utility industry. The third, pre-crisis concentration in funds' equity holdings of firms with headquarters in outbreak areas. Consistent with prior studies that find agents tend to react aggressively to salient risks (Lichtenstein et al. (1978), Dessaint and Matray (2017)), we show the increased derivative use at the start of the pandemic came from fund managers residing in states which were early adopters of Stay-at-home orders

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<sup>18</sup>For each short derivative position, we calculate a buy-and-hold cumulative close-to-close return by varying the initiation date. Such an approach cannot exactly match the unrealized PnL due to the intraday return on the initiation date. We treat it as a match if we can find an initiation date so that the cumulative return is within the 1% range of the reported unrealized PnL.



or having a concentrated ex-ante holding of industries that were severely impacted by the pandemic, who were essentially more exposed to a potential recession.

Having identified increased derivative use during the COVID-19 outbreak, a natural follow-up is to investigate how funds' derivative positions perform and how they contribute to funds' returns. We decompose monthly fund returns into two parts, *DIR* and *non-DIR*. Within *DIR* (*non-DIR*), we further decompose it into hypothetical *DIR* (hypothetical equity holding returns), and returns due to active derivative (equity) trading. To construct hypothetical *DIR*, we hand-collect security returns for each derivative position using security names provided in Form N-PORT. For each fund, similar to hypothetical equity holding return, we create its hypothetical *DIR*, assuming derivative positions are held throughout the following quarter. Specifically, hypothetical *DIR* are the sum of products between derivative return and its notional exposure. The return of active derivative trading is the difference between *DIR* and hypothetical *DIR*.

Table 8 shows the return decomposition for both the outbreak and recovery periods. During the outbreak, long index users underperformed all other derivative users by 4.85% per month. Out of the 4.85% underperformance, 0.85% came from *DIR*, and 4% from *non-DIR*. In other words, derivatives contributed to 18% of the performance gap. Moreover, long index users failed to outperform nonusers during the crash despite their significant increase in short index derivatives, which is consistent with our finding that they were late in initiating short derivative positions. Regarding the derivative component, focusing on the row showing the difference between Long Index and All others and computing the ratio between Hypo DIR and DIR shows that 74% ( $-62.55/(-84.71)$ ) of the difference in *DIR* between long index users and all other users stemmed from their derivative holding differences, whereas there was no significant return difference in active derivative trading. In contrast, for the equity component, the key driver of the differences was active equity trading, with 51% ( $-204.67/(-400.51)$ ) of the return difference due to the difference in their active equity trading. It could be that all other users' derivative positions in place provided insurance against a market crash and facilitated better execution of equities, as these funds can be more patient and engage less in fire sales than long index users.

Panel B shows the decomposition for the recovery period. Long index users gained from *DIR* by only 6.3 bps per month, which was attributed to their slow response in unwinding short positions entered in

the later part of the outbreak period. When the market rebounded unexpectedly in late March, they lost on their short positions. All other derivative users took losses from derivative positions (-0.55%), consistent with the fact that a large fraction of them use derivatives to hedge equity exposure.

We then examine funds' risk-adjusted performance during the COVID-19 outbreak. Risk-adjusted performance is estimated using a one-year rolling window. For each fund at date  $t$ , we regress its net returns in excess of risk-free rate on factor returns in the past year between  $t - 252$  and  $t - 1$ , estimate the factor loading, and predict the alpha at date  $t$ .<sup>19</sup> Figure 5 presents the cumulative performance of funds starting from the beginning of the crisis. During the outbreak period, long index users performed very similarly to nonusers, losing almost 35% in returns and 5% in risk-adjusted alphas, as shown by the figure.<sup>20</sup> Throughout the outbreak and recovery period, long index users did not outperform nonusers in returns, CAPM alpha, FF4 alpha, or FF5 alpha. The lack of outperformance by long index users is consistent with the finding that they did not close their long derivative positions during the market crash, were slow to initiate short positions, and were adversely affected by the swift market rebound following the Federal Reserve's intervention.

On the contrary, all other derivative users outperformed nonusers during the outbreak by a large margin, as indicated by the green line in Figure 5. Throughout the crisis, they maintained a slight edge over nonusers in terms of returns, CAPM alpha, and FF5 alpha. It's important to note that the difference in fund returns is not driven by funds having differential stock-picking skills, as the hypothetical returns based on their equity holding are fairly similar throughout the crisis.

Instead of solely aiming for superior performance, derivatives may assist funds in effectively managing risk. For example, one could envision utilizing derivatives to reduce tracking error relative to their benchmark. This may be especially valuable for investors who are particularly risk-averse in periods like a crisis, where the benchmark is likely to be extremely volatile. To examine whether derivatives can reduce a fund's tracking error, we first estimate a fund's realized tracking error as the annualized 30-day rolling standard deviation of return difference between the fund and its benchmark portfolio. Similar to hypothetical equity returns, we also calculate a fund's hypothetical tracking error based on returns

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<sup>19</sup>The results are very similar and available upon request if we add lags of factor returns in the estimation, following Lewellen and Nagel (2006).

<sup>20</sup>The fact that mutual funds as a group earned negative alpha during the outbreak is also documented in Pástor and Vorsatz (2020). One potential explanation is that they lost to other institutions, such as hedge funds.

generated from the fund’s reported equity holding rather than the realized fund returns. The disparity between realized and hypothetical tracking errors allows us to tease out the effect of equity holding and concentrate on the effect of derivatives and active trading on tracking errors.

Figure 6 plots the daily rolling tracking error during the COVID-19 crisis. First, the realized and hypothetical tracking errors of nonusers are very similar in magnitude and in movement throughout the crisis. They started at 3% annually and peaked at 14%, as shown in the figure. The peak of tracking error after March 23 is due to the 30-day rolling estimation. Long index users have lower realized tracking errors than nonusers but comparable hypothetical tracking errors, suggesting that their derivative strategies and active trading effectively curbed tracking errors, which would have otherwise been akin to nonusers.

On the other hand, all other derivative users also have lower realized tracking errors than hypothetical tracking errors, but the underlying mechanism is very different. Their hypothetical tracking error started to increase sharply in late February when the market crash began. It then peaked at around 27%, as shown by the green line in Figure 6(b). However, the realized tracking error only peaked at around 17%. Interestingly, the result suggests that their equity holdings behave similarly to their benchmark in normal times but exhibited significant divergence during the crisis. Their derivative and active trading help reduce tracking error substantially, potentially because of the downside protection provided by their short derivative positions, which also allowed managers to be less constrained in equity trading than other managers.

Overall, during the COVID-19 episode, long index users tried to take advantage of the market crash by shorting equity indices with derivative positions. Still, they were late to do so and suffered losses due to the sharp market rebound induced by the Fed intervention. As a result, they did not outperform nonusers and underperform all other derivative users who, going into the crisis, were better hedged with their derivative positions. Although their derivative strategies did not yield superior financial performance, they were effective in reducing the tracking error in such a volatile market.

## 5.2 Derivative Use During the Fed Rate Hike

In 2022, the Federal Reserve undertook a series of interest rate hikes to address persistently high inflation. The first of these hikes, a 0.25% increase, was officially announced in March 2022. However,

discussions and signs of impending rate hikes had emerged earlier, especially as inflation soared to 7% in December 2021. Rate hikes became highly anticipated after the Fed’s December 2021 meeting, as the dot plot, which represents the FOMC members’ interest rate projections, indicated that most members expected three rate hikes in 2022. Contrasting with the exogenous and concentrated impact of the COVID-19 pandemic, the Fed’s rate hikes were more endogenous to financial markets, spanned the entire year, and were well anticipated. This ongoing scenario presents a unique opportunity to observe how derivative-using funds respond to such a prolonged macroeconomic shock.

First, we examine whether funds change their derivative use to respond to rate hikes. For each quarter and each fund, we calculate the change in gross notional exposure from the previous quarter. Figure 7 plots the quarter-by-quarter change in gross notional exposure and its 95% confidence interval by funds’ derivative strategies.<sup>21</sup> While the initial rate hike was in the first quarter, Long index users only increased derivative use in the second quarter of 2022 by about 3.4%, corresponding to a 31% relative increase. This is consistent with their late response during the COVID-19 episode. Meanwhile, the magnitude of their response is much milder than the COVID-19 episode, in which they almost doubled derivative use. All other derivative users, on the other hand, increased their derivative use when the first rate hike took place, but the magnitude is also fairly small, with only a 1.1% increase in gross notional exposure. Furthermore, no derivative users seem to have changed their derivative strategies prior to the rate hike, especially given the surge in inflation and all the early discussions of potential rate hikes in 2021.

Next, we examine their performance during the Fed rate hike period. Figure 8 plots funds’ cumulative returns and alphas starting from the beginning of 2022. Similar to the COVID-19 episode, we do not find evidence that long index users can consistently outperform nonusers across various performance measures. Specifically, compared to nonusers, long index users have slightly higher returns and CAPM alphas but lower FF4 and FF5 alphas. All other derivative users, however, underperform nonusers and long index users by over 3% in 2022 in all risk-adjusted alphas, as indicated by the green line. Their underperformance is mostly driven by non-equity users, who specialize in interest rate and currency derivatives, as shown in Figure IA2. Note that around 36% of their gross notional exposure is in long interest rate derivatives, as shown in Panel A of Table 2, the value of which moves inversely to changes

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<sup>21</sup>The results are very similar when we just focus on the set of funds that report in March, June, September, and December.

in interest rates. Therefore, when the interest rate increased, they suffered largely from their derivative positions.

Lastly, we study whether derivatives help reduce funds’ tracking error during the rate hikes. Figure 9 plots funds’ realized and hypothetical tracking errors starting from 2022. Consistent with our finding during the COVID-19 episode, derivatives can help reduce tracking errors, as the realized tracking errors are lower than hypothetical tracking errors for all derivative users, while there is no difference for nonusers.

To sum up, long index users are slow to react in their derivative strategies to both the COVID-19 pandemic and Fed rate hikes. Even though they specialize in long equity index derivatives, being able to quickly amplify their equity exposure does not enable them to outperform nonusers in these special periods.

## 6 Fund Performance and Flows over an Extended Sample

Examining fund performance and flows in our sample imposes a challenge, as it only contains three years of data. One would require a long time series of data to get reliable statistical significance of fund performance. Therefore, in this section, we rely on the CRSP data since 2010 to test the performance and flows of derivative users. First, we identify derivative users using CRSP holding data. Unlike Form N-PORT, where derivatives can be identified directly with a tag, derivative positions in CRSP need to be inferred based on the security names. We summarize the pattern of derivative security names in the Appendix. Second, to separate long index users from all other derivative users, we also manually identify equity index derivative contracts and label a derivative-using fund as a long index user if over 80% of their derivative positions are long equity index derivatives.<sup>22</sup> Lastly, we form equal-weighted portfolios for nonusers, long index users, and all other derivative users, respectively, and regress portfolio excess return on various factor models to assess their performance between 2011 and 2022. The sample starts in 2011 because we form portfolios based on the derivative use in the lagged year, and CRSP began to report derivative positions in 2010. Different from previous sections, where we can separate

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<sup>22</sup>Identifying equity index derivative contracts requires intensive manual labor work. Since our focus is on long index users, we do not further label derivatives in other asset classes for this analysis. In the previous version of the paper, derivative users that amplify equity returns are identified as the ones in the top tercile of return correlation between derivative and non-derivative components prior to the COVID-19 crisis, and we back-filled the derivative user types in the earlier years between 2010 and 2019. The results are similar to the ones presented in this section and are available upon request from the authors.

out token users based on gross notional exposure, we do not further exclude token users in the analyses using CRSP data, because CRSP does not provide gross notional exposure of derivative positions, and the derivative weights provided are often not reliable as discussed in Section 2.2. Note that token users behave very similarly to nonusers in our recent sample. As a result, pooling token users and non-token users underestimates any potential difference between derivative users and nonusers that we will find in this section. We consider five risk-adjusted performance measures: benchmark adjust returns, CAPM alpha, Fama-French three-factor alpha, four-factor alpha, and five-factor alpha.<sup>23</sup>

The fund performance results are reported in Panel A of Table 9, and all numbers are in annualized percentage points. Over the extended sample period between 2011 and 2022, long index users underperform nonusers by all five performance measures, ranging from 0.36% using benchmark adjusted returns to 0.62% using the Fama-French five-factor model. Therefore, the amplification strategy imposed by long index users does not yield superior performance over either the extended sample or the two special episodes in our recent sample. The underperformance of long index users is not driven by fees, as long index users have lower expense ratios than nonusers (Table 3). It is also not driven by a set of small funds, as the result is fairly similar in magnitude when we form value-weighted portfolios rather than equal-weighting all funds. The result of fund performance using gross returns and the one using value-weighted portfolios are shown in Internet Appendix Table IA2. On the contrary, the hedging strategies adopted by the majority of all other derivative users yield a similar performance over the extended sample, but they do offer superior performance during the COVID-19 market crash, which provides benefits to investors who especially value fund performance in bad times.

After documenting the underperformance of long index users, we next examine whether investors allocate their capital differently. We regress fund flows on derivative user dummies and control for funds' past performance, return volatility, expense ratio, turnover ratio, fund size, lagged fund flows, time fixed effects, and style fixed effects. The regression results are shown in Panel B of Table 9. In columns (1)-(3), flows of nonusers serve as the baseline, and long index users receive 0.2% more flows monthly (2.4% annually) than nonusers, after controlling for fund performance and other characteristics, as shown by the positive coefficient estimates of long index dummy. To discern the source of these additional

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<sup>23</sup>In untabulated results, we also examined the Fung-Hsieh hedge fund eight-factor model, and we find no significant difference in performance between users and nonusers. The results are available upon request.

flows—whether retail or institutional—we conducted share-class level regressions in columns (4)-(6), and flows of nonusers’ institutional share class serve as the baseline. Long index users attract more flows from institutional share classes compared to nonusers, while their flows from retail share classes are similar to nonusers. This inference is drawn from the combined coefficient estimates of the long index dummy and its interaction with the retail share-class dummy. All other derivative users receive 0.1% more flows monthly than nonusers within institutional share classes. The difference in institutional flows between all other derivatives and long index users is not statistically significant. Similar to long index users, all other derivative users do not attract additional flows from retail share classes. In summary, derivative users generally attract more capital from institutional investors than nonusers, but not from retail investors. Interestingly, while institutional investors can identify funds using derivatives, their capital allocation does not vary based on whether derivatives are used for amplifying or hedging fund returns.

Why do long index users underperform nonusers but still receive abnormally higher flows than nonusers from institutional investors? As suggested by the model in Glode (2011), a potential rationale for the underperformance of long index users is that their strategies could be tailored to outperform in times of crisis.<sup>24</sup> However, we showed earlier that they also failed to outperform nonusers during the COVID-19 market crash. To shed light on this puzzle, we propose two potential channels. The first is through a risk-shifting channel, where institutional investors bet on long index users to actively deviate from the benchmark during the crisis, which is a necessary but not a sufficient condition for superior performance. Due to the Fed’s unanticipated intervention and sharp market rebound, these funds failed to deliver superior performance on the realized price path. Alternatively, there could be a reverse causality explanation through a flow-management channel.<sup>25</sup> Specifically, long index users receive extra flows for some unobserved reasons unrelated to performance and need to use long equity index derivatives as a cash-equitization tool (Frino et al. (2009)).

To test which of these two explanations holds in the data, we conduct the following analysis. We sort long index users by the change in tracking error between the end of 2019 and the start of the recovery period on March 24, 2020, into high and low groups, which capture the increased or decreased deviation of

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<sup>24</sup>The argument is not that because they hold long index derivatives, they will outperform in bad times, but instead that their overall strategy that combines equity and derivative positions and trading could be tailored to perform well in those states of the world.

<sup>25</sup>We thank Veronika Pool for her suggestion on the reverse causality.

a fund from its benchmark entering into the crisis. Tracking error is calculated as the annualized 30-day rolling standard deviation of return difference between a fund and its benchmark. Suppose institutional investors indeed provide extra flows in normal times to long index users that will shift their strategy during a crisis. In that case, we should expect only the funds in the high change-in-tracking-error (CTE) group to be the ones that experienced abnormally high flows to begin with. If, on the other hand, the result is driven by the flow-management explanation, then both high and low CTE funds would have received abnormally high flows in the pre-crisis period.

The results are consistent with the risk-shifting channel. First, we estimate a set of regressions with the same specification as the one in columns (4) to (6) of Panel B in Table 9, except that we replace the dummy variable of long index users by two dummy variables, high and low CTE long index users. As shown in Panel A of Table 10, high CTE long index users received more institutional flows than nonusers, but low CTE users did not, as shown by the positive coefficient estimate of high CTE dummy and insignificant coefficient estimate of low CTE dummy. Moreover, high CTE long index users are the ones that significantly increased short notional exposure by 17.5% during the crash, whereas there was no significant change among low CTE long index users.<sup>26</sup> In summary, we partly rationalize the extra flows by institutions to long index users by showing that institutional investors may direct extra capital to high CTE funds in exchange for anticipated outperformance in a crisis. These funds indeed shifted their derivative strategies during the crash by increasing short notional exposure, but such a shift did not yield superior performance on the realized price path exhibited during the pandemic due to the unexpected Fed announcement that led to the quick market rebound.

## 7 Conclusion

Research on derivative use by mutual funds and the impact of derivative trades on funds' performance has been hampered by the lack of sufficiently granular data. Taking advantage of data that has become available only recently, we are able to shed new light on questions that were hard to evaluate earlier and overturn some prior conclusions. Importantly, our data allow us to estimate funds' derivative performance so that we can test how derivative positions correlate and contribute to funds' overall return. In contrast

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<sup>26</sup>In untabulated results, we also find that high and low CTE long index users have similar characteristics, such as expense ratio, turnover ratio, and fund size. They also have very similar performance and factor exposures in the past decade.



to the commonly perceived view in the literature, we show that the majority of derivative users employ derivatives to enhance their equity returns, rather than to hedge.

Using a data-driven machine learning approach, we classify derivative users based on their allocations in underlying assets. This reveals five distinct and economically meaningful derivative strategy patterns closely aligned with theory. We gain further insight through textual analysis of derivative-related discussions in fund prospectus. The predominant category among derivative users is long index users, who primarily focus on long equity index derivatives. Their strategy involves leveraging derivatives to gain market exposure and amplify fund returns. Additionally, they utilize equity index derivatives for cash equitization and cash flow management. Long stock and most short stock users engage in individual stock derivatives to leverage firm-specific information, albeit in opposite directions, while some short stock users also short stock derivatives for downside protection of their existing individual positions. In contrast, short index users mostly use short equity index derivatives to hedge against systemic risks. The final group, non-equity users, are specialized in interest rate and currency derivatives, employing these to mitigate non-equity risks and gain exposure to non-equity asset classes.

Taking advantage of the fact that our sample encompasses two special episodes, the COVID-19 pandemic in early 2020 and the ten-month bear market induced by Fed rate hikes in 2022, we investigate how funds trade derivatives during times of crisis and the implications to fund returns and risks. Long index users, the archetypal amplifiers, traded more derivatives during both episodes. During the COVID-19 episode, they doubled derivative use and modified their derivative strategies, all coming from short positions, which they rarely held. Their response to the rate hike episode is qualitatively similar but much milder, as the financial market well-anticipated the rate hikes compared to the COVID-19 pandemic. However, they responded late in both episodes and failed to outperform nonusers and other derivative users.

Our paper has potential policy implications on risk-taking in the mutual fund industry. While access to derivatives allows fund managers to hedge and manage risk, it may also encourage managers to take on unnecessary risk to the detriment of fund investors. Retrospectively, long index users, the majority of derivative users, underperform in non-crisis times and fail to outperform in the crisis period. Nevertheless, they receive more flows than nonusers. As a result, fund managers benefit at the expense of investors.

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Figure 1

### The Extent of Derivative Use and Derivative Contribution to Fund Returns

The figure shows the cumulative distribution functions of the fund-level derivative use and (signed) derivative relative contribution to fund returns. The extent of derivative use is proxied by gross notional exposure in Panel (a), and by absolute derivative weight in Panel (b). The gross notional exposure is the sum of the notional amounts of derivative positions scaled by the fund's total net assets. The absolute derivative weight is the sum of the absolute value of portfolio weights of all derivative positions for a fund. Signed derivative relative contribution is the ratio between DIR and non-DIR and is shown in Panel (c). Derivative induced return (DIR) in month  $t$  is calculated as the sum of realized PnL and change of unrealized PnL in month  $t$ , normalized by the fund total net assets in month  $t - 1$ . Non-DIR is the difference between fund return and DIR. Derivative relative contribution is the absolute value of the signed derivative relative contribution and is shown in Panel (d).

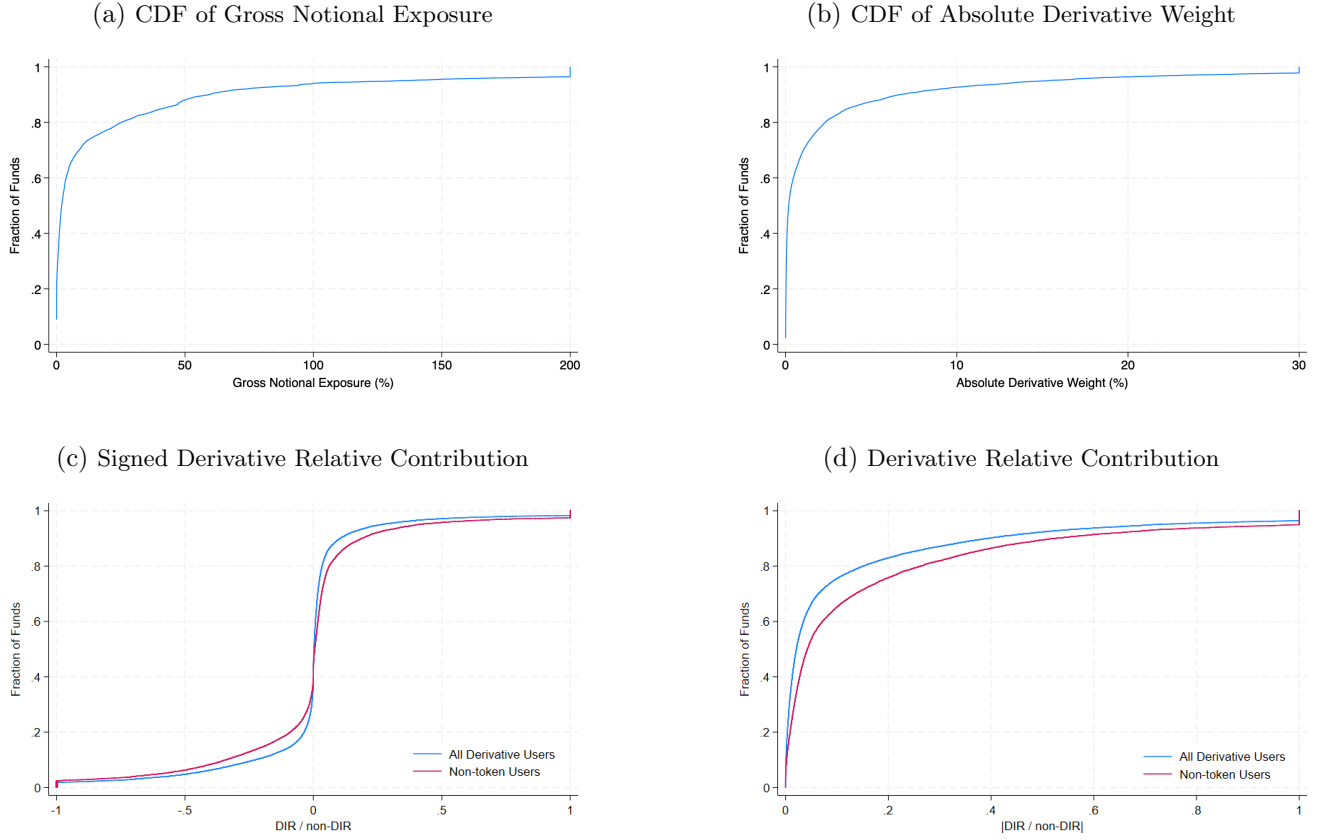
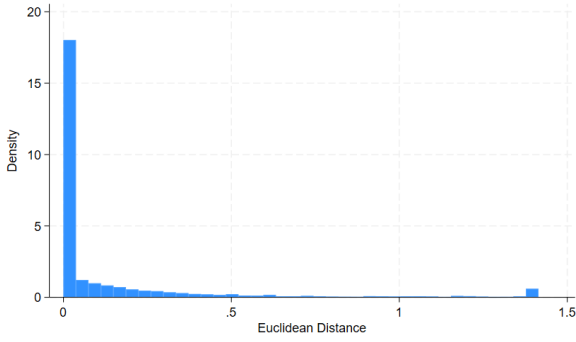


Figure 2

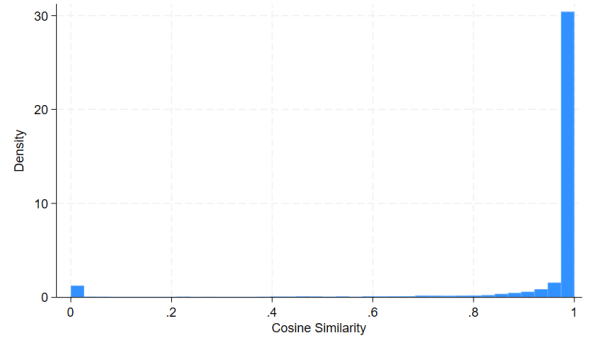
### Persistence of Derivative Underlying Assets and Classification

The figure shows the persistence of derivative underlying assets by derivative users in Panels (a) and (b), and the persistence of the classification in Panel (c). We calculate the fraction of gross notional exposure in the following six underlying asset categories and for long and short positions for each derivative user at each quarter. The six underlying asset categories include equity index, individual stock, interest rate securities, foreign exchange, commodity, and other assets. In Panel (a), we calculate and plot the histogram of the Euclidean distance between the previous and current quarter allocations. The measure is bounded between zero and  $\sqrt{2}$ . The maximum distance is achieved when the fund completely changes the derivative underlying asset from one category to another, and the minimum distance is achieved when there is no change in the underlying asset category. In Panel (b), we calculate and plot the histogram of the cosine similarity between the previous and current quarters' allocations. The maximum value of 1 is achieved when there is no change in the underlying asset category. In Panel (c), we plot the probability of a derivative user deviating from its major user group, which is defined as the most frequent classification of the fund throughout the sample.

(a) Euclidean Distance between Previous and Current Quarter Allocation



(b) Cosine Similarity between Previous and Current Quarter Allocation



(c) Probability of Deviation from Major User Group

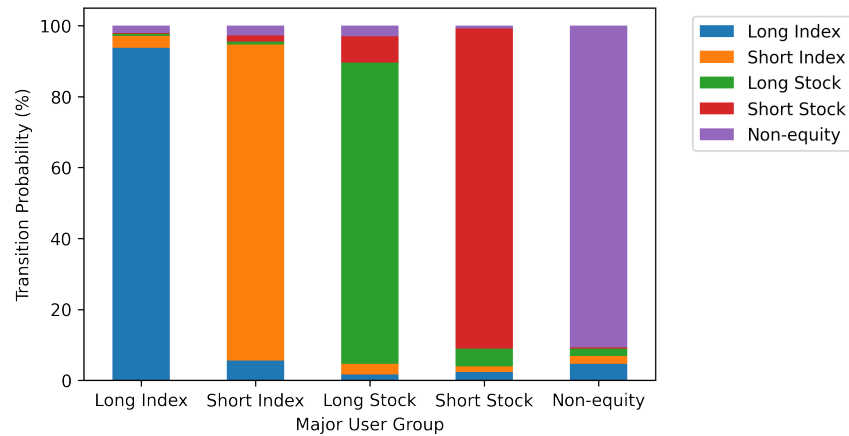
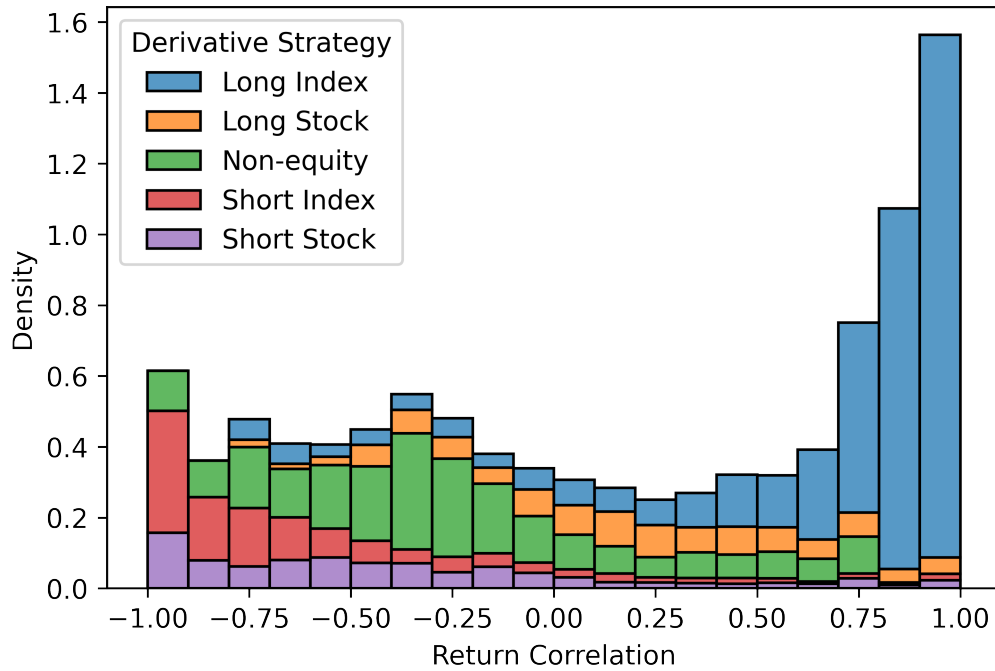


Figure 3

### Distributions of Correlation between Derivative and Non-derivative Induced Returns

The figure shows the histogram of the correlation between DIR and non-DIR. DIR in month  $t$  is calculated as the sum of realized PnL and change of unrealized PnL in month  $t$ , normalized by the fund total net assets in month  $t - 1$ . Non-DIR is the difference between the fund return and DIR. The correlation is calculated based on the availability of N-PORT data between July 2019 and December 2022. The figure also indicates which derivative strategies contribute to the histogram, and the detailed discussion of different derivative strategies is documented in Section 4.1.



Word-Cloud of Derivative-related Discussions in Principal Investment Strategy

The figure shows the Word-Cloud of derivative-related discussions in the Principal Investment Strategy section of a fund's prospectus using Form N-1A. We identify and extract derivative-related sentences using keywords: derivative, futures, options, and swaps. We also extract one sentence before and after each identified sentence. Lastly, we plot the Word-Cloud based on the frequencies of bigrams in our extracted sentences after removing common words. The font size of bigrams increases with the frequency, and we manually highlight some representative bigrams in red for each derivative user group. The list of common words includes 'fund', 'security', 'portfolio', 'invest', 'investment', 'underlying', 'contract', 'manager', 'series', and 'adviser'.

(b) Other Equity-based Derivative Users



(c) Non-equity User



Figure 5

### Fund Performance in COVID-19 Pandemic

The figure shows the cumulative returns and alphas for funds starting from the outbreak on January 20, 2020, to June 8, 2020, when the S&P 500 index completely rebounded from the crash. The figure shows the performance of nonusers, long index users, and all other users. Daily alphas are estimated using a one-year rolling window. The dotted vertical line indicates the start of the recovery period (March 24, 2020).



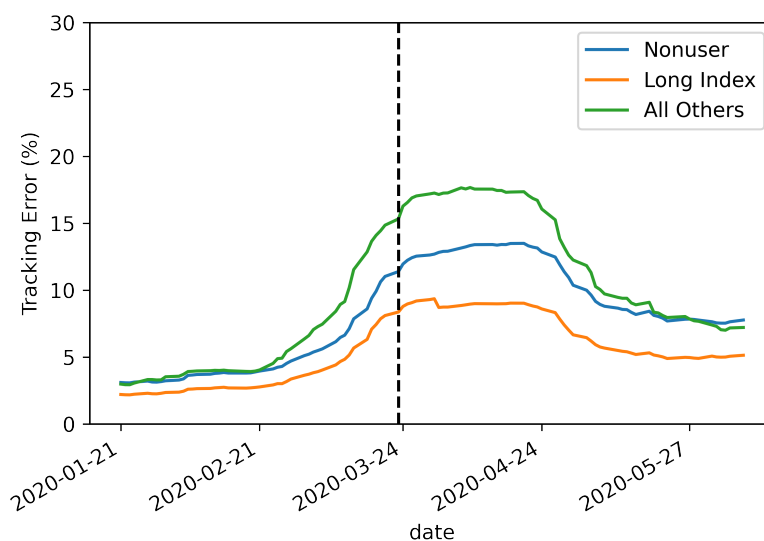


Figure 6

### Tracking Error in COVID-19 Pandemic

The figure shows the funds' tracking error starting from the COVID-19 outbreak on January 20, 2020, to June 8, 2020, when the S&P 500 index completely rebounded from the crash. Panel (a) shows funds' tracking error, which is the 30-day rolling annualized standard deviation of the difference between fund returns and benchmark returns. Panel (b) shows the hypothetical tracking error based on the reported equity positions at the beginning of a quarter. The dotted vertical line indicates the start of the recovery period (March 24, 2020).

(a) Tracking Error



(b) Hypothetical Tracking Error

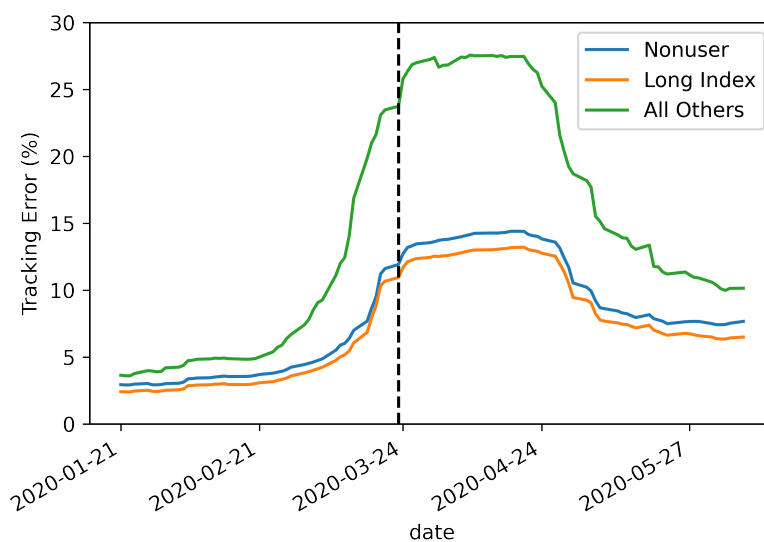


Figure 7

Quarter-by-quarter Change in Derivative Use During Fed Rate Hike Period

The figure shows the funds' quarter-by-quarter change in gross notional exposure during the Fed Rate Hike period. For each quarter and each fund, we calculate the change in gross notional exposure from the previous quarter. We then plot the average change and its 95% confidence intervals for long index users and all other derivative users, respectively. The initial Fed rate increase took place in Q1 of 2022.

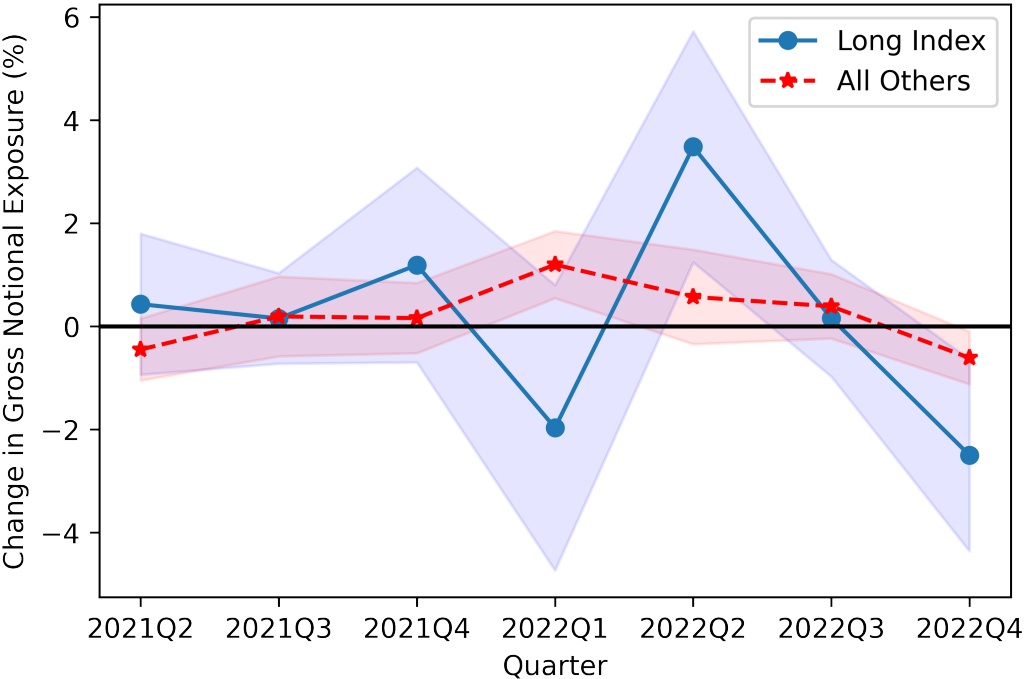


Figure 8

### Fund Performance in Fed Rate Hike Period

The figure shows the cumulative returns and alphas for funds starting from January 1, 2022, to December 31, 2022. The figure shows the performance of nonusers, long index users, and all other users. Daily alphas are estimated using a one-year rolling window. The dotted vertical lines indicate the announcement dates of rate hikes.

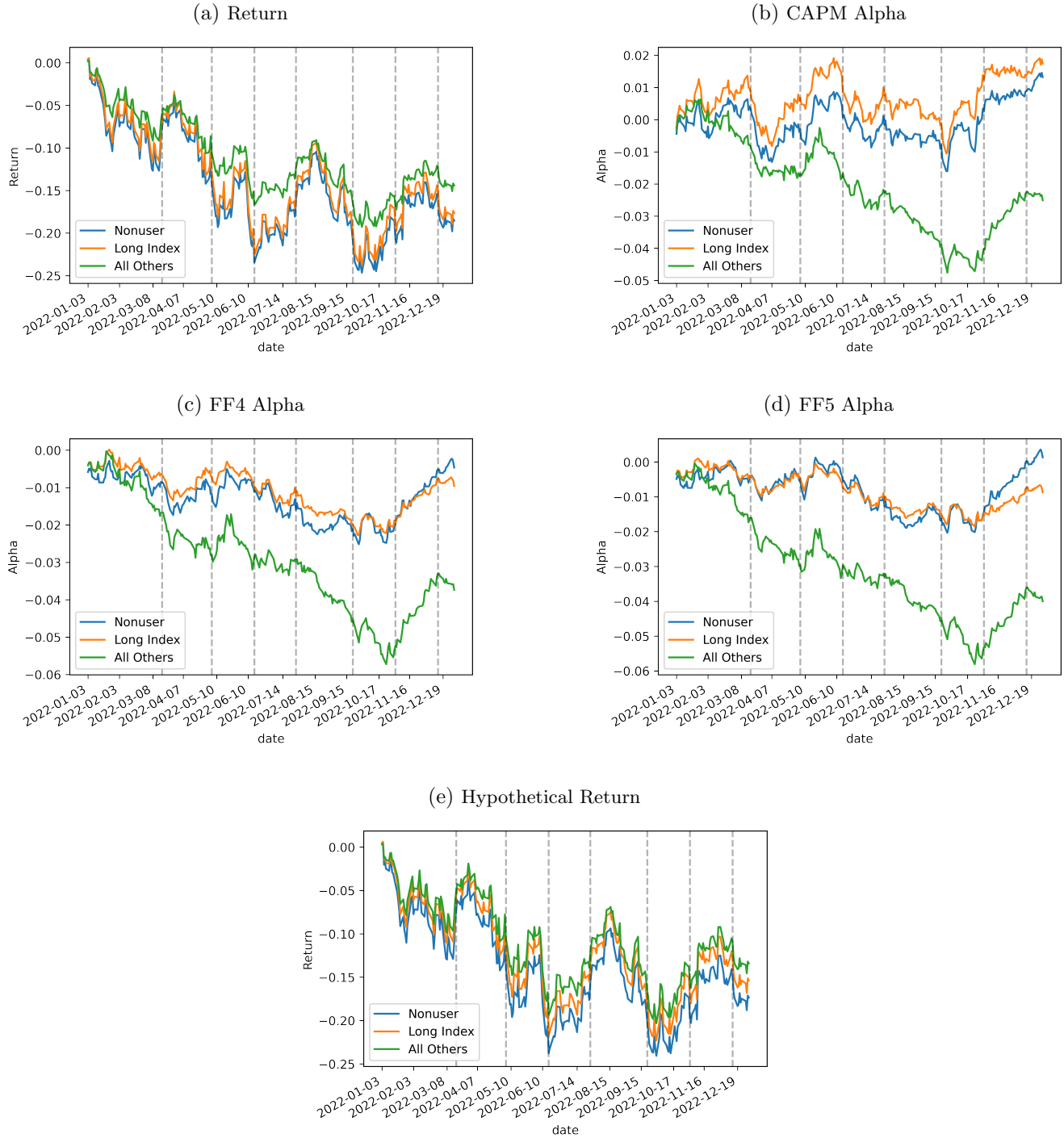
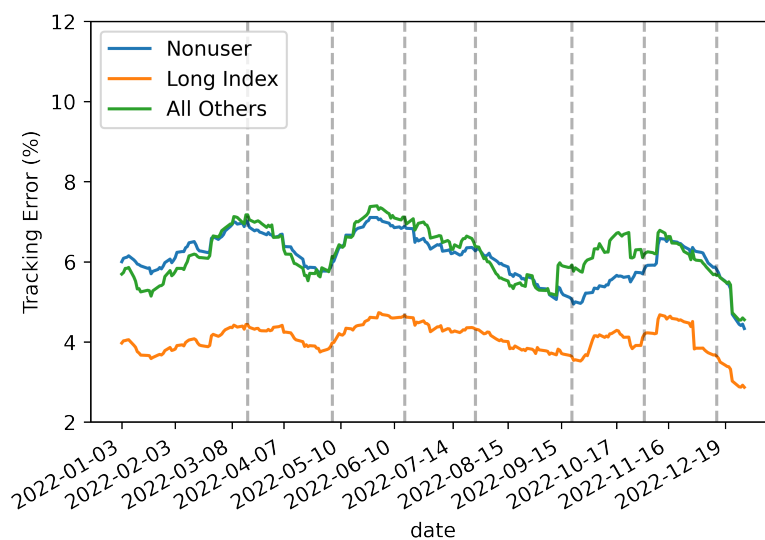


Figure 9

### Tracking Error during Fed Rate Hikes

The figure shows the funds' tracking error starting from January 1, 2022, to December 31, 2022. Panel (a) shows funds' tracking error, which is the 30-day rolling annualized standard deviation of the difference between fund returns and benchmark returns. Panel (b) shows the hypothetical tracking error based on the reported equity positions at the beginning of a quarter. The dotted vertical lines indicate the announcement dates of rate hikes.

(a) Tracking Error



(b) Hypothetical Tracking Error

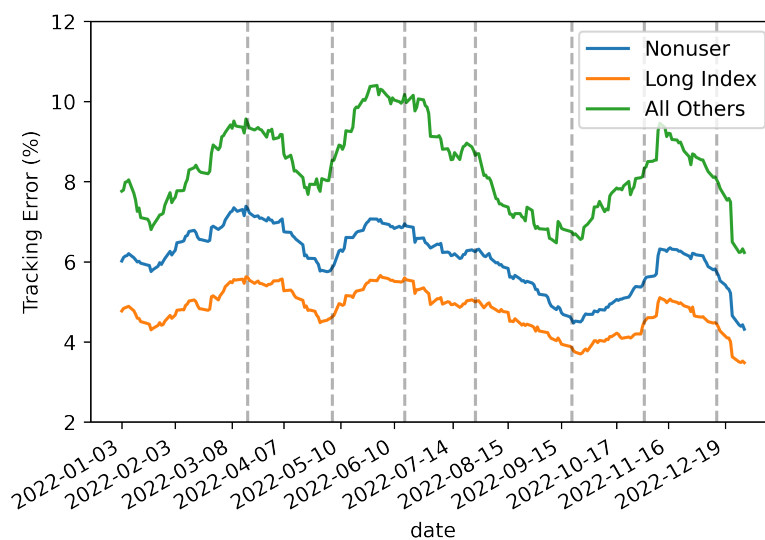


Table 1

## Overview of Derivative Use

The table shows the summary of derivative use. The sample includes all actively managed domestic equity funds that use derivatives from September 2019 to December 2022. Panel A shows the number of funds with derivative positions and the breakdown of derivative use by categories. Panel B shows the summary statistics of key variables. *Absolute Derivative Weight* is the sum of portfolio weights of derivative positions in absolute value, measured in percentage points. *Gross Notional Exposure* is the sum of the notional amounts of derivative positions, normalized by the fund's total net assets (TNA) and shown in percentage points. *Derivative Induced Return (DIR)* is the sum of monthly realized PnL and change in unrealized PnL from derivative positions, normalized by the fund size from the previous month and shown in basis points. *Non-Derivative Induced Return (non-DIR)* is the difference between the fund return and DIR shown in basis points. *Signed Derivative Relative Contribution* is the ratio between DIR and non-DIR. *Derivative Relative Contribution* is the absolute value of the signed derivative relative contribution. All variables are winsorized at 1% level.

Panel A: Breakdown of Derivative Usage

	No. of Funds	Absolute Weight	Gross Notional Exposure
All Derivatives	1079	2.48	23.52
Future/Forward	606	0.93	10.46
Swap	197	0.83	11.8
Option	585	0.42	0.55
Foreign Exchange	269	0.3	0.71

Panel B: Summary Statistics of Key Variables

Variable	Mean	StdDev	Min	10%	20%	30%	40%	50%	60%	70%	80%	90%	Max
Absolute Derivative Weight (%)	2.48	8.65	0.00	0.01	0.02	0.04	0.08	0.18	0.46	1.04	2.32	6.68	62.92
Gross Notional Exposure (%)	23.52	76.98	0.00	0.00	0.01	0.43	1.05	1.97	3.72	8.76	25.24	59.43	531.55
Derivative Relative Contribution	0.37	1.39	0	0	0	0.01	0.02	0.03	0.05	0.1	0.24	0.6	11.17
Signed Derivative Relative Contribution	0.01	0.83	-4.24	-0.3	-0.05	-0.01	0	0	0.01	0.02	0.05	0.19	4.85
Derivative Induced Return (bps)	-6.53	78.01	-521.69	-49.81	-12.61	-4.07	-0.67	0.09	1.81	5.3	12.82	43.25	576.46
Non-Derivative Induced Return (bps)	20.71	531.19	-1494.27	-635.4	-317.23	-140.18	2.98	102.99	207.91	313.63	445.23	677.68	1463.07

Table 2

## Derivative Underlying Asset Allocation and Instrument Allocation

The table reports the average allocation of derivative securities for each derivative strategy in Panel A, and the allocation of derivative instruments in Panel B. Derivative securities are grouped by their underlying assets into six major categories: equity index, individual stock, interest rate, foreign exchange, commodity, and other assets. We further split each major category into long and short positions. Therefore, there are twelve categories in total. In Panel A, for each derivative strategy, we report the average fraction of gross notional exposure invested in each category. We also report the fraction of derivative users for each derivative strategy. In Panel B, we report the average gross notional exposure of all derivatives, the fraction of gross notional exposure by derivative instrument types, and the percentage of long positions in each instrument category.

Panel A: Underlying Asset Allocation

Cluster Derivative Strategy	(1) Long Index	(2) Long Stock	(3) Short Index	(4) Short Stock	(5) Non-equity
Fraction of Derivative Users	0.414	0.126	0.114	0.085	0.261
Long Equity Index	<b>0.964</b>	0.008	0.132	0.015	0.111
Short Equity Index	0.010	0.006	<b>0.817</b>	0.025	0.059
Long Individual Stock	0.002	<b>0.951</b>	0.007	0.113	0.010
Short Individual Stock	0.002	0.027	0.014	<b>0.843</b>	0.001
Long Interest Rate	0.008	0.001	0.011	0.000	<b>0.362</b>
Short Interest Rate	0.003	0.000	0.006	0.000	0.179
Long USD	0.006	0.001	0.004	0.001	0.114
Short USD	0.001	0.000	0.008	0.003	0.033
Long Commodity	0.000	0.000	0.000	0.000	0.002
Short Commodity	0.000	0.000	0.000	0.000	0.002
Long Other Assets	0.001	0.004	0.001	0.000	0.096
Short Other Assets	0.002	0.000	0.001	0.000	0.031

Panel B: Derivative Instrument Allocation

Derivative Strategy	Long Index	Long Stock	Short Stock	Short Index	Non-equity
Gross Notional Exposure of All Derivatives (%)	9.55	48.74	52.77	22.56	28.11
% in Futures/Forwards	57.9	2.9	1.3	76.6	66.6
% in Long	92.1	75.5	46.2	11.9	65.1
% in Swaps	39.2	91.3	95.1	15.5	26.1
% in Long	90.4	91.3	38.6	32.1	40.2
% in Options	1.9	5.6	3.0	6.9	1.3
% in Long	49.4	51.7	21.6	28.2	42.6
% in Foreign Exchange	1.0	0.2	0.6	1.0	6.0
% in Long USD	86.8	21.5	9.9	74.6	76.5

Table 3  
Fund Characteristics and Benchmarks

The table reports fund characteristics in Panel A and the distribution of fund benchmarks in Panel B. *Cash* is the weight of cash and cash equivalents held by the fund. *Excess cash* is calculated by subtracting 20% of gross notional exposure of derivative positions (excluding the purchase of call and put options) and short equity positions from cash and cash equivalents. *Equity* is the weight of stock positions. *Num Stock* is the number of stocks held by the fund. *Holding HHI* is the HHI of stock positions. *CAPM Beta* is the coefficient estimate from regressing a fund's excess return on market excess return. *Flow Volatility* is the standard deviation of fund flows in the past year. *Return Volatility* is the standard deviation of fund returns in the past year. *Cash Volatility* is the standard deviation of cash holding over the sample period. *DIR and non-DIR Correlation* is the correlation between a fund's DIR and non-DIR over the sample period. *Std Dev of DIR* is the standard deviation of a fund's DIR over the sample period.

Panel A: Fund Characteristics

Strategy Group	Nonusers	Token Users	Long Index	Long Stock	Short Stock	Short Index	Non-equity
Cash (%)	3.30	4.36	6.20	6.35	12.28	8.67	7.28
Excess Cash (%)	3.30	4.26	4.39	0.44	4.99	4.03	2.57
Equity (%)	96.67	95.13	92.69	87.39	83.85	86.04	77.24
Num Stock	81.26	187.46	253.04	150.86	192.63	130.08	206.25
Holding HHI	0.04	0.02	0.04	0.05	0.02	0.09	0.05
Expense Ratio (%)	0.99	0.95	0.82	1.29	1.35	1.10	0.86
Turnover Ratio (%)	53.98	61.63	67.47	137.04	183.18	71.54	78.56
TNA (\$billion)	1.77	2.77	2.23	0.49	0.27	1.09	3.08
CAPM Beta	0.95	0.94	0.94	0.74	0.52	0.52	0.60
Flow Volatility (%)	0.52	0.57	0.62	0.72	0.58	0.57	0.37
Return Volatility (%)	5.72	5.76	5.37	5.01	3.91	3.61	3.87
Cash Volatility (%)	1.85	1.94	2.53	5.80	4.60	3.49	2.58
Absolute Derivative Weight		0.67	1.54	10.87	7.99	3.09	4.40
Gross Notional Exposure		0.37	9.55	48.74	52.77	22.56	28.11
DIR and non-DIR Correlation		0.20	0.64	0.12	-0.25	-0.58	-0.06
Derivative Relative Contribution		0.09	0.24	0.66	0.78	0.56	0.15
Std Dev of DIR (bps)		41.39	76.73	121.52	147.35	148.47	56.82

Panel B: Fund Benchmark

Benchmark	Nonusers	Token Users	Long Index	Long Stock	Short Stock	Short Index	Non-equity
S&P 500	19.26	18.77	14.03	29.91	40.17	25.6	6.94
Russell 1000 Value	7.33	7.93	7.42	0	0	0.14	3.99
Russell 1000 Growth	6.11	6.69	5.14	0	0	0.28	0
Russell 2000 Value	5.43	2.62	3.39	0	0	0	0
Russell 2000	5.06	4.91	10.58	0	1.67	1.42	0.64
Russell 2000 Growth	4.77	4.45	1.87	5.13	0	0.14	0
Russell Mid Cap Growth	4.41	5.62	2.4	0	0	0.28	1.12
Russell Mid Cap Value	3.48	2.98	1.93	0	0	0	0
Russell 2500 Growth	2.51	0.79	0.88	5.98	0	0	0
Russell Mid Cap	2.27	0.69	0.06	1.71	0	0	0
Russell 3000 Value	2.26	4.88	0.12	0	0	0.28	2.95
Russell 3000	2.25	3.18	6.25	1.71	0	2.7	4.39
Morningstar US LM Brd Growth	2.21	1.63	0.88	0	0	0	0
Russell 1000	2.02	3.54	5.96	0	0	1.56	1.91
Russell 2500	1.99	1.35	0.7	0	0	0	0.48
Russell 3000 Growth	1.74	0.66	0.41	0	0	0	0
Russell 2500 Value	1.49	0.92	0.76	0	0	0	0
S&P Target Risk Aggressive	1.14	0.1	3.57	0	0	1.28	3.83
Morningstar US Mod Tgt Alloc NR USD	0.77	0.41	1.29	0	0	5.69	11.24
S&P 500 Daily Risk Control 10%	0.12	0.53	3.27	0	0	17.35	6.06
Other Benchmark	23.38	27.37	29.11	55.56	58.16	43.24	56.46

Table 4

## Funds' Derivative Use, Past Performance, and Flow

The table examines the change in derivative notional exposure with respect to funds' past-quarter performance and flows. The dependent variable is the change in gross notional exposure from the previous quarter to the current quarter. The independent variables are the fund's previous quarter's performance, flow, expense ratio, turnover ratio, fund size, time fixed effects, and Lipper style fixed effects. Standard errors are clustered at the fund level.

	(1) Token	(2) Long Index	(3) Long Stock	(4) Short Equity	(5) Non-equity
Previous Quarter Performance	-0.609* (-1.78)	-4.294* (-1.88)	-13.44 (-1.47)	-4.623 (-0.87)	-2.835 (-0.44)
Previous Quarter Flow	-0.339 (-0.79)	3.800** (1.99)	10.34 (0.78)	-0.859 (-0.17)	-7.702 (-1.56)
Fund Controls	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y
Adjusted R-squared	0.007	0.048	0.190	0.192	0.092
N	3403	1598	104	860	1150

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



Table 5  
Funds' Excess Cash Holding and Flow

The table examines the relationship between funds' flows and change in equity holding and excess cash holding after considering the margin requirement of their derivative positions. A fund's excess cash holding is its weight of cash holding minus 20% of the gross notional exposure of a fund's derivative positions (excluding the purchase of options) and short equity positions. In Panel A (B), we regress a fund's change in excess cash holding (equity holding) from quarter  $t - 1$  to quarter  $t$  on a fund's flow in quarter  $t$ . Control variables include expense ratio, turnover ratio, fund size, time fixed effects, and Lipper style fixed effects. Standard errors are clustered at the fund level.

Panel A: Change in Excess Cash Holding						
	Dependent Variable = Change in Excess Cash Holding					
	(1) Nonusers	(2) Token	(3) Long Index	(4) Long Stock	(5) Short Equity	(6) Non-equity
Flow	0.0305*** (6.44)	0.0523*** (4.10)	-0.0383** (-2.21)	0.0602 (0.69)	0.102*** (2.75)	0.0184 (0.60)
Fund Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.0199	0.0179	0.0365	0.203	0.0160	0.0190
N	17520	3523	1590	106	880	1150

Panel B: Change in Equity Holding						
	Dependent Variable = Change in Equity Holding					
	(1) Nonusers	(2) Token	(3) Long Index	(4) Long Stock	(5) Short Equity	(6) Non-equity
Flow	-0.0297*** (-8.14)	-0.0573*** (-5.52)	0.0252* (1.76)	-0.0703 (-0.92)	-0.0432 (-1.50)	0.0371* (1.67)
Fund Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.0258	0.0331	0.0508	0.175	0.255	0.145
N	17520	3523	1590	106	880	1150

$t$  statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 6

## Performance-flow Sensitivity

This table shows the performance-flow sensitivity of funds by their derivative strategies. For funds in each derivative strategy group, we regress the fund's flows on past-year performance, controlling the fund's lagged flows, expense ratio, turnover ratio, the natural logarithm of fund size, and past-year return volatility. All regression estimations include Lipper-style fixed effects and time fixed effects, and standard errors are clustered at the fund level. We consider four performance measures: return, CAPM alpha, Fama-French four-factor alpha, and Fama-French five-factor alpha. We then report the coefficient estimates of past-year performance for each derivative strategy group.

Performance Measure	(1) Return	(2) CAPM Alpha	(3) FF4 Alpha	(4) FF5 Alpha
Nonusers	2.383*** (10.65)	3.553*** (11.42)	8.445*** (15.29)	6.862*** (14.26)
Token	1.915*** (3.67)	2.893*** (3.92)	5.428*** (4.44)	4.138*** (4.02)
Long Index	1.279* (1.76)	1.706* (1.68)	5.133** (2.43)	4.360** (2.38)
Long Stock	13.78 (1.56)	19.23* (2.02)	24.37* (2.01)	17.77** (2.26)
Short Equity	10.46*** (5.03)	16.23*** (5.51)	20.86*** (4.79)	18.55*** (4.65)
Non-equity	2.851* (1.83)	3.531 (1.60)	3.546 (0.98)	3.337 (1.01)

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 7

## Change in Notional Exposure during the COVID-19 Outbreak

The table shows the gross notional exposure of derivative positions before and during the COVID-19 Outbreak. The first row includes non-token derivative users who mostly held long equity index derivatives before the COVID-19 outbreak. The second row includes all other non-token derivative users. We also report the change in gross notional exposure and its statistical significance both within and across derivative strategy groups. All numbers are in percentage points.

Strategy Group	Long Positions			Short Positions		
	2019/Q4	2020/Q1	Dif	2019/Q4	2020/Q1	Dif
Long Index	11.22	10.71	-0.51	0.69	10.97	10.28***
All Others	16.66	18.42	1.76*	13.39	15.72	2.33**
Long Index - All Others			-2.27**			7.95**

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 8

## Fund Return Decomposition during the COVID-19

The table shows the monthly fund return decomposition for the outbreak and recovery periods. For each fund-month observation, fund return is decomposed into two parts: DIR and non-DIR. We also calculate the monthly hypothetical DIR (non-DIR) based on the most recent derivative (equity) holdings. The active DIR (non-DIR) is then the difference between DIR (non-DIR) and hypothetical DIR (non-DIR). All numbers are at monthly frequency and in basis points. The outbreak period is between February 2020 and March 2020. The recovery period is between April 2020 and June 2020. The first row includes all nonusers. The second row includes non-token derivative users who mostly held long equity index derivatives before the COVID-19 outbreak. The third row includes all other non-token derivative users. The statistical significance is only shown for rows "Long Index - All Others".

## Panel A: Outbreak Period

Strategy Group	Fund	DIR	Non-DIR	Hypo DIR	Active DIR	Hypo Non-DIR	Active Non-DIR
Nonusers	-1177.90						
Long Index	-1147.13	-47.60	-1099.53	-65.64	18.04	-644.80	-454.73
All Others	-661.91	37.11	-699.02	-3.08	40.20	-448.96	-250.06
Long Index - All Others	-485.22***	-84.71***	-400.51***	-62.55**	-22.16	-195.84**	-204.67**

## Panel B: Recovery Period

Strategy Group	Fund	DIR	Non-DIR	Hypo DIR	Active DIR	Hypo Non-DIR	Active Non-DIR
Nonusers	688.50						
Long Index	624.28	6.30	617.98	5.90	0.40	641.70	-23.72
All Others	363.99	-54.92	418.90	-49.89	-5.02	519.30	-100.40
Long Index - All Others	260.29***	61.22**	199.08**	55.79**	5.42	122.4*	76.68*

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 9

## Performance and Flows of Derivative Users

The table shows the performance and flows of derivative users using an extended sample between 2011 and 2022. Derivative users are identified using CRSP mutual fund holding, and we further separate derivative users into long index users and other users. In Panel A, we form equal-weighted portfolios based on derivative user types and report the annualized alphas and benchmark adjusted returns. In columns (1) to (3) of Panel B, we regress monthly fund flows on derivative user type dummies and report the coefficient estimates, which capture the excess flows to nonusers. In columns (4) to (6), we run regressions on the share-class level and interact derivative user type dummies with retail share class dummy, and institutional flows to nonusers serve as the baseline. The regressions also control past quarter performance, past quarter performance squared, expense ratio, turnover ratio, the natural logarithm of fund size, past-year return volatility, lagged flows, time fixed effects, and fund style fixed effects. The standard errors are two-way clustered at fund and time levels.

Panel A: Fund Performance					
Strategy Group	Benchmark Adj Return	CAPM Alpha	FF3 Alpha	FF4 Alpha	FF5 Alpha
Nonusers	-0.755 (-0.34)	-1.298* (-1.70)	-0.905** (-2.05)	-0.917** (-2.08)	-0.834* (-1.90)
All Others	-1.896* (-1.70)	-1.157* (-1.83)	-0.822 (-1.59)	-0.864* (-1.67)	-0.436 (-0.88)
Long Index	-1.110* (-1.84)	-1.886** (-2.11)	-1.380*** (-2.72)	-1.410*** (-2.81)	-1.450*** (-2.91)
All Others - Nonusers	-1.141 (-1.38)	0.141 (0.46)	0.083 (0.19)	0.054 (0.13)	0.398 (1.01)
Long Index - Nonusers	-0.355* (-1.79)	-0.588** (-1.99)	-0.474* (-1.75)	-0.492* (-1.72)	-0.617** (-2.20)

Panel B: Fund Flows						
	(1) Flow	(2) Flow	(3) Flow	(4) Flow	(5) Flow	(6) Flow
Long Index	0.201** (2.21)	0.193** (2.09)	0.182* (1.92)	0.198** (2.14)	0.187** (2.22)	0.184** (2.15)
All Others	0.0992 (1.40)	0.128 (1.51)	0.103 (1.43)	0.113* (1.72)	0.124* (1.83)	0.102 (1.56)
Retail				-0.425*** (-6.24)	-0.417*** (-6.18)	-0.421*** (-6.45)
Long Index X Retail				-0.235* (-1.93)	-0.202* (-1.89)	-0.199* (-1.89)
All Others X Retail				-0.093 (-1.25)	-0.089 (-1.16)	-0.082 (-1.17)
Level	Fund	Fund	Fund	Share	Share	Share
Performance	Return	CAPM	FF5	Return	CAPM	FF5
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 10

## High and Low CTE Long Index Users

The table examines the flows and gross notional exposure of high and low CTE long index users. For each long index user, we calculate the change in tracking error (CTE) between the end of 2019 and the start of the recovery in 2020. We then sort long index users into high and low CTE groups. Panel A shows the monthly fund flows between 2010 and 2019. The sample includes all derivative users and nonusers. The dependent variable is the monthly fund net flows in percentage points. We run regressions of monthly flows on the share-class level and interact the fund types dummy with the retail share-class dummy. We only report the coefficient estimates of High (Low) CTE dummy and its interaction with the retail share class in the table. The fund controls include past quarter performance, past quarter performance squared, expense ratio, turnover ratio, the natural logarithm of fund size, past-year return volatility, and lagged flows. Past quarter performance measures include fund returns, CAPM alpha, and FF5 alpha. We also include time fixed effects and fund style fixed effects. The standard errors are two-way clustered at fund and time levels. Panel B shows the notional exposure of derivative positions and the difference between 2019 Q4 and 2020 Q1 for high and low CTE long index users. We only report the statistical significance for the “Dif” columns.

Panel A: Flow Regression			
	(1)	(2)	(3)
	Flow	Flow	Flow
Long Index Low CTE	0.089 (1.11)	0.095 (1.13)	0.092 (0.95)
Long Index High CTE	0.284*** (3.16)	0.288*** (3.04)	0.275*** (3.25)
Long Index Low CTE $\times$ Retail	-0.074 (-0.32)	-0.055 (-0.45)	-0.064 (-0.36)
Long Index High CTE $\times$ Retail	-0.291** (-2.50)	-0.303** (-2.37)	-0.292** (-2.48)
Retail	-0.427*** (-6.21)	-0.412*** (-6.74)	-0.415*** (-6.28)
Performance	Return	CAPM	FF5
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

Panel B: Notional Exposure

Group	Long Positions			Short Positions		
	2019/Q4	2020/Q1	Dif	2019/Q4	2020/Q1	Dif
High CTE	14.35	13.85	-0.50	0.76	18.28	17.52***
Low CTE	8.09	7.57	-0.52	0.62	3.66	3.04
High - Low			0.02			14.48**

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Internet Appendix

## IA.1 CRSP Derivative Positions

Starting from late 2010, CRSP mutual fund holding dataset contains derivative positions. These positions typically have missing cusip and permno, and need to be identified using security names. The following table summarizes the pattern we use to identify derivatives.

Derivative Type	Pattern	Example
Call Options	ending with a digit, an optional space, and a letter "C"	GE Feb8 16.0 C
	ending with word "Call"	Centurylink Inc Call
	containing with word "Warrant"	WARRANTS 2013-15.4.15 ON SHS
Put Options	ending with a digit, an optional space, and a letter "P"	WMB Nov5 50.0 P
	ending with word "Put"	Cerner Corp Put
Futures	ending with three-letter month abbreviation, and a digit	MSCI EMERG MAR7
	ending with two-letter month abbreviation and two digits	EMINI S&P JN20
Swaps	ending with "TRS"	FTSE 100 Index TRS
	containing word "Swap"	S&P 500 Index Swap

Not all positions are listed in CRSP holding. Some funds may report a catch-all category, such as "other assets", "other assets less liabilities", etc. We exclude these positions. Some fixed-income securities also share the same pattern as call options or futures. To exclude these positions, we filter out any positions that have the following keywords in their security names: "bond", "notes", "euro", "tb-day", "loans", "mortgage", "loan trust", "loan program", "loan frn", "home equity", "lease trust", "equipment trust", "credit card mast", "small business admin", "receivables".



## IA.2 Salience in Derivative Use During the Crisis

Section 5.1 shows an increase in derivative use associated with the Covid-19 outbreak. In this section, we explore cross-sectional variation in derivative use during the initial outbreak. We hypothesize that the change in derivative use was likely to be greater for fund managers who faced a more salient risk of recession. We explore three potential channels of variation in risk related to the pandemic. The first, staggered Stay-at-home orders implemented at the state level. The second, pre-crisis concentration in funds' industry holdings and differential exposure of industries to the pandemic crisis. For example, the airline industry was more severely hit by COVID-19 disruptions than the utility industry. The third, pre-crisis concentration in funds' equity holdings of firms with headquarters in outbreak areas.

### IA.2.1 Stay-at-home Order

As the number of COVID-19 cases rose in the US, many states imposed state-level Stay-at-home Order (SAH) to reduce COVID-19 spread. The staggering SAH introduction at the state level allows us to test, in the cross-section, how the pandemic influenced funds' trading strategies on derivative positions. By the end of March, 25 states implemented SAH in place, and 11 states did not. We only focus on states with at least one mutual fund. Figure IA4 shows a map of states with SAH status by March 31, 2020. Focusing on a sample of funds reported in March 2020, we have 377 derivative users in states with SAH before March 31, 2020, and 72 without SAH.

Panel (a) of Figure IA3 shows derivative notional exposure before and during the COVID-19 pandemic. The sample includes funds that report holdings in September 2019, December 2019, and March 2020. The orange (blue) bars show the average notional exposure of funds residing in states with (without) SAH in place before the end of March 2020. The top (bottom) row shows the notional exposure of all (new) positions. The solid black lines represent the corresponding 95% confidence interval. The number in the parenthesis shows the number of funds in each group. The total number of derivative users here is smaller than the one in our full sample because not all funds' reporting dates are exactly at the calendar quarter-end. As we can see from the figure, there was a large jump in the notional exposure of short derivative positions for SAH funds, whereas there was no response for non-SAH funds. The first column of Panel A in Table IA1 further confirms the increased notional exposure in short positions for SAH

funds. Our results suggest that as the risk of economic downturn became more salient in states with SAH in place, managers actively sought to hedge against the market downturn. Moreover, the pandemic had a long-lasting effect on funds' derivative allocation, as SAH funds only unwound half of the increments in short notional exposure by the end of June when the market fully recovered from the crash. Specifically, as shown in Panel B of Table IA1, SAH funds reduced short notional exposure by only 2.68% in the recovery phase, compared with an increase of 6.55% in the outbreak phase.

One may be concerned that the results might stem from funds in states with early SAH being inherently different from funds in states with later implementation or those without SAH. For example, New York, Massachusetts, and California implemented SAH before the end of March, and these states have large financial centers and a large number of registered mutual funds. To rule out this alternative explanation, we conduct analyses on a subsample, where states with and without SAH are geographically adjacent to each other and have a comparable number of funds. Specifically, we include funds in the following states: Colorado, Ohio, Minnesota, Wisconsin, Kansas, Texas, Pennsylvania, Missouri, Iowa, and Nebraska. The first five states had SAH before March 31, 2020, and the remaining five states did not.

Panel (b) of Figure IA3 shows the notional exposure of funds in these ten states. Note that the number of funds in each group is balanced, 63 funds in states with early SAH, and 69 funds in states without SAH. Funds in states with early SAH increased derivative use, which was mainly driven by short positions, whereas funds in the remaining five states had little change in derivative use. This further supports the hypothesis that managers' response to the COVID-19 outbreak was more prevalent when the risk of a potential recession became more salient, and it was not simply driven by some unobserved characteristics among managers in large financial centers.

### **IA.2.2 Fund-level COVID-19 Exposure**

Funds equity holdings' exposure to the pandemic may also impact funds' derivative trading decisions. We explore variations in equity exposure through two channels. The first is funds' concentration of industry holdings. As the nationwide business activities started to shrink, certain industries, such as the airline industry, experienced larger shocks than others. Our identification takes advantage of the ex-ante fund-level industry concentration. We use the Fama-French 30-industry classification and returns.

For each industry, we measure the CAPM-adjusted 10-day cumulative abnormal returns starting from February 20, the beginning of the market crash. For each fund  $i$ , we then use its latest equity holdings before February 2020 to construct the following variable, *Industry Exposure<sub>i</sub>*,

$$Industry\ Exposure_i = - \sum_k w_{k,i} CAR_k,$$

where  $w_{k,i}$  is the portfolio weight of industry  $k$  in fund  $i$  prior to the crash, and  $CAR_k$  is the CAPM-adjusted 10-day cumulative abnormal return of industry  $k$ . We multiply the measure by -1 so that the greater the measure *Industry Exposure<sub>i</sub>* is, the more exposed the fund  $i$ 's ex-ante holdings are to the pandemic.

We then sort funds by *Industry Exposure* into high and low exposure groups and study how derivative use changes for each group. There was a significant increase in short notional exposure by 5.3% among funds in high COVID industry-exposure group, but no changes for low exposure funds, which is shown in Panel A of Table IA1.

Panel B reports changes in notional exposure from the outbreak period to the recovery period. The high exposure group significantly reduced short notional exposure. However, the magnitude was less than half of the increase in notional exposure during the outbreak. Therefore, funds did not fully unwind the overall increment, suggesting that the pandemic had a long-lasting effect on funds' derivative allocation.

Panel C reports changes in notional exposure from the third to the last quarter of 2019 as a falsification test. There was no clear pattern of change in notional exposure among the high exposure group prior to the crisis.

An alternative COVID exposure channel is through the concentration of corporate headquarters in the portfolio, in states which suffered a severe COVID-19 outbreak. The outbreak severity can be measured by the number of confirmed cases per capita at the end of March. Specifically, for each fund  $i$ , we use its latest equity holdings before February 2020 and construct the following variable, *HQ Exposure<sub>i</sub>*,

$$HQ\ Exposure_i = \sum_s w_{s,i} severity_s,$$

where  $w_{s,i}$  is the portfolio weight of firm  $s$  in fund  $i$ , and  $severity_s$  is the number of cases per population

of the state where firm  $s$  is headquartered. The greater the measure  $HQ\ Exposure_i$  is, the more exposed fund  $i$ 's ex-ante holdings could be to the pandemic. However, we find no evidence that fund managers reacted to  $HQ\ Exposure$ . One explanation could be that the headquarter may not necessarily capture locations of business activity.

Figure IA1

### Silhouette Coefficients of K-Means Clustering

The figure shows the silhouette coefficients for the number of clusters ranging from 1 to 10. The peak of silhouette coefficient indicates the optimal number of clusters.

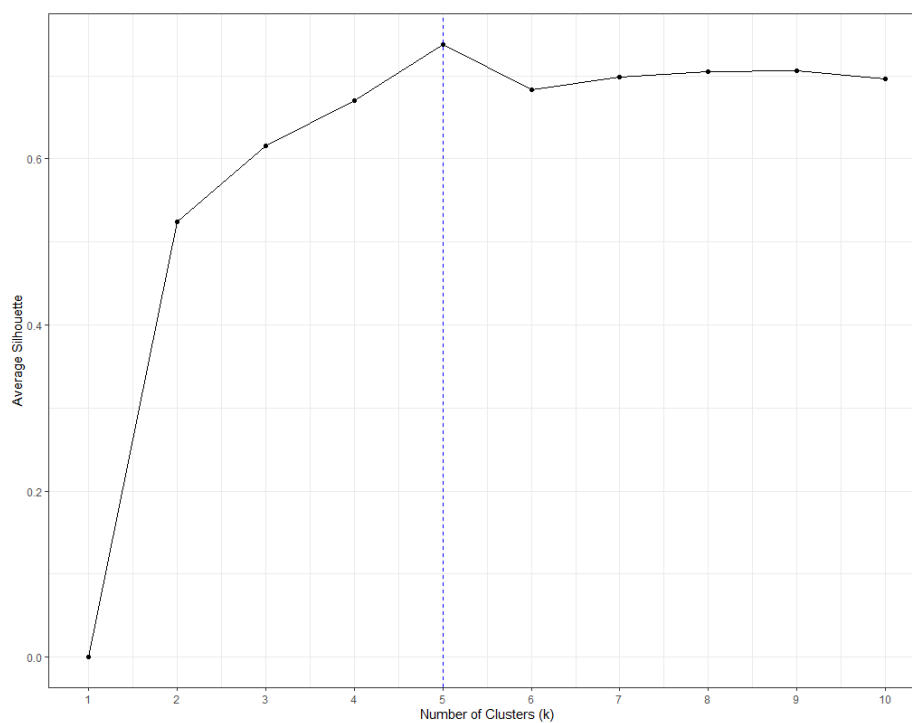


Figure IA2

### Performance of All Other Derivative Users in Fed Rate Hike Period

The figure shows the cumulative returns and alphas for all other derivative users starting from January 1, 2022, to December 31, 2022. The figure shows the performance of nonusers, short equity users, long stock users, and non-equity users. Daily alphas are estimated using a one-year rolling window. The dotted vertical lines indicate the announcement dates of rate hikes.

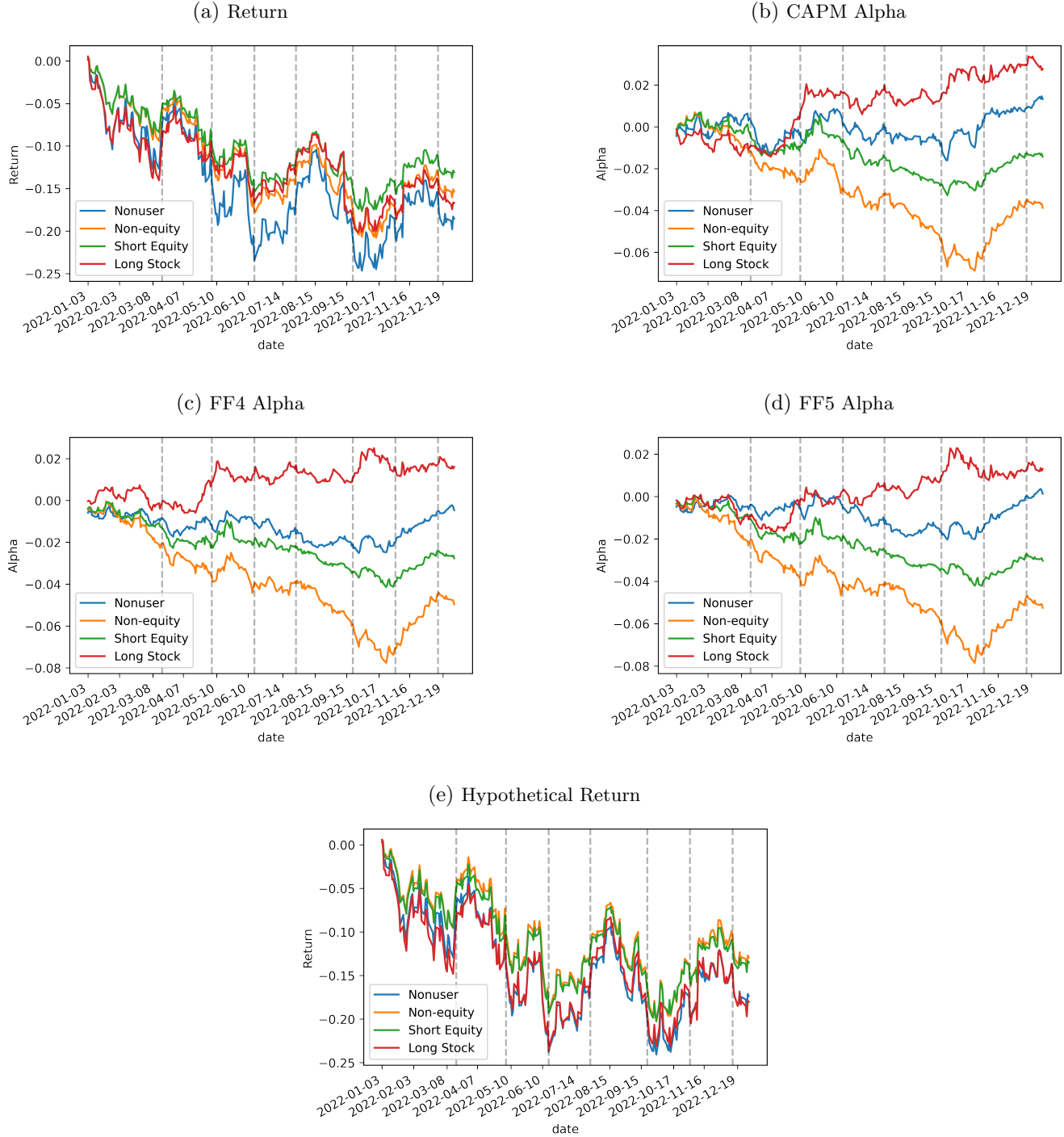
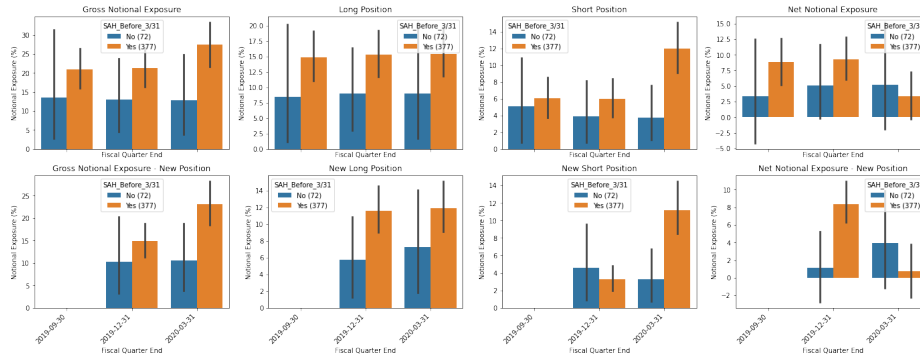


Figure IA3

### Derivative Use and Stay-at-home Orders

The figure shows funds' derivative use before and during the COVID-19 pandemic. The sample includes funds that report holdings in September 2019, December 2019, and March 2020. The orange (blue) bars show the average derivative use of funds residing in states with (without) the Stay-at-home order in place before the end of March 2020. The solid black lines represent the corresponding 95% confidence interval. The number in the parenthesis shows the number of funds in each group. Panel (a) shows the gross notional exposure and net notional exposure for both existing positions and new positions of funds in all states. Panel (b) only includes funds in the following states: CO, OH, MN, WI, KS, TX, PA, MO, IA, NE, where the first five states have SAH before March 31, 2020.

(a) Notional Exposure of Funds in All States



(b) Notional Exposure of Funds in Border States

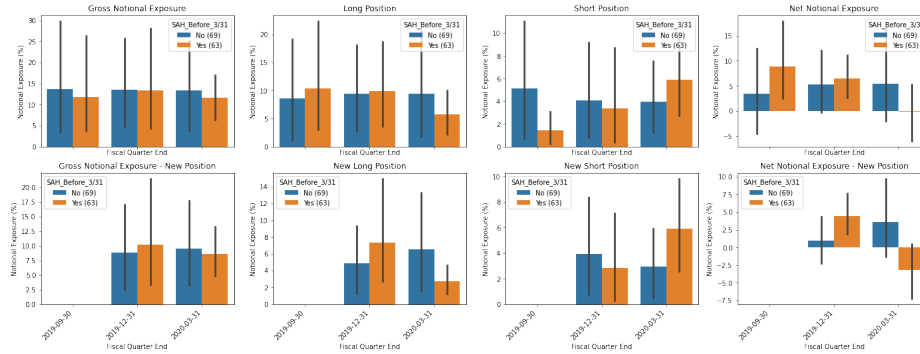


Figure IA4

Map of Stay-at-home Order

The figure plots the status of the Stay-at-home order by March 31, 2020. The pink (green) states have SAH in place before (after) March 31, 2020. The white states do not have active domestic equity funds registered.

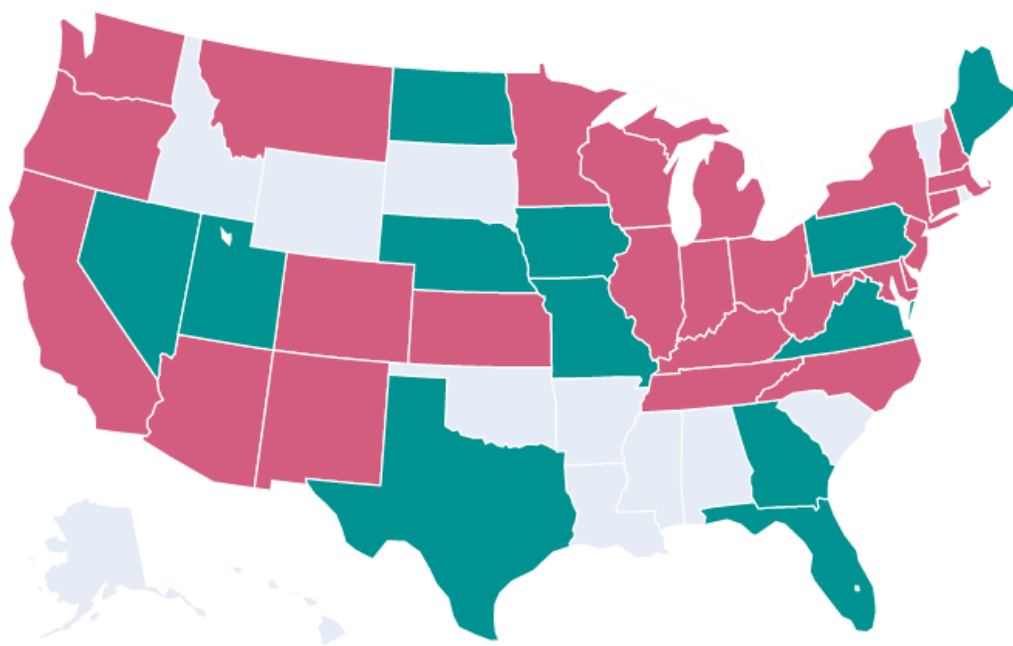




Table IA1

## COVID Exposure and Change in Notional Exposure

The table shows the change in notional exposure of funds in high and low COVID exposure groups. We measure COVID exposure using three proxies. The first proxy is whether funds are registered in states with Stay-at-home orders by the end of March 2020. The second proxy is the industry exposure, which is the sum of products between the industry weight in the fourth quarter of 2019 and the negative of the 10-day cumulative abnormal returns of the industry starting from February 20, 2020. The third proxy is the headquarter exposure, which is the sum of products between the firm weight in the fourth quarter of 2019 and the number of cases per population by the end of March 2020 in the state where the firm's headquarter is located. Funds are sorted by the three proxies into high and low groups. The panels report the change in notional exposure for long and short derivative positions from one quarter to another. For SAH columns, the sample only includes funds reported at the calendar quarter-end.

Panel A: Outbreak phase from Q4/2019 to Q1/2020

Group	SAH		Industry Exposure		HQ Exposure	
	Long	Short	Long	Short	Long	Short
Low	-0.38	0.64	-0.17	1.17	0.07	2.07*
High	1.08	6.55***	0.64	5.32***	0.15	1.94
High - Low	1.46	5.91***	0.81	4.15**	0.08	-0.13

Panel B: Recovery phase from Q1/2020 to Q2/2020

Group	SAH		Industry Exposure		HQ Exposure	
	Long	Short	Long	Short	Long	Short
Low	4.60	-0.71	1.39	-0.54	1.71	-1.01
High	-1.81	-2.68***	0.66	-1.34*	-0.96**	-0.32*
High - Low	-6.41	-1.97***	-0.73	-0.80**	-2.67	0.69**

Panel C: Pre-crisis phase from Q3/2019 to Q4/2019

Group	SAH		Industry Exposure		HQ Exposure	
	Long	Short	Long	Short	Long	Short
Low	2.72	-0.59	1.12	-0.48	0.54	-0.27
High	0.21	-0.10	1.18	-0.44	1.12	-0.39
High - Low	-2.51	0.49	0.06	0.04	0.58	-0.12

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table IA2

## Performance of Derivative Users: Alternative Specifications

The table shows the performance of derivative users using an extended sample between 2011 and 2022. Derivative users are identified using CRSP mutual fund holding, and we further separate derivative users into long index users and other users. In Panel A, we form equal-weighted portfolios based on funds' gross returns and report the annualized alphas and benchmark adjusted returns. In Panel B, we form value-weighted portfolios based on funds' net-of-fee returns and report the annualized alphas and benchmark adjusted returns. In Panel C, we run a Fama-MacBeth regression, where the dependent variables are benchmark-adjusted returns and alphas, and the independent variables are dummy variables of derivative user types, which capture the difference in performance between derivative users and nonusers.

## Panel A: Fund Performance Using Gross Returns

Strategy Group	Benchmark Adj Return	CAPM Alpha	FF3 Alpha	FF4 Alpha	FF5 Alpha
Nonusers	0.213 (0.23)	-0.358 (-0.43)	0.034 (0.07)	0.026 (0.05)	0.116 (0.24)
All Other Users	-0.832 (-1.58)	-0.060 (-0.10)	0.202 (0.42)	0.166 (0.34)	0.534 (1.15)
Long Index Users	-0.252 (-1.24)	-0.983 (-1.54)	-0.488 (-1.49)	-0.510 (-1.25)	-0.545* (-1.67)
All Other Users - Nonusers	-1.045* (-1.68)	0.297 (0.52)	0.168 (0.42)	0.139 (0.35)	0.419 (1.12)
Long Index - Nonusers	-0.465* (-1.73)	-0.625* (-1.89)	-0.522* (-1.71)	-0.536* (-1.77)	-0.661** (-2.17)

## Panel B: Value-weighted Fund Performance

Strategy Group	Benchmark Adj Return	CAPM Alpha	FF3 Alpha	FF4 Alpha	FF5 Alpha
Nonusers	-0.756 (-1.03)	-0.319 (-0.80)	-0.255 (-0.66)	-0.263 (-0.69)	-0.167 (-0.44)
All Other Users	-0.859 (-0.75)	0.034 (0.07)	0.119 (0.26)	0.045 (0.10)	0.335 (0.74)
Long Index Users	-0.714 (-0.76)	-0.937 (-1.51)	-0.835** (-2.03)	-0.787* (-1.93)	-0.807** (-1.97)
All Other Users - Nonusers	-0.103 (-0.13)	0.354 (0.95)	0.374 (1.11)	0.309 (0.94)	0.503 (1.53)
Long Index - Nonusers	0.042 (0.05)	-0.618 (-1.24)	-0.580* (-1.74)	-0.524 (-1.60)	-0.640* (-1.93)

## Panel C: Fama-MacBeth Approach

Strategy Group	Benchmark Adj Return	CAPM Alpha	FF3 Alpha	FF4 Alpha	FF5 Alpha
All Other Users - Nonusers	-1.141 (-1.38)	0.109 (0.24)	0.115 (0.27)	0.092 (0.33)	0.401 (1.31)
Long Index - Nonusers	-0.355* (-1.79)	-0.512** (-2.13)	-0.414* (-1.89)	-0.501* (-1.79)	-0.599** (-2.32)

*t* statistics in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$