Unmasking Mutual Fund Derivative Use

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Abstract

Using new SEC data enabling us to compute performance of mutual funds' derivative positions, we study how funds use derivatives and how derivatives contribute to performance. Despite small portfolio weights, derivatives significantly impact funds' leverage and contribute largely to returns and cross-sectional differences in returns. In contrast to prior research concluding derivatives are used for hedging, we find most active equity derivative using funds buy index derivatives to amplify market exposure. These amplifying funds underperform nonusers, yet receive more flows. To test whether their strategy is designed to outperform in a crisis, we use the COVID-19 pandemic as an exogenous shock to financial markets. During the crisis, amplifying funds failed to outperform nonusers and suffered a double whammy. In the initial outbreak, they still held onto substantial long positions and were slow to undertake short exposure derivative positions, so that they experienced similarly large losses to nonusers. By the time they shifted strategy, the market already started to rebound, and they lost on their short positions.

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1 Introduction

Around 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 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 recently in September 2019, we infer 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.[1] We show that, contrary to the common belief that derivatives are used for hedging, most (63%) of derivative using funds use derivatives to amplify market exposure, and reveal that filtering out funds that use negligible amount of derivatives overturns prior conclusions in the literature that derivative users have similar performance and risk exposure as nonusers.

Prior research has discussed 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)). Despite potential performance enhancement through derivatives, we find that amplifying funds

[1]Throughout the paper, we generally use the term funds to refers to active equity mutual funds.

underperform nonusers, and at the same time receive disproportionate flows.

A natural conjecture rationalizing the observed underperformance and extra flows, based on an argument first proposed by Glode (2011), is that these funds' derivative strategies might be constructed to outperform in crisis periods, where investors especially value good performance. However, evidence we provide from the COVID-19 induced crisis in financial markets generally refutes this hypothesis.

Our central contributions are threefold. First, 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 exposure. To buttress this, in addition to showing effective derivative exposure is typically positively correlated with the rest of the portfolio, we conduct a detailed examination of which derivative instruments are used. This analysis provides evidence consistent with the preponderance of an amplification motive. Second, we challenge prior conclusions in the literature regarding the insignificant impact of derivatives on fund performance and risk exposure, by providing evidence supporting the hypothesis that derivatives contribute substantially to fund returns. Third, 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.

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 absolute derivative weight and gross notional exposure. Among derivative users, over 50% are *token* users, which have derivative weights of less than 0.2% and perform similarly to nonusers. In contrast, 20% of derivative users (*heavy* users) have an absolute derivative weight of more than 3%, with a substantial gross notional exposure of 24%. The prevalence of *token* users helps explain why prior work concluded that derivative users have similar performance and risk exposure as nonusers (see for example, Koski and Pontiff (1999), Cao, Ghysels, and Hatheway (2011)). Furthermore, prior work on derivative use by funds focuses almost exclusively on options and futures, but has overlooked an important derivative class: swaps.[2] 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. 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 is the first to empirically measure funds' derivative performance, and utilizes these measures to test through which channel 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.[3] Surprisingly, we find that most derivative using funds use derivatives to amplify exposure. The data we use is unique in providing fund-level and security-level information on over-the-counter and exchange-traded derivative instruments. This allows us to accurately estimate from realized and unrealized derivative Profit-and-Loss (PnL) the component of fund returns stemming from derivative positions, and to directly calculate correlation between derivative and non-derivative components of fund returns. Prior to the COVID-19 outbreak, 63% of derivative users had a positive correlation, and the median correlation was 0.34. The prevalence of funds that use derivatives to amplify returns is not driven by token users. After excluding token users, 57% of derivative users had a positive correlation, and the median correlation was 0.25.

[2]Koski and Pontiff (1999), Deli and Varma (2002), Almazan et al. (2004) study options and futures; Frino, Lepone, and Wong (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.

[3]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.

To delve into the mechanism behind funds' amplification motives and to facilitate a more refined analysis, we further rank derivative users by the correlation into terciles and define a fund as an amplifying (hedging) fund if its correlation is in the top (bottom) tercile. The majority (74%) of amplifying funds' derivatives are long positions on equity indices, and they seldom hold single stock derivatives, further supporting the characterization of these funds as amplifying funds. Over the past decade, non-token amplifying funds significantly underperform nonusers by an annualized Fama-French five-factor (FF5) alpha of 1.5%, yet receive 4.6% more flows, mainly from institutional investors. Hedging funds, on the contrary, have similar performance and flows to nonusers, but significantly lower market beta. The lower beta is consistent with their hedging style. Furthermore, in stark contrast to amplifying funds' that have derivative positions dominated by long equity index derivatives, they invest significantly in single stock derivatives, and have substantial short derivative positions.

A potential rational for the underperformance of amplifying funds that use derivatives extensively, is that their strategies are tailored to outperform in times of crisis (Glode (2011)). Furthermore, expertise in using derivatives could be especially valuable at times when financial markets are excessively volatile. To evaluate the validity of these hypotheses we focus on the COVID-19 induced crisis in financial markets. Unlike other financial crises that may have stemmed from deteriorating economic conditions, the COVID-19 pandemic represents a fairly clean exogenous unanticipated shock to markets, allowing us to identify changes in derivative trading behavior and the associated contribution of derivative positions and trading to fund performance, both in the time-series and the cross-section. The stock market crash and the following recovery occur in a concentrated period (the S&P 500 tanked over 30% between February 20 and March 23, rebounded, and recovered to its 2019 year-end close on June 8), enabling us to zoom in on funds' trading behavior that is unlikely to be affected by other confounding factors and to estimate changes in fund strategies that would have been difficult to identify in normal times.[4]

[4]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 (2020)

We find that, entering into the pandemic, funds' derivative use doubled compared to pre-crisis, and this increase was concentrated in short positions. The increased usage came from the intensive margin, as the number of funds using derivatives remained almost unchanged, with only 12 new ones. The restriction from fund advisors to use derivatives is unlikely to explain this result, as 82% of funds were permitted to trade derivatives. Rather, trading derivatives, especially over-the-counter, requires high-level of expertise, so that it is not easy for a nonuser to suddenly become a derivative user in the midst of the pandemic. Moreover, consistent with prior studies that find agents tend to react aggressively to salient risks (Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978), Dessaint and Matray (2017)), we show the increased derivative use came from fund managers residing in states which were early adopters of Stay-at-home orders 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.

Leveraging the COVID outbreak as a shock to financial markets, we evaluate the hypothesis that amplifying funds compensate for underperformance in normal times by delivering superior performance at times of crisis. The evidence does not seem to support this hypothesis. They performed as poorly as nonusers. Combining this with the fact that these funds attract more flows raises the question of what benefits do they provide to fund investors. Although they could potentially use derivatives to quickly and cheaply change exposure during volatile times, we find that they suffered similar losses to nonusers in the outbreak phase as well as throughout the recovery. First, they barely reduced notional exposure on long positions, which incurred large losses during the outbreak. Second, although they increased short notional exposure, we find they were slow to do so. By the time they shifted, the market already started to rebound, and they lost on their short positions.

The fact that amplifying funds underperform in normal times and fail to outperform during the crisis raises the natural question: why do institutional investors allocate extra capital

that focus on financial fragility in corporate bond funds.

to these funds? There are two potential explanations. The first explanation is through the risk-taking channel. Specifically, institutional investors, who provide extra flows, are able to, ex-ante, identify funds that will 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 the flow-management channel, where these amplifying funds receive extra flows for some unobserved characteristics that are uncorrelated with performance and need to long equity index futures or swaps as a cash-equitization tool. To test which explanation drives the result, we sort amplifying funds into high and low groups by their changes in tracking error from pre-crisis to crisis period, which capture managers' deviation from benchmarks. Our evidence supports the risk-taking channel, as funds that substantially increase their tracking error during 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-taking 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.

Unlike amplifying funds, hedging funds significantly outperformed by an annualized return of 52% and FF5 alpha of 10% during the outbreak, as well as throughout the crisis. The outperformance did not come from their reported equity holdings. Instead, derivatives contributed to 23% of the return difference between hedging and amplifying funds, and active equity trading contributed to the rest. To further delineate between hedging and amplifying funds, we hand-collect returns of each individual derivative position, impute hypothetical derivative returns, and show that most differences in derivative performance between hedging and amplifying funds were driven by differences in derivative holdings, coming into the crisis, and not by their active derivative trading during the crisis. The tracking error of hedging funds is slightly lower than nonusers in normal times. Interestingly, the access to derivatives leads hedging funds to hold equities that behave similarly to their benchmark in normal times but very differently in bad times. The tracking error of their hypothetical fund returns spiked up to 22% at the peak, but their realized tracking error amounted to only 15%. Having short derivative positions in place to provide insurance, hedging fund managers were potentially less constrained than other managers in trading equities, so that their active equity trading allowed them to significantly reduced the tracking error that would otherwise explode.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 provides an overview of derivative use. Section 4 analyzes the change in funds' trading behavior during the COVID-19 pandemic and studies how derivatives impact fund returns and risks. Finally, section 5 concludes.

2 Data

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. Large funds that together with other investment companies in the same group of related investment companies had net assets of $1 billion or more as of the end of their most recent fiscal year, were required to start reporting from June 1, 2019. Smaller entities were required to start reporting on March 1, 2020. Note that the requirement of early filing is at family level, so 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 quarterly and monthly levels from N-PORT. 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, which are not available in traditional mutual fund data sources, such as the CRSP and Thompson Reuters. We extract derivative instruments, names of underlying assets, portfolio weight, notional amount, expiration date, and unrealized appreciation or depreciation for each derivative position. 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, which have not been documented in prior studies.[5] Due to the small fraction of swaptions and warrants and their similarities to options, 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. For foreign exchange contracts, we further identify the currency sold/purchased.

The monthly level data include realized and unrealized PnL of each derivative instrument; information that has not been recorded in other data sources. 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.

Our sample covers 10,619 unique funds with form N-PORT available starting from September 2019. After merging with CRSP, we have 2909 active domestic equity funds, representing 89% of unique names in CRSP and 94% of total net assets. We use Morningstar Direct to obtain funds' reported benchmark. For each fund, we also download and extract "Principal Investment Strategy" section of its prospectus in 2019. We obtain county-level

[5]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 (74H) but not on other derivatives.

COVID-19 statistics from the New York Times.

We use ***pre-crisis period*** to denote the time before January 20, 2020; ***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 outbreak and recovery periods. For analyses with only monthly frequency available, we denote outbreak period as February 2020 and March 2020, and recovery period as the months between April 2020 and June 2020.[6] 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.[7] 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.[8] We choose June 8, 2020 as the recovery ending date because it is the first time S&P 500 index closes higher than its December 31, 2019 close since the crash.

3 How are Derivatives Used in Mutual Funds?

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

[6] 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.

[7] 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

[8] See news source here: https://www.americanactionforum.org/insight/timeline-the-federal-reserve-responds-to-the-threat-of-coronavirus.

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 return. This section addresses these unanswered questions.

In Section 3.1, we show there is 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 funds' portfolio. Section 3.3 examines in detail the impact on fund performance and also considers flows of derivative users.

3.1 The Extent of Derivative Use

We extract 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 in 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 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 June 2020. A fund is classified as a derivative user if it uses derivatives at least once in the sample. Our sample contains 2909 active funds, 756 (26%) of which use derivatives and manage 31% of total assets. Interestingly, the fraction of derivative users has only mildly increased by 5% from the 21% reported in Koski and Pontiff (1999). Using funds' most recent N-SAR reports, 82% of funds are permitted to trade derivatives. Among derivative users, 432 funds use futures or forwards, 124 swaps, 317 options, and 179 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 highlights the importance of swap contracts. On average, funds have a derivative weight of 2.05%, with futures (0.7%) being the largest derivative type, closely followed by swaps (0.64%). Options represent 0.43% of the portfolio. When measuring derivative use by gross notional exposure, futures provide gross notional exposure of 10.16% , and swaps are close behind with 9.07%. Options merely provide gross notional exposure of 1.09%.

One may be concerned that the quarterly snapshot may not correctly reflect funds' derivative usage, as derivative holding may have short duration. We show that it 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 quarter. Second, our evidence suggests that these derivatives have fairly long time-to-maturity. For example, the median time-to-maturity of futures is 80 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 121 days to over 3 years.

Furthermore, whether to use derivatives is highly persistent across quarters in our sample. Panel C of Table 1 reports a fund's switching probability between users and nonusers, conditional on its derivative use status in the previous quarter. For example, the probability of a futures (swaps) user to stop using it in the subsequent quarter is only 6% (2%). Options usage is only slightly less persistent than futures and swaps, with merely 12% of options users not using options in the next quarter.

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 some other funds using derivatives heavily. Such a pattern is also documented in Cao et al. (2011) but has received little attention in subsequent studies. Panel B of Table 1 shows that the absolute derivative weight has a mean of 2% and a standard derivation of 4.3%. Although 2% seems small in absolute terms, derivatives provide funds ample market exposure because of the embedded leverage. Specifically, gross notional exposure has a mean of 20.9% and a standard deviation of 51%. Figure 1 visualizes the cross-sectional variations in derivative use. On the one hand, over 50% of funds have derivative weights (gross notional exposure) of less than 0.2% (0.3%). On the other hand, 20% of funds have derivative weights (gross notional exposure) of more than 3% (24%).

To gain deeper insight into how funds use derivative positions, we further group derivative users by the extent of usage into three categories: **token; medium; heavy**. For each quarter, funds are ranked by the absolute derivative weight into deciles.[9] We define ***token users*** as funds in the bottom five deciles, ***medium users*** between the sixth and eighth deciles, and ***heavy users*** in the top two deciles. We use an uneven 50/30/20 cut to take into account that a large number of funds only use a negligible amount of derivatives.

Table 2 shows derivative weights and long/short compositions by derivative user types. For options, a purchased (written) call or a written (purchased) put is counted as a long (short) position. If a fund receives (pays) equity returns and pays (receives) a fixed or floating rate to (from) its counterparty in a swap position, it is labeled as a long (short) position. In Panels A and B, we show that while futures are the most extensively used derivative class among token and medium users, swaps are the dominant derivative class among heavy users. Prior studies that rely on N-SAR to classify derivative users will omit swap users, which tend to be heavy derivative users.

Furthermore, the extent of derivative use is highly persistent over time. Panel C of Table 2 shows the transition matrix of user types between September 2019 and June 2020. For instance, the probability of a fund staying as a token (heavy) user in the next quarter is 82% (72%).

[9] Our results are robust and quantitatively similar when we sort funds by 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 studies systematically examine the performance of derivative positions. Using monthly level realized and unrealized PnL from N-PORT between July 2019 and June 2020, we are the first to shed light on funds' derivative performance, compare it with a fund's non-derivative performance, and test the central hypothesis of whether derivatives are used for hedging or amplification.[10]

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. 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.

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

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

Table 1 shows that the average monthly *DIR* (*non-DIR*) is -9 (4) bps, with a standard deviation of 127 (690) bps. The fact that non-derivative positions weigh over 40 times more than derivative positions, yet the standard deviation of *non-DIR* is only five times larger than *DIR*, highlights how volatile fund derivative returns are.

The blue curve in Figure 2 shows the CDF of (signed) derivative relative contribution in our sample between July 2019 and June 2020. Signed derivative relative contribution is

[10]The first report is available in September 2019, which contains monthly performance measures starting in July 2019.

winsorized between -1 and 1 in the figure for ease of presentation, and derivative relative contribution is winsorized between 0 and 1. Derivatives contribute largely to fund returns: over 40% of the fund-month observations have a derivative relative contribution over 0.1, and 20% of observations have a derivative relative contribution of 0.8. Derivatives play a larger role in fund returns among medium and heavy users, which is shown by the blue curve in Figure 2(c).

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 0.22, and only 0.003 among non-swaps users. Within swaps users, funds solely using swaps (31 funds) have a median derivative relative contribution of 0.59, whereas funds that use swaps together with other contracts (93 funds) have a median derivative relative contribution of 0.17. A Mood's Median Test shows differences in median contribution are all highly significant.[11] The substantial differences in contributions further buttress the importance of including swaps users when examining funds' derivative use.

Hedging or Amplifying?

Taking advantage of the time-series *DIR*, we test whether funds use derivatives to hedge or amplify market exposure. For each fund, we first calculate the correlation between *DIR* and *non-DIR* from July 2019 to January 2020. We stop in January 2020 so that the estimation will not be affected by the COVID-19 crisis. Figure 3 shows the histogram and its fitted kernel of the correlation. Contrary to the commonly perceived notion that funds use derivatives for hedging purposes, the analysis reveals that the majority of derivative users use derivatives to amplify exposure. The median correlation of 0.34 is large and positive, and 63% of users have a positive correlation. After excluding token users, the median correlation is 0.25, and 57% of non-token users have a positive correlation.

[11] 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.

To take into account the clusters of funds in both tails of the correlation histogram, we rank funds into terciles. A fund is classified as an **amplifying** (**hedging**) fund if its correlation is in the top (bottom) tercile. The rest are classified as neutral funds. The correlation of amplifying funds ranges between 0.78 and 1, whereas the correlation of hedging funds ranges between -1 and -0.08. In other words, unlike amplifying funds with highly positive correlation, some hedging funds have a relatively weak negative correlation between *DIR* and *non-DIR*.[12] Amplifying and hedging funds have similar sizes as nonusers. Specifically, hedging funds on average have a size of $1.65 billion, amplifying funds $1.69 billion, and nonusers $1.73 billion. In terms of the total market capitalization across funds, amplifying funds have assets-under-management of $0.46 trillion, hedging funds $0.54 trillion, and nonusers $3.8 trillion.

The orange (green) curve in Figure 2(b) shows the CDF of signed derivative relative contribution for amplifying (hedging) funds. The green curve sits higher than the orange one in negative contribution region, as *DIR* and *non-DIR* are negatively correlated for hedging funds. As a result, hedging funds' CDF has more density in the negative region. The p-value of the Kolmogorov-Smirnov test, which examines the difference between two distributions, is less than 1%.

To further evaluate the source of the differences between amplifying and hedging funds, we then examine derivative weight and gross notional exposure for both fund types in Table 3, as well as their composition of underlying assets in Table 4. One key advantage of our dataset is that it contains detailed information of underlying assets for each derivative position, which allows us to study funds' derivative selection. For equity derivatives, we decompose underlying assets into stocks, funds' benchmark related index, and non-benchmark related

[12] We have examined the alternative cutoff of correlations by assigning amplifying funds with a correlation above 0.5 and hedging funds with a correlation below -0.5. The results are robust to such an alternative definition. To address the concern of a potential noisy estimation of correlation with monthly data, we also use our hand-collected daily derivative returns based on quarterly holding and calculate an alternative measure of correlation with daily data. The monthly and daily correlation measures have a correlation of 0.58. For example, only 31 amplifying funds would have been classified as neutral funds using daily correlation measure.

index, based on security names.

Amplifying funds and hedging funds differ not only by the composition of long and short positions, but also the types of underlying assets their derivative positions build on. First, most amplifying funds' derivatives are in long positions. Take heavy users in Table 3 as an example.[13] They have 85% futures and 87% swaps in long positions. Second, they hold very little options, representing only 0.05% of their portfolio. Third, 74% of amplifying funds' derivative exposure comes from equity index derivatives, and they seldom hold single stock derivatives, which is shown in Panel A of Table 4. This, together with the fact that they have mostly long derivative positions, buttresses the hypothesis that they use derivatives to amplify overall performance. Within equity index derivatives, 33% have the underlying asset being exactly the benchmark index, and the remaining being non-benchmark index. Moreover, we also hand-collect returns of non-benchmark indices and examine the return correlation between non-benchmark index and benchmark. We find that most of amplifying funds' non-benchmark index derivatives are highly correlated with their own benchmarks, as the median (average) correlation is 0.97 (0.8). In other words, the non-benchmark index derivatives are close substitute to their benchmark, which allows them to cheaply maintain tracking error. Panel B shows the correlation between *non-DIR* and *DIR* of each derivative type. The average correlation is 0.94 for amplifying funds. The high correlation is consistent with their index derivative holding, as they mainly use index derivatives to amplify market exposure. Most of the high correlation between *DIR* and *non-DIR* is driven by futures and swaps.

Hedging funds, to the contrary, hold a balanced derivative portfolios in long and short positions. For example, 46% (49%) of their futures (swaps) are in long positions. They also differ from amplifying funds by investing relatively more on options, especially in short positions. The gross notional exposure of options is still a modest level of 3.38%, representing merely 7.8% of overall derivative exposure. Unlike amplifying funds, hedging funds invest

[13] Within amplifying funds, 51% are token users, 28% medium users, and 21% heavy users. Within hedging funds, 46% are token users, 30% medium users, and 24% heavy users.

a large proportion in single stock derivatives.[14] The pattern of whether to use single stock derivatives is highly persistent across quarters. Moreover, the average correlation between *DIR* and *non-DIR* is -0.61, consistent with their hedging motives. When hedging funds trade non-benchmark index derivatives, the median (average) return correlation between benchmark and non-benchmark index is 0.84 (0.61), which is considerably smaller than that of amplifying funds.

Around 36% of hedging funds' single stock derivative positions are built without holding underlying stocks. We extract its underlying stock for each of these positions, compute the daily return correlation across all stocks held by the fund in the same date range as we compute derivative correlation, and obtain the maximum correlation. We then calculate the average of the maximum correlation across positions at the fund level. The average correlation is 0.46, and the statistics are similar for both long and short derivative positions. The magnitude of 0.46 is on par with what we get from a similar analysis, in which we compute and aggregate the maximum pairwise correlation of stocks held by the fund. In other words, these single stock derivative positions are likely to be picked from the same investment pools of their equity research rather than to hedge exposure from specific stocks.

3.3 Derivative Use, Fund Performance, and Flows

Derivatives can potentially increase fund performance for the following reasons. First, derivatives allow managers to better utilize information. For example, a manager can use derivatives to trade on a negative signal. Also, she can better exploit firm specific information she obtains by using derivatives to hedge away systematic risk. Second, derivatives can reduce transaction cost if a manager wants to quickly increase or decrease market exposure.

So far, there is little empirical evidence on the performance difference between derivative using funds and nonusers. We reexamine this result by taking into account the extent of

[14] Over 60% of single stock derivatives are in swaps, and the remaining ones in options. 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.

derivative use and regressing equal-weighted fund returns on various asset pricing models between 2010 and 2019.[15] Portfolios are formed based on derivative user types. Data on the extent of derivative use is available only for the period September 2019 onward. To facilitate the analysis, we take advantage of the persistence in the extent of derivative use we noted earlier, and back-fill derivative use for periods prior to the availability of N-PORT, by using funds' derivative extent of use classification in September 2019. Table 5 shows annualized alphas in percentage points and the corresponding factor loading. As shown in Panel A, consistent with Koski and Pontiff (1999), there is no significant difference in performance between derivative users and nonusers after accounting for common risk factors.

Even though derivative users as a whole have similar performance to nonusers, we show that the extent of use can explain substantial cross-sectional differences in performance. In Panel B, we split derivative users by their extent of derivative use into three groups. Nonusers and token users have very similar returns, benchmark adjusted returns, and CAPM and Fama-French five-factor (FF5) alphas; consistent with the fact that token users hold a tiny fraction of derivatives. In contrast, heavy (median) users significantly underperform nonusers by 1.32% (1.08%) per year under FF5 model and by 1.92% (1.2%) per year in benchmark-adjusted returns.[16]

The use of derivatives not only impacts fund performance, but also affects a fund's factor exposure. For example, a fund that uses derivatives for risk management may have lower market beta, whereas a fund that uses derivatives to gain cheap exposure to the market or to utilize information better should have similar market beta to nonusers. Focusing on factor loading, token users have similar factor loading as nonusers, which is consistent with their negligible derivative usage. Medium and heavy users' factor loading significantly differs from nonusers and token users by having a lower market beta and a lower size beta, suggesting that some derivative users indeed use derivatives to manage overall fund exposure. Thus, for

[15] Our results are robust to alternative time windows.

[16] In untabulated analysis, we find that the underperformance of heavy users is not a result of fund fees. We regress raw returns on factor returns and find a similar gap in alphas. The results are available upon request.

non-token users the findings in Koski and Pontiff (1999) that derivative users and nonusers have similar performance and beta no longer hold. Instead, non-token users perform worse and have lower market and size betas.

The use of derivatives can further impact a fund's risk-taking in equity positions, which could also affect fund performance. For example, managers who have information implying Apple is undervalued can better utilize this information by combining over-weighting Apple with shorting the technology industry through derivatives, so that they do not overweight the technology industry. To see whether derivative users differ in equity holding from nonusers, we generate hypothetical equity returns for each fund, assuming reported equity holdings from CRSP and Thompson Reuters are held throughout the quarter.[17] We then form portfolios based on hypothetical equity returns and regress them on factor returns. Panel C of Table 5 reports results. The difference in hypothetical market beta between heavy users and nonusers is -0.07, which explains 27% of the difference in market beta between heavy users and nonusers. The remaining 73% stems from derivative positions and intra-quarter trading. It is possible that derivative positions impact not only a fund's market exposure and its overall performance, but also its equity trading strategy more broadly.

We also examine whether derivatives are used for amplifying or hedging has any impact on fund performance. Similarly, we back-fill our classification of amplifying/hedging funds and examine their performance in the past decade. A key distinction between amplifying and hedging funds is whether they trade single stock derivatives, and the pattern is highly persistent across quarters in our sample, which alleviates the concern of back-filling. To further ensure that our classification of amplifying and hedging funds are persistent over time, we then hand-collect each non-token funds' N-Q back in 2010.[18] The disadvantage of Form N-Q is that it does not provide monthly derivative performance, from which we

[17] We also construct an alternative version of hypothetical equity returns, which takes into account funds' cash positions, as cash positions can have an impact on the leverage. Our results are robust to this alternative version.

[18] Collecting derivative holding data from Form N-Q is very time-consuming, as Form N-Q does not have a standardized format, and all funds in a family report holdings in one filing.

can calculate its correlation with non-derivative positions as we did in N-PORT, but N-Q does allow us to verify whether funds' derivative holding styles back in 2010 fit in our existing classification. We find that, even back in 2010, 73.4% of amplifying funds were using long-only futures and swaps on major equity indices, while 70.9% of hedging funds were trading either single stock derivatives through swaps and options, or short derivative positions on equity indices. Therefore, it is reassuring that funds' derivative using styles are highly persistent over time, which greatly alleviates the concern of the back-filling.

We find that amplifying funds, on average, underperform hedging funds and nonusers. In Panel A of Table 6, amplifying funds underperform nonusers (hedging funds) by CAPM alpha of 0.5% (0.8%) per year. They also significantly underperform by FF5 alpha of 0.5% per year.[19] The difference in performance is not driven by fees, as they all have an average expense ratio of 1% with a standard deviation of 30 basis points.[20] Despite the fact that they use index derivatives to amplify equity returns, they have similar market exposure as nonusers. This is because they hold 7% less equity but more cash than nonusers, so that their equity index derivatives fill the gap in beta.[21] The gap in performance widens when we zoom in onto non-token users. In untabulated results, we show that non-token amplifying funds significantly underperform nonusers by 1.5% per year. A potential explanation for the difference in fund performance is that the equity holding of amplifying funds perform worse than nonusers. We test and rule out this explanation. Panel B of Table 6 shows the factor loading and alpha of hypothetical equity returns, assuming equity positions are held throughout the quarter. All fund types have the same hypothetical market beta, and they perform similarly. Our results suggest that the difference in ex-post performance is due to their different strategies of derivative use and active equity trading.

Hedging funds, on the other hand, have similar risk-adjusted returns to nonusers. An-

[19] Amplifying funds also underperform nonusers in terms of value-added, constructed following Berk and Van Binsbergen (2015), whereas hedging funds and nonusers have similar value-added.

[20] We also perform the analysis using funds' raw returns and find similar underperformance of amplifying funds.

[21] The average equity weights are 93.7%, 87.4%, and 82.9% for nonusers, amplifying funds, and hedging funds, respectively.

other distinction from amplifying funds is that, hedging funds have lower market beta than nonusers, suggesting that they use derivatives to hedge against market risk.

Having documented amplifying funds' underperformance, it is interesting to see whether investors allocate their capital differently. We regress fund flows on a set of 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 Table 7. When splitting funds into nonusers, token users, and non-token users, we find that non-token users receive 2.5% more net flows per year than nonusers, whereas token users receive similar flows to nonusers. Further splitting non-token users into amplifying, neutral, and hedging funds reveals that the additional flows to non-token users are driven by amplifying funds, as they receive 4.6% more flows per year than nonusers. To ascertain whether the additional flows come from retail or institutional share classes, we estimate regressions on the share-class level. We find that amplifying funds receive more flows than nonusers within institutional share classes, but statistically indistinguishable flows to nonusers within retail share classes.[22]

The abnormal flow to amplifying funds is puzzling, given that they significantly underperform nonusers after adjusting for common risk factors. A potential explanation for the abnormal flows received by amplifying funds is that they are more likely to have extremely high returns, which may attract investors with lottery preferences. Following Bali, Cakici, and Whitelaw (2011) and Agarwal, Jiang, and Wen (2019), we construct maximum daily return within a month for each fund and compare this measure between amplifying funds and other funds. We find no evidence supporting the lottery preference explanation. Both amplifying funds and hedging funds have lower maximum daily return measure than nonusers. We also construct maximum daily hypothetical return based on their reported equity holding. The rationale for this measure is that investors may react to lottery stocks reported

[22] We also examine whether different types of funds have differential flow-performance sensitivity (FPS), in untabulated results. Although non-token funds on aggregate have similar FPS to nonusers, amplifying (hedging) funds have higher (lower) FPS than nonusers.

in their holdings. We find that amplifying funds also have lower maximum measure using hypothetical equity returns. We also find that flow volatility is similar across fund types, so that fund liquidity is unlikely to explain amplifying funds' underperformance and high flows.

Another potential explanation for amplifying funds' abnormal flow is that investors react to attention-grabbing keywords that are related to derivatives in prospectus. To test this channel, we hand-collect the "Principal Investment Strategies" section of each fund's prospectus in our sample and conduct a series of textual analysis.[23] We find that 21.2% of derivative users in our sample mention derivative-related keywords, compared to 5.4% of nonusers. The likelihood of mentioning these keywords also increases with the extent of derivative use. Among derivative users, 56% of heavy users mention derivatives, 16% medium users, and 10.6% token users. Amplifying funds and hedging funds have a similar probability of mentioning derivatives. Funds that mention derivative-related keywords receive higher flows, but we do not find any heterogeneous effects between hedging funds and amplifying funds. In other words, derivative-related keywords alone do not explain amplifying funds' abnormal flows. We also analyze the sentence with derivative-related keywords and examine whether the sentence also contains risk-related keywords or speculation-related keywords.[24] Conditional on mentioning derivatives, 20% of hedging funds mention risk-related keywords, compared to only 3.9% of amplifying funds. The probability of mentioning speculative-related keywords is a low 2% for both fund types. It could be that the relatively frequent mentioning of risk-related keywords by hedging funds deters flows, so that they receive less flow than amplifying funds. However, given the low frequency of mentions, it is difficult to achieve any reliable inference in a regression setting.

Having documented that the abnormal flow to amplifying funds is unlikely to be driven by investors' lottery preference, fund liquidity, or attention to derivative-related keywords, we conjecture that amplifying funds underperform in normal times because their strategy

[23]The list of keywords that we search for include derivative, futures, options, and swaps.

[24]The risk-related keywords include risk, exposure, volatility, and volatile. The speculation-related keywords include speculation, speculate, speculative, boost, and enhance.

may be constructed to deliver outperformance in crisis periods. After all, the last decade has been the longest expansion in US history, and it is the first time ever that the US economy started and ended an entire decade without entering a recession. The COVID-19 pandemic offers an exogenous shock to financial markets and allows us to test this conjecture in the following section.

4 Derivative Use During the COVID-19 Pandemic

Unlike the financial crisis, the COVID-19 pandemic started as a healthcare crisis, providing researchers an essentially exogenous and unanticipated shock to financial markets. The pandemic offers good identification of the impact and drivers of funds' performance and strategies. The unexpected market crash and unprecedented recovery allow us to test whether amplifying funds' derivative strategy is designed to outperform in bad times. It could be that their derivative positions on equity index enable them to quickly adjust market exposure without excess trading in a volatile market, which attracts flows from institutional investors in normal times.

The volatile nature of the market also allows us to identify any potential cross-sectional variation in derivative trading more easily than in normal times. 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.[25] 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 work from home, which may further

[25]The S&P 500 index dropped by 34% between 02/20/2020 and 03/23/2020, and the VIX index soared from 15.56 on 02/20/2020 to 82.69 on 03/16/2020, and then fell to 53.54 on 03/31/2020.

reduce their trading activity.

On the other hand, derivative positions allow funds to take short positions, which is especially important because funds' equity holdings are predominantly long positions. Such flexibility provides hedging against market downturn. Moreover, since agents tend to react to salient risks (Lichtenstein et al. (1978), and Dessaint and Matray (2017)), and since the pandemic 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 test whether changes in derivative allocation were greater when risks were more salient to fund managers. Third, we study how derivative positions contributed to fund returns during a crisis. Lastly, we analyze how derivative strategies impacted funds' risk-taking behavior.

4.1 Time-series Change in Derivative Use

First, we test whether funds increased derivative use during the crisis. Panel A of Table 8 shows changes in portfolio allocation from the last quarter of 2019 to the first quarter of 2020. Derivatives were used more extensively during the pandemic. From column (1) of Table 8, absolute derivative weight increased by 1.22%, from 1.39% in pre-crisis to 2.61% during the outbreak, a relative increase of 87.83%. Moreover, the increased derivative use was driven by funds increasing their bets on short positions. On a relative scale, derivative use in short positions increased by 108%, almost doubled the 76% increase of long positions. When we measure derivative use by gross notional exposure, short notional exposure increased by 4.65%; an increase of 130% relative to the amount in 2019. Meanwhile, long notional exposure did not materially change. The difference between absolute derivative weight measure and gross notional exposure measure is analogous to the difference between market value and book value.

The increased derivative use stemmed from the intensive margin, as the number of derivative users only changed slightly, from 742 in the last quarter of 2019 to 754 in the first quarter of 2020. Trading derivatives requires high-level expertise, so that funds were unlikely to start trading derivatives for the first time in the midst of the pandemic. Moreover, the increased derivative use was not driven by a small number of funds heavily building up their derivative positions. Instead, it reflected a shift in employing more derivatives by the industry as a whole. As shown in Panel A of Figure 1, the CDF of the absolute derivative weight shifted to the right during the outbreak. The absolute derivative weight in the pre-crisis period is first-order stochastic dominated by the outbreak period with a p-value less than 0.1% in the one-sided Kolmogorov–Smirnov test, suggesting a shift toward extensively using derivatives by funds.

4.2 Cross-section Variation in Derivative Use during Crisis

The previous section shows the time-series increase in derivative use. 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 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.

4.2.1 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 of 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.[26] 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.

Figure 4 shows derivative weights 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 weights of funds residing in states with (without) SAH 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. 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 shown in Panel (a) of Figure 4, derivative use, proxied by absolute derivative weight, more than doubled from 1.3% in December 2019 to 3% in March 2020 for SAH funds, whereas there was no significant reaction for non-SAH funds. Focusing separately on long and short positions of SAH funds revealed a larger jump for short positions on a relative scale than for long positions. The results suggest that on aggregate funds actively tilted toward short derivative positions when entering into the pandemic, and the pattern was predominantly due to funds in states with early SAH in place, as the risk of a potential recession was likely to be more salient to managers in those states. Moreover, the change in derivative use between September 2019 and December 2019 was insignificant, which rules out an alternative explanation of a common trend of increased derivative use for SAH funds.

Panel (b) of Figure 4 further decomposes the long and short derivative positions on whether the weight is positive or negative. Consider the two graphs on the right-hand side of Panel (b) as an example. The distance between the top bar and the bottom bar widens substantially in March 2020. Even though funds traded more derivatives in short positions when entering the pandemic, they entered at different times so that funds that entered early

[26] We only study states with at least one mutual fund. Figure A5 shows a map of states with SAH status by March 31, 2020.

had positive weights, while others had negative weights. Note that the market rebounded sharply after March 23. The value of short derivative positions depended largely on when funds opened positions.

Panel (c) of Figure 4 shows how derivative notional exposure changes quarter-by-quarter. The top (bottom) row shows the notional exposure of all (new) positions. We show that there was a large jump in the notional exposure of short derivative positions for SAH funds, whereas no response for non-SAH funds. The first column of Panel A in Table 9 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 9, 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 have SAH before March 31, 2020, and the remaining five states do not.

Figure A1 shows derivative weight and 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.[27]

4.2.2 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 channel is funds' concentration of industry holdings. As the nation-wide 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 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 market crash. For each fund i, we then use its latest equity holdings before February 2020 to construct the following variable, $\textit{Industry Exposure}_i$,

$$\textit{Industry Exposure}_i = -\sum_k w_{k,i} CAR_k,$$

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 $\textit{Industry Exposure}_i$ 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. Table 9 reports changes in notional exposure for both long and short derivative positions. Panel A reports changes from pre-crisis quarter to

[27] Due to the small number of non-SAH funds, we do not further investigate the differences in derivative use between amplifying funds and hedging funds for SAH and non-SAH states, separately. Instead, we dedicate the relevant discussion in Section 4.3.

outbreak period. 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.

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, so that 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 quarter of 2019 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 large 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, $\textit{HQ Exposure}_i$,

$$\textit{HQ Exposure}_i = \sum_s w_{s,i} \textit{severity}_s,$$

where $w_{s,i}$ is the portfolio weight of firm s in fund i, and $\textit{severity}_s$ is the number of cases per population of the state where firm s is headquartered. The greater the measure $\textit{HQ Exposure}_i$ 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 headquarter may not necessarily capture locations of business activity.

4.3 Derivative Performance During the Crisis

4.3.1 Distribution of *DIR*

Having identified increased derivative use during the COVID-19 outbreak, a natural followup is to investigate how funds' derivative positions perform and how they contribute to funds' returns. Specifically, we compare the return distribution between derivative and non-derivative parts, across pre-crisis, crash, and recovery periods, for amplifying and hedging funds, separately.

Panels (a) and (b) of Figure 5 show distributions of *DIR* and *non-DIR* before and during the outbreak. The distribution of *non-DIR* follows a bell curve centered slightly positive before the outbreak, and it shifts, not surprisingly, with massive density to the left during the outbreak.

Interestingly, distributions of *DIR* are centered around zero both pre-crisis and during the outbreak. What is different in the outbreak period is that the distribution has fatter tails than the pre-crisis period. The kurtosis of *DIR* in outbreak period is 11.03, and 3.34 in the pre-crisis period. This is consistent with the increased short derivative positions and the divided opinions on when to open these positions shown in Figure 4. Funds that built short derivative positions before or during the initial market crash gained, whereas funds that were slower to react lost substantially when the market rebounded. The distributions are significantly different from each other, as the p-values of Kolmogorov-Smirnov tests are less than 1%.

Although we do not directly observe the exact date when funds trade derivatives, we show that our pre-crisis classification of amplifying and hedging funds can explain cross-sectional variation in *DIR* during the outbreak. Panels (c) and (d) of Figure 5 compare return distributions for amplifying and hedging funds. Note that *DIR* of hedging funds are more likely to have large positive returns than amplifying funds, whereas the distributions of *non-DIR* are similar across the two groups. We then further decompose *DIR* by derivative instruments and find that most of the cross-sectional variation in *DIR* comes from swaps, followed by futures, highlighting the importance of swaps to active equity funds.[28] Options and foreign exchange related contracts provide limited variation in *DIR*.

How did amplifying funds lose from derivative positions during the outbreak? First, as shown in Table 10, although amplifying funds significantly increased short notional exposure from pre-crisis level of 1.3% to 6.9% during the outbreak, they still had substantial market exposure due to outstanding long positions, which incurred large losses. Second, amplifying funds also lost from newly opened short positions. We find that the unrealized PnL of outstanding short positions was -15 bps in March 2020. Given that these short positions were on major equity index, a negative PnL suggests that they were late to trade and lost on short derivative positions when the market unexpectedly rebounded.

4.3.2 Decomposition of Fund Returns

Having documented the distribution of *DIR* during the crisis, we now study how derivative strategies impact fund returns. In Section 3.2 we have shown that amplifying funds underperform in normal times but receive abnormally high flows relative to nonusers. To help evaluate the hypothesis that their strategies might be designed to outperform in bad times, we decompose monthly fund returns into four parts, hypothetical *DIR*, returns of active derivative trading, hypothetical equity holding returns, and returns of active equity trading. The sum of the first two components is *DIR*, and the sum of the latter two components is *non-DIR*.

Since N-PORT only reports derivative PnL at a monthly frequency, it is difficult to track derivative performance at a more granular level. To overcome this pitfall, we hand-collect daily 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.

[28] The histograms of *DIR* by derivative instruments are shown in Appendix Figure A2.

Specifically, hypothetical *DIR* are the sum of products between derivative return and its notional exposure.

Table 11 shows return decomposition for outbreak and recovery periods. During the outbreak, amplifying funds underperformed hedging funds by 4.23% per month. Out of the 4.23%, 0.96% came from *DIR*, and 3.27% from *non-DIR*. In other words, derivative contributed to 23% of the performance gap. Moreover, amplifying funds failed to outperform nonusers during the crash, as the return gap was insignificantly different from zero, which rejects the hypothesis that their strategies are designed to outperform in bad times.

On the derivative part, 74% of the difference in *DIR* between amplifying and hedging funds was contributed to their derivative holding differences, whereas there was no significant return difference in active derivative trading. On the equity part, we find that 94% of the difference between amplifying funds and hedging funds came from their difference in active equity trading, which is in contrast with the derivative part. It could be that the derivative positions in place of hedging funds provided insurance against market crash and facilitated better execution of equities, as these funds can be more patient and engage less in fire sale than amplifying funds or nonusers.

Panel B shows the decomposition for the recovery period. Hedging funds took losses from derivative positions (-0.64%) and active equity trading (-2.09%), consistent with their hedging strategy. Amplifying funds gained from *DIR* by only 5 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. In addition to their sub-par derivative performance, they also lost due to active equity trading by 0.75% per month.

4.3.3 Fund Performance

One caveat of the previous analysis in Section 4.3.2 is that we only have monthly-level *DIR*, which does not facilitate an estimation of risk-adjusted returns that would require a longer sample. To complement the analysis, in this section, we use funds' daily returns, estimate factor loading with a one-year rolling window, and examine their risk-adjusted performance.

Figure 6 shows the cumulative performance of funds starting from the beginning of the crisis.[29] During the outbreak period, amplifying funds performed very similarly to nonusers, losing almost 35% in returns. They underperformed nonusers by the CAPM and FF5 models in the first half of outbreak period and outperformed in the second half of the outbreak, which could be driven by their increased short derivative positions. Throughout the outbreak and recovery period, amplifying funds did not outperform nonusers in returns, CAPM alpha, or FF5 alpha. Therefore, we still find no empirical evidence to support the conjecture that the underperformance in normal times is offset by outperform in crisis periods, so as to rationalize the abnormally high flows they receive.

Hedging funds, on the other hand, outperformed nonusers during the outbreak by a large margin. Throughout the crisis, they had similar performance to nonusers when measured in return or CAPM alpha, but outperformed when measured in FF5 alpha. Moreover, there was no difference in hypothetical equity returns among all funds, suggesting that the gap in performance at least partially came from derivative positions.[30]

To test the statistical significance of the performance gap, we estimate a series of regressions and show derivative user performance relative to nonusers in Table 12. All coefficient estimates are in annualized percentage points. The dependent variables in columns (1) to (4) are fund returns, benchmark adjusted returns, CAPM alphas, and FF5 alphas. The dependent variables in columns (5) to (8) are hypothetical equity returns and alphas. We also control for time fixed effects, fund size, expense ratio, and turnover ratio.

Amplifying funds underperformed nonusers by an annualized return (CAPM alpha) of 1.1% (0.7%) in pre-crisis periods. The recent data also suggests that amplifying funds underperform in normal times, consistent with our previous finding using a longer historical

[29]The graph only shows the cumulative performance for hedging funds and amplifying funds. The full performance comparison among all derivative user groups is available upon request.

[30]In the appendix, we zoom in on heavy derivative users and examine their performance (Table A2 and Figure A3).

window. Similar to Figure 6, the evidence of their performance in the outbreak is mixed. They significantly underperformed in benchmark-adjusted return, did not differ in either return or CAPM alpha, and outperformed in FF5 alpha. During the recovery, amplifying funds underperformed nonusers both in returns and risk-adjusted alphas. One potential driving force of amplifying funds' underperformance is that they opened short derivative positions fairly late in March so that derivative positions dragged down their overall performance. Throughout the crisis cycle, unambiguously, amplifying funds did not outperform nonusers by any risk-adjusted performance measures, and they significantly underperformed nonusers by an annualized 3% in returns.

Hedging funds significantly outperformed nonusers by a large magnitude in all our performance measures during the outbreak, as expected. Such outperformance was from their derivative positions and active trading, since the hypothetical equity returns of the two groups were indistinguishable. Like most insurance products, although hedging users outperformed during the outbreak, they underperformed nonusers during the recovery. Throughout the cycle of outbreak and recovery periods, the evidence of hedging funds' outperformance is mixed. They outperformed nonusers by an annualized 3% in FF5 alpha, but underperformed by 2% in benchmark-adjusted returns.

As an investor, it may not be clear which funds use derivatives to hedge or amplify market exposure. Therefore, it is interesting to see how derivative users in general performed throughout the crisis. In appendix Table A1, we show that funds that use a non-negligible amount of derivatives significantly underperformed nonusers both in benchmark-adjusted return and CAPM alpha throughout the crisis. Our results cast some doubts on the overall benefits to fund investors of funds using derivatives.

One potential explanation for the unsatisfactory performance of derivative users is that, they could face a non-linear pricing model, as their derivative payoffs could be non-linear. First, swaps and futures, which are the majority of derivatives used by funds, have linear payoff structure. Although options have non-linear payoff, they only constitute a small portion. Second, the first argument withstanding we incorporate non-linear market-downturn factors into the CAPM model. The factor model includes a down-market dummy that is equal to one if the market return is negative, the excess return of the market and its squared term, and their interaction terms with the down-market dummy. The quadratic term takes into account extreme market returns. We then use 5-year daily returns before 2020 to estimate factor loading and calculate out-of-sample daily alphas in 2020. Specifically, for each fund, we estimate the following regression:

$$r_t - rf_t = \beta_0 + \beta_1 \mathbb{1}_{mktrf_t<0} + \beta_2 mktrf_t + \beta_3 mktrf_t^2 + \beta_4 mktrf_t \mathbb{1}_{mktrf_t<0} + \beta_5 mktrf_t^2 \mathbb{1}_{mktrf_t<0} + \epsilon_t,$$

where *mktrf* is the market excess return, r is the fund return, and rf is the risk-free rate.

Panel (e) of Figure 6 shows the cumulative alpha since the beginning of the crisis. After controlling for market downturn risk, hedging funds significantly outperformed other types of funds by a large margin, which is expected. Interestingly, the gap in alphas did not diminish during recovery period, which is in contrast to linear factor models. Specifically, the performance gap was as large as 4% on March 23, and it remained around 4% afterward. Moreover, the gap was not driven by different equity holdings, as the hypothetical alphas were very similar across all funds during crisis. Our result has important implications for investors with strong hedging motives, who value performance the most when the market crashes.

4.3.4 Why do Amplifying Funds Receive Abnormal Flows?

Results in previous sections have shown that amplifying funds underperform in normal times and fail to outperform in crisis, yet they receive abnormally high institutional flows compared to other funds, after controlling for fund performance and characteristics. There are two potential competing explanations. The first is through a risk-taking channel, where institutional investors bet on these amplifying funds to actively deviate from benchmark during the crisis, which is a necessary but not sufficient condition for superior performance. Due to 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 the flow-management channel.[31] Specifically, amplifying funds receive extra flows for some unobserved reasons unrelated to performance and need to use long equity index derivatives as a cash-equitization tool.

To test which of these two explanations hold in the data, we conduct the following analysis. We sort amplifying funds by the change in tracking error between the end of 2019 and the start of recovery period in 2020 into high and low groups. Tracking error is calculated as the annualized 30-day rolling standard deviation of return difference between a fund and its benchmark. The change in tracking error is an ideal measure to capture a fund's deviation from its benchmark. If institutional investors indeed pay extra flows in normal times to funds that will shift their strategy during a crisis, then we should expect that amplifying funds in high change-in-tracking-error (CTE) group received abnormally high flows, whereas amplifying funds in low CTE group did not. If the result is driven by the flow-management explanation, funds in both groups should receive abnormally high flows.

We first show that amplifying funds in high change in tracking error (CTE) group received abnormally higher institutional flows than nonusers in the past decade, and amplifying funds in low CTE group did not. The result is shown in Panel A of Table 13. The regression model is exactly the same as the one in columns (7) to (9) of Table 7, except that we replace the dummy variable of amplifying funds by two dummy variables, high and low CTE amplifying funds. Keep in mind that institutional flows of nonusers serve as the baseline in the regression. The coefficient estimate of high CTE dummy is positive and significant, suggesting that high CTE amplifying funds received more institutional flows than nonusers. The coefficient estimate of low CTE dummy is insignificantly different from zero. The sum of

[31] We thank Veronika Pool for her suggestion on the reverse causality story.

coefficient estimates of high CTE dummy and its interaction with retail share-class dummy is close to zero and insignificant, suggesting that retail investors do not offer extra flows to either high or low CTE amplifying funds.

Next, we show that high CTE amplifying funds are the ones significantly increased short notional exposure during the crash. As shown in Panel B of Table 13, their short notional exposure increased by 7.68% from the last quarter of 2019 to the first quarter of 2020, whereas there was no significant change in short notional exposure for low CTE amplifying funds. The difference in change between high and low CTE funds is also significant. The result suggests that high CTE funds indeed reacted by entering into short positions during the crisis, but they were slow to do so and suffered losses when the market unexpectedly rebounded.

Lastly, we find that high CTE amplifying funds are twice as likely (37%) to mention derivative-related keywords as low CTE funds (18%).[32] In summary, we partly rationalize the extra flows by institutions to amplifying funds 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 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 likely led to the quick market rebound.

4.3.5 The Impact of Derivatives on Fund Risk

Instead of providing superior performance, derivatives may assist funds in better 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

[32] High and low CTE amplifying funds have similar characteristics, such as expense ratio, turnover ratio, and fund size. They also have very similar performance in the past decade. Results are available upon request.

formally test whether derivatives and active trading help reduce tracking error, we estimate a series of monthly panel regression, where the dependent variables are tracking error, hypothetical tracking error, and the difference between realized and hypothetical tracking errors. Tracking error is calculated as the annualized 30-day rolling standard deviation of return difference between a fund and its benchmark. The difference 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 error.

The regression results are shown in Table 14. First, we show that both amplifying funds and hedging funds have lower tracking error than nonusers in normal times, but the mechanism is different. For amplifying funds, the low tracking error mainly stems from their equity holding, which deviates less from benchmarks than nonusers, as the coefficient estimate of "Amplify" dummy is negative and significant in columns (1) and (2) but insignificant in column (3). Specifically, amplifying funds have 74 bps (17% on a relative scale) lower tracking error than nonusers in normal times. These funds achieve their desired overall exposure by buying index derivatives to cheaply increase market exposure, which facilitates holding an equity portfolio that deviates less from the benchmark. However, the lower tracking error is not sufficient to explain why amplifying funds' underperform but receive abnormally high flows, as the sensitivity between fund flows and tracking error is small and positive.[33] During the market crash, the differences between realized and hypothetical tracking error did not further widen, which is shown by the insignificant interaction term "Amplify X crash" in column (3), suggesting that being an amplifying fund does not further reduce its tracking error beyond the effect of equity holding.

Hedging derivative users, on the contrary, hold equities that deviated from their benchmark as much as nonusers in pre-crisis period, which can be seen from the insignificant coefficient estimate of "Hedge" dummy in column (2) of Table 14. During the crash, their

[33]In untabulated result, we find that the sensitivity between flows and tracking error is 0.03 for institutional share class, and 0.019 for retail share class. That is, one percentage point increase in tracking error corresponds to merely three basis points increase in flows, after controlling for past performance and fund characteristics.

hypothetical tracking error spiked by more than 4.5% than nonusers, whereas their realized tracking error only increased by 1.1%. Our result suggests that their equity holding behaves similarly to benchmark in normal times but very differently during the crisis.

Although most interaction terms between fund type dummies and crash/recovery dummy are negative and significant in column (3) of Table 14, suggesting that derivatives may further reduce tracking error during the crisis, this result could be driven by spiked benchmark volatility during the crisis. To tease out the effect of spiked benchmark volatility, we scale the difference in tracking error by benchmark volatility in column (4). The interactions with crash/recovery dummies are no longer significant in column (4), suggesting that in fact there was no additional reduction in tracking error during crisis period. In column (4), only the coefficient estimate of hedging funds is significant. This result is consistent with the mechanism that derivatives and active trading allow hedging funds to maintain a certain level of tracking error, even though their equity holding may deviate more from the benchmark than nonusers.

Figure 7 focuses on the daily rolling tracking error, which allows us to examine the difference among funds at a higher frequency than the regression table. In addition to the construction of hypothetical equity tracking error, we also construct a version of full hypothetical tracking error based on hypothetical returns from both derivative and equity holdings. Consistent with the regression result, the mechanism of reduced tracking error is different between amplifying and hedging funds. The widening gap in tracking error between amplifying funds and nonusers was mainly driven by their equity holding, which can be seen from the similar wedge in Panels (a) and (b).[34] To the contrary, the hypothetical tracking error of hedging funds peaked at 22%, and realized tracking error was reduced to 15%. Such a reduction was not directly driven by derivative holding, as the full hypothetical tracking error is statistically indifferent from hypothetical equity tracking error, or by active derivative trading, as the hypothetical derivative returns and realized derivative returns were

[34]The peak of tracking error after March 23 is due to the 30-day rolling estimation.

closely matched for hedging funds during the crisis. But rather, the reduction in tracking error of hedging funds was driven by their active equity trading, potentially because the downside protection provided by their short derivative positions allowed managers to be less constrained in equity trading than other managers.

Overall, our results suggest that derivative users, especially amplifying funds, do not provide a sufficiently large reduction in tracking error in normal times compared to nonusers. Moreover, there is no additional reduction in tracking error during bad times, which begs the question of what value these funds provide to investors.

5 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.

Early research identified the usage but not the extent of use of options and futures, and ignored swaps. To a large extent, that research failed to find differences in performance and risk between derivative users and nonusers. Our analysis shows that this non-result stems from the fact that over 50% of derivative users are token users with negligible derivative use and perform similarly to nonusers. Non-token users underperform and have lower market beta than nonusers.

Furthermore, our data allows us to estimate funds' derivative performance, so that we can test how derivative positions correlate and contribute to funds' overall return. In contrast to the commonly perceived view in the literature, we show that the majority of derivative users use derivatives to amplify market exposure, rather than for hedging. These funds significantly underperform nonusers in normal times, but receive abnormally high flows stemming mostly from institutional investors.

Utilizing the COVID-19 pandemic as an exogenous shock to financial market, we find amplifying funds did not outperform during the crisis, refuting the hypothesis that their underperformance but extra flows in normal times is compensated for by outperformance in crisis periods. They lost from existing long derivative positions and were late to initiate short positions during the crisis outbreak, and were slow to unwind short positions in the recovery. As a result, they performed similarly to nonusers throughout the crisis. We do find that institutional investors can, ex-ante, identify and allocate flows to funds that will shift their strategy and deviate from their benchmarks, a necessary but not sufficient condition for outperformance during the crisis. These funds indeed shifted their strategies in the crisis and increased tracking error, evidence that potentially helps rationalize the combination of underperformance and extra flows in regular times. However, their performance still suffered on the specific price path that materialized, in which the FED intervened unexpectedly and subsequently the market rebounded sharply.

Hedging funds, on the contrary, gained substantially from their derivative positions and outperformed others during the outbreak. Moreover, their equity holding behave similarly to the benchmark in normal times but differently during the crisis. Having short derivative positions in place as a protection against market crash, hedging funds can significantly reduce tracking error, that would otherwise explode, through active equity trading during the crisis.

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, amplifying funds, the majority of derivative users, underperform during the non-crisis period and fail to outperform in crisis period. Nevertheless, they receive more flows than nonusers. As a result, fund managers benefit at the expense of investors.

There are a few natural extensions one could consider. First, consider fixed income funds. In a different paper, we are analyzing the relation between reaching for yield and derivative use. Second, it is interesting to consider their market timing ability in derivative trading.

Third, consider how derivative strategies vary throughout the calendar year and how they are related to interim past performance. These are left for future research. Specifically, since N-PORT reports became a requirement only recently, it will probably be a couple of years until one can carefully consider the second and third extensions.

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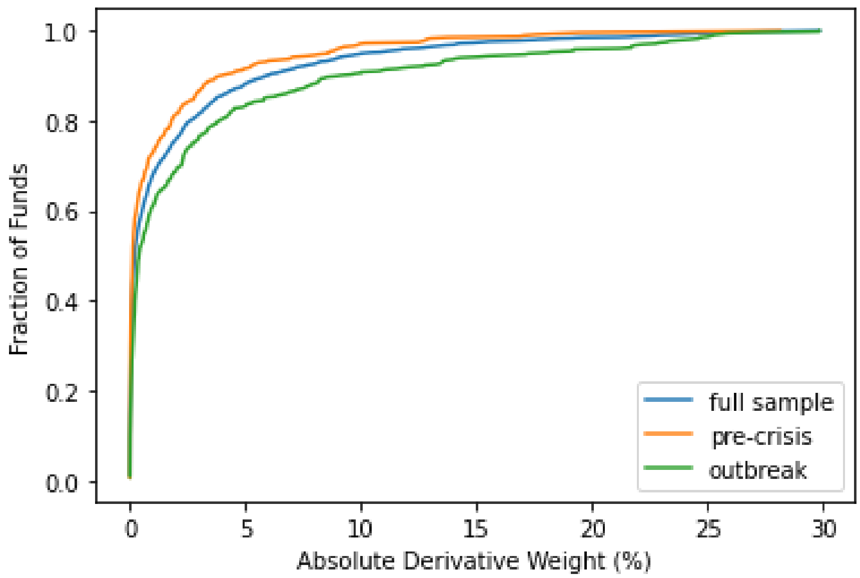
Figure 1

Cumulative Distribution Function of Derivative Use

The figure shows cumulative distribution functions of the fund-level derivative use. The derivative use is proxied by absolute derivative weight in Panel (a), and by gross notional exposure in Panel (b). The numbers in x-axis are in percentage. The blue curve represents the full sample between July 2019 and June 2020. The orange curve represents the pre-crisis sample between July 2019 and January 2020. The green curve represents the COVID-19 outbreak sample between February 2020 and March 2020.

(a) CDF of Absolute Derivative Weight



(b) CDF of Gross Notional Exposure

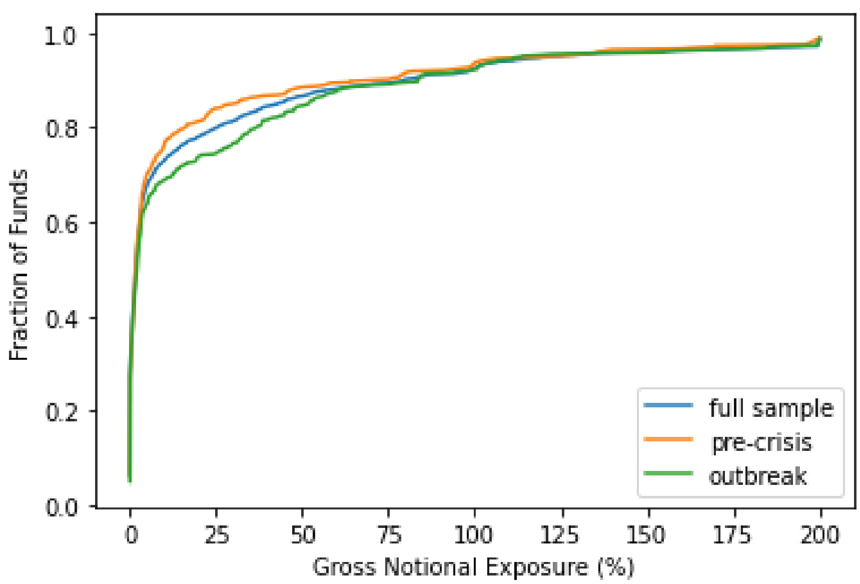
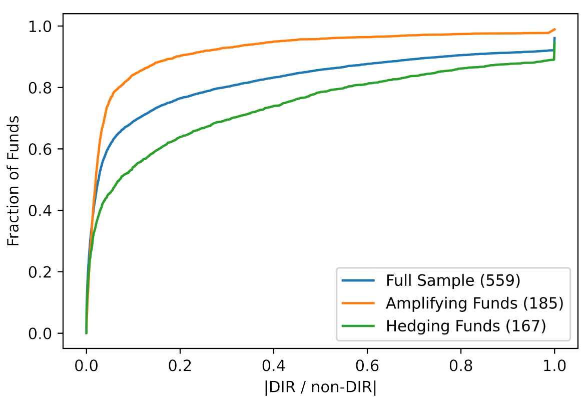


Figure 2

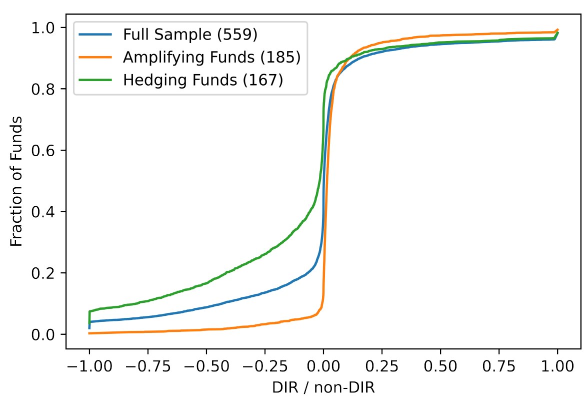
Derivative Contribution to Fund Return

The figure shows the cumulative distribution function of the fund-level (signed) derivative relative contribution. 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 $t-1$. Signed derivative relative contribution is the ratio between *DIR* and *non-DIR*. Derivative relative contribution is the absolute value of signed derivative relative contribution. For each fund, we calculate the correlation between *DIR* and *non-DIR* from July 2019 to January 2020. Funds are sorted by the correlation into terciles. A fund is classified as an amplifying (hedging) fund if its correlation is in the top (bottom) tercile. Funds are also sorted by the absolute derivative weight into deciles. Panels (c) and (d) show the CDF for funds in the top five deciles. The blue curve shows the CDF in the full sample. The orange curve shows the CDF for amplifying funds. The green curve shows the CDF for hedging funds. The numbers in parentheses show the average number of funds per month.

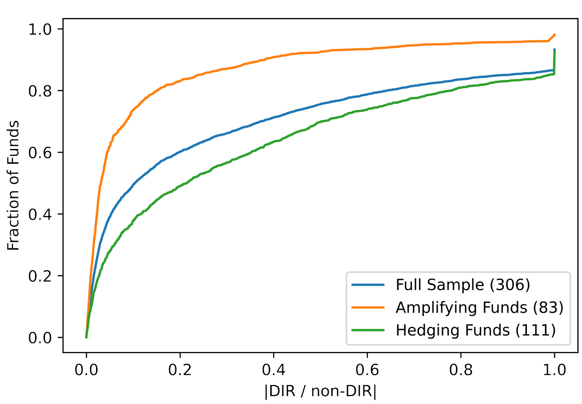
(a) Derivative Relative Contribution for All Funds



(b) Signed Derivative Relative Contribution for All Funds



(c) Derivative Relative Contribution for non-Token Users



(d) Signed Derivative Relative Contribution for non-Token Users

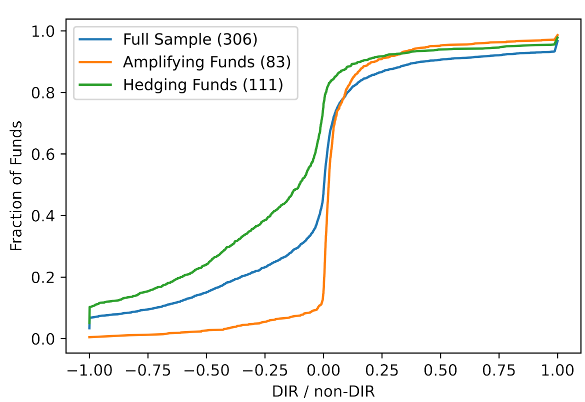


Figure 3

Distribution of the Correlation between *DIR* and *Non-DIR*

The figure shows the histogram and fitted kernel 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 fund return and *DIR*. The sample contains all derivative users between July 2019 and January 2020.

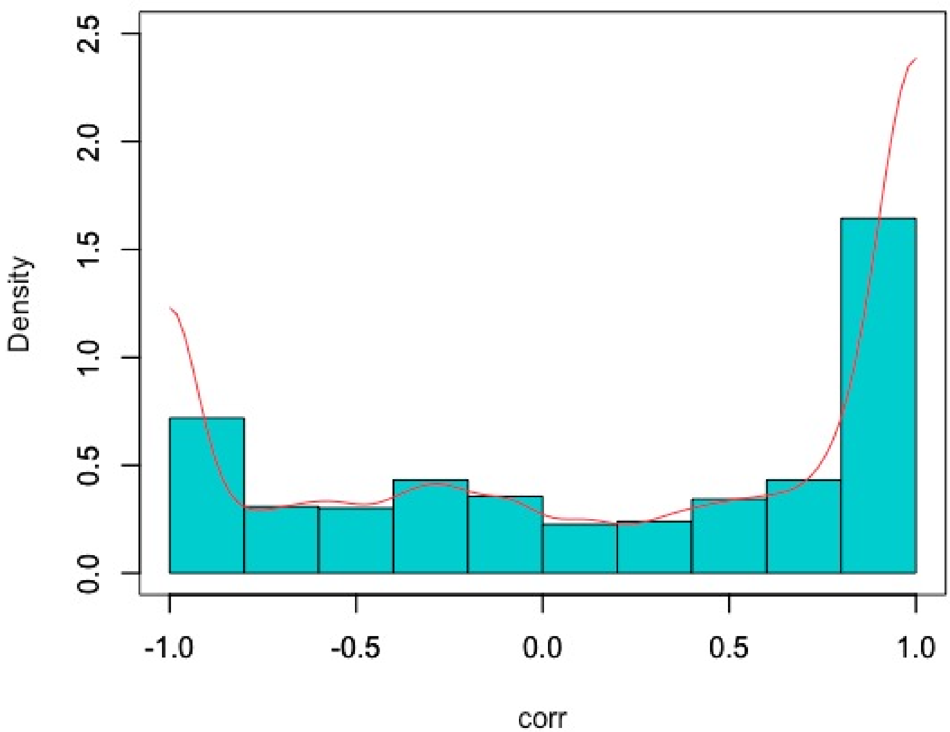
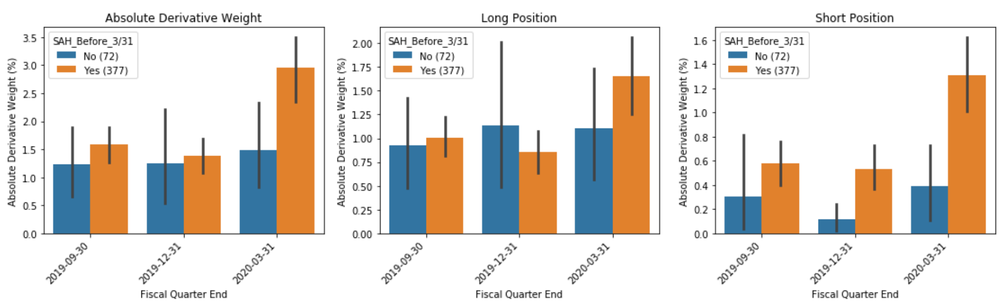


Figure 4

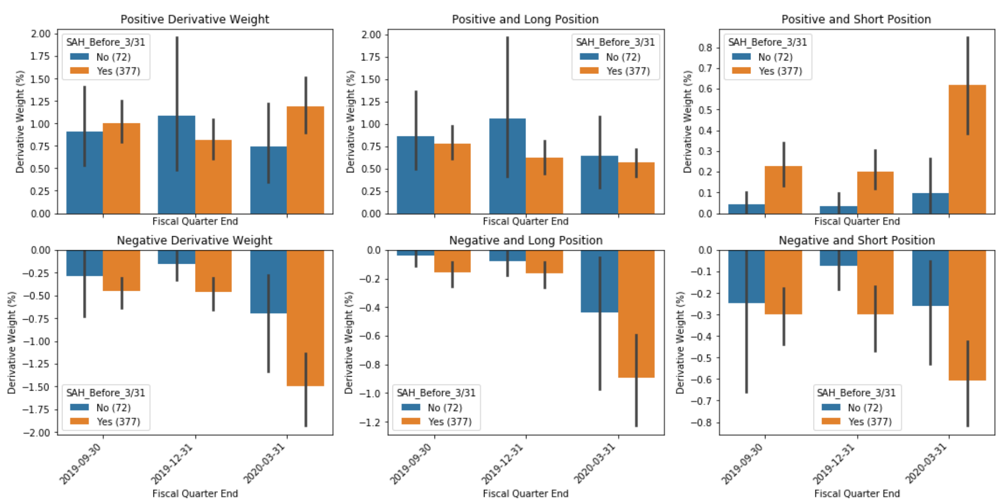
Derivative Use and Stay-at-home Orders

The figure shows derivative use of active funds 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 absolute derivative weight for two groups. Panel (b) further decomposes the derivative weight by whether it is long or short positions, and by whether the weight is positive or negative. Panel (c) shows the gross notional exposure and net notional exposure for both existing positions and new positions.

(a) Absolute Derivative Weight and SAH



(b) Derivative Weight Decomposition



(c) Notional Exposure

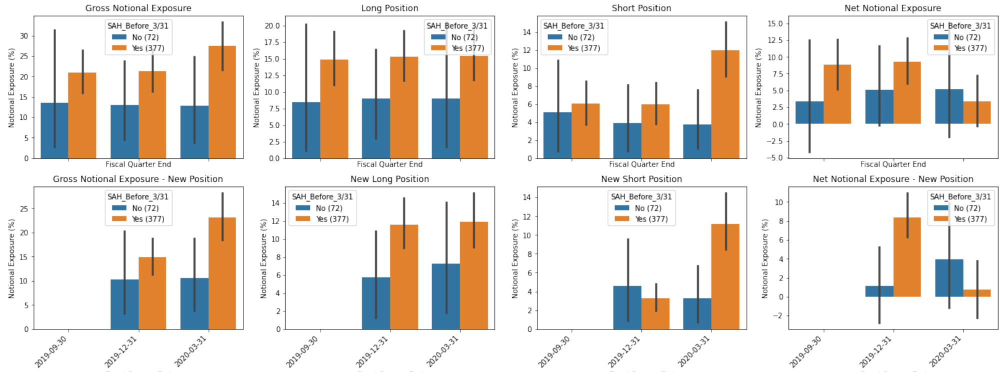
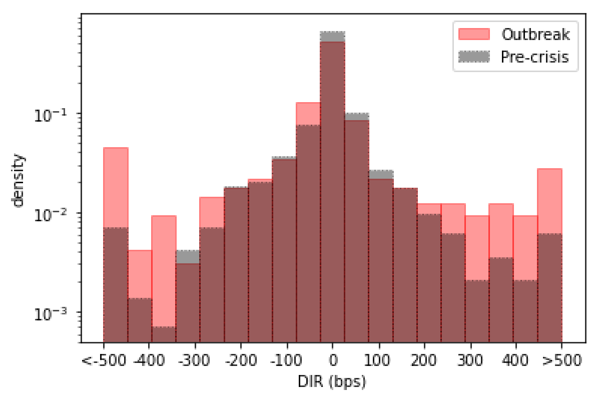


Figure 5

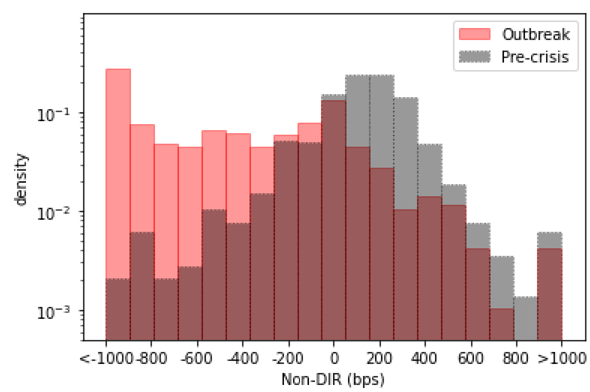
Distribution of *DIR* in Crisis

The figure shows the distribution of *DIR* and *non-DIR*. Panel (a) and (b) compare the distributions in pre-crisis and outbreak periods. Panel (c) and Panel (d) compare the distributions of amplifying and hedging funds during the outbreak. For panels (a) and (c), *DIR* are plotted between -5% and 5%, with a bandwidth of 50 bps. Densities of returns that are greater (smaller) than 5% (-5%) are stacked at the boundary for the ease of presentation. For panels (b) and (d), *non-DIR* are plotted between -10% and 10%, with a bandwidth of 100 bps. Densities of returns that are greater (smaller) than 10% (-10%) are stacked at the boundary. Outbreak period is defined as February 2020 and March 2020. Pre-crisis period is between July 2019 and January 2020. The y-axis is in log-scale.

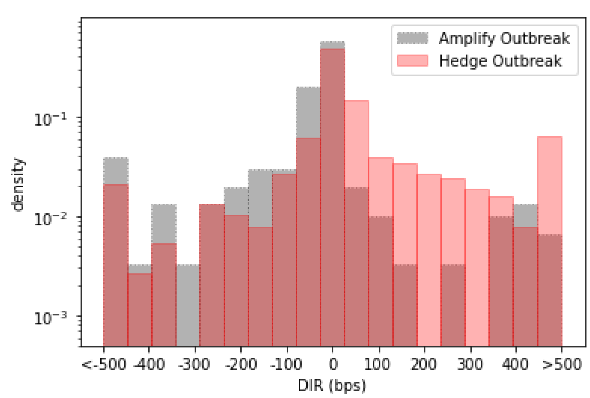
(a) *DIR*



(b) *Non-DIR*



(c) *DIR* in Outbreak
Amplifying vs Hedging Funds



(d) *Non-DIR* in Outbreak
Amplifying vs Hedging Funds

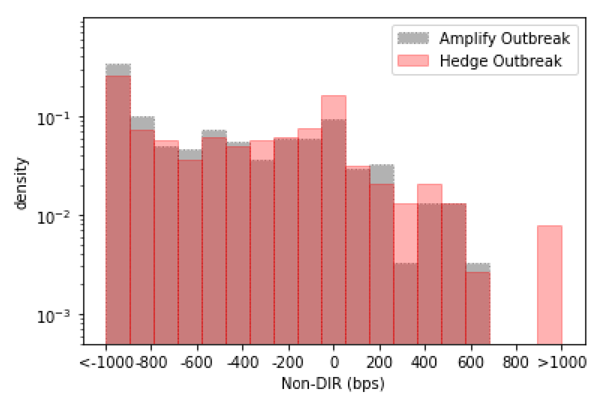
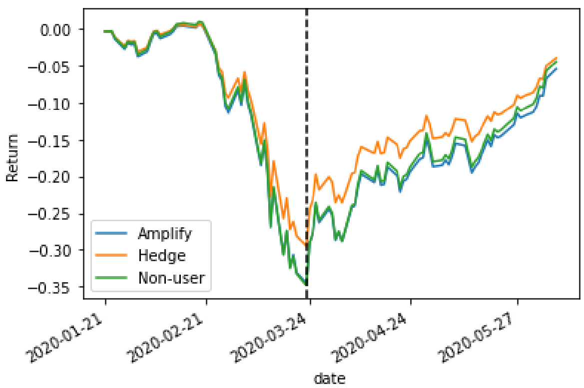


Figure 6

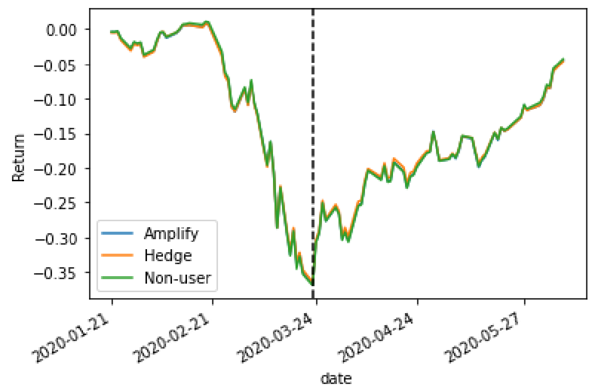
Fund Performance in COVID-19 Pandemic

The figure shows the cumulative returns and alphas for active funds starting from the outbreak on January 20, 2020. Nonusers are the funds without derivative positions. Derivative users are partitioned by the correlation between *DIR* and *non-DIR* prior to February 2020 into three terciles. Amplifying (hedging) funds are in the top (bottom) tercile. The figure shows the performance of nonusers, amplifying users, and hedging 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).

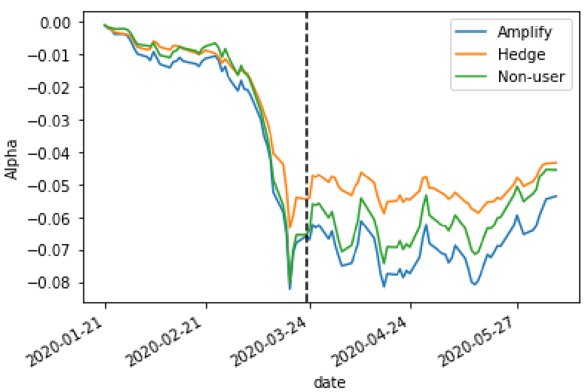
(a) Return



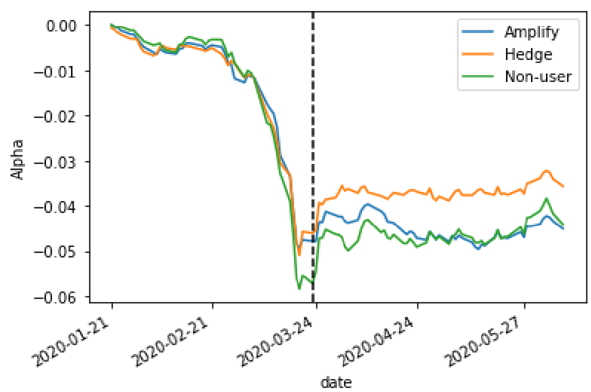
(b) Hypothetical Return



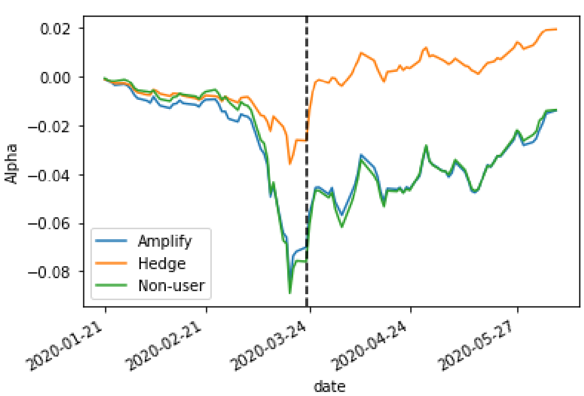
(c) CAPM Alpha



(d) FF5 Alpha



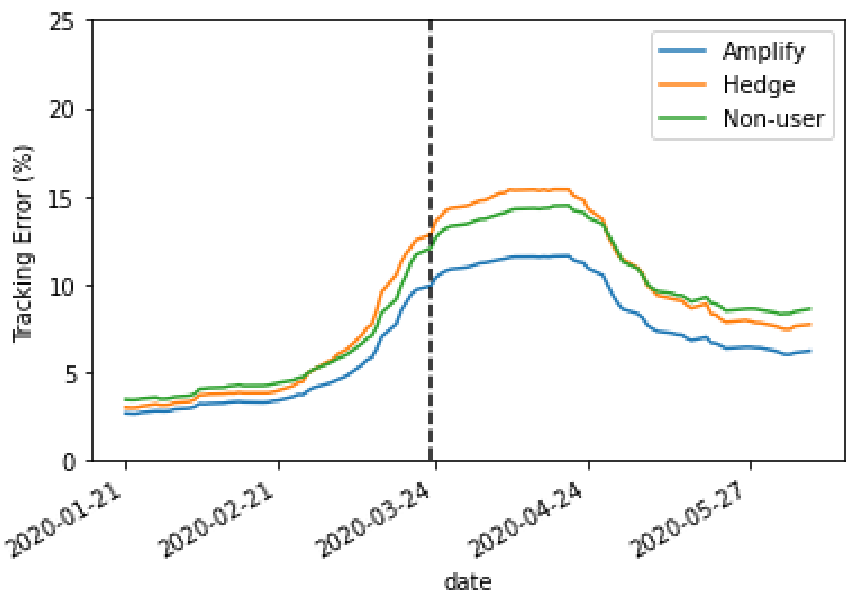
(e) Down-market Alpha



(f) Hypothetical Down-market Alpha

Figure 7
Fund Risk in COVID-19 Pandemic
The figure shows the tracking error of active funds starting from the outbreak on January 20, 2020. Derivative users are partitioned by the correlation between *DIR* and *non-DIR* prior to February 2020 into three terciles. Amplifying funds are in the top tercile, and hedging funds are in the bottom tercile. 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 two sets of hypothetical tracking error. Hypothetical equity tracking error is based on returns of equity holding reported at the beginning of a quarter. Full hypothetical tracking error is based on returns of both equity and derivative holding reported at the beginning of a quarter. For both hypothetical tracking errors, we assume holding is unchanged throughout a quarter. The dotted vertical line indicates the start of the recovery period (March 24, 2020).

(a) Tracking Error



(b) Hypothetical Tracking Error

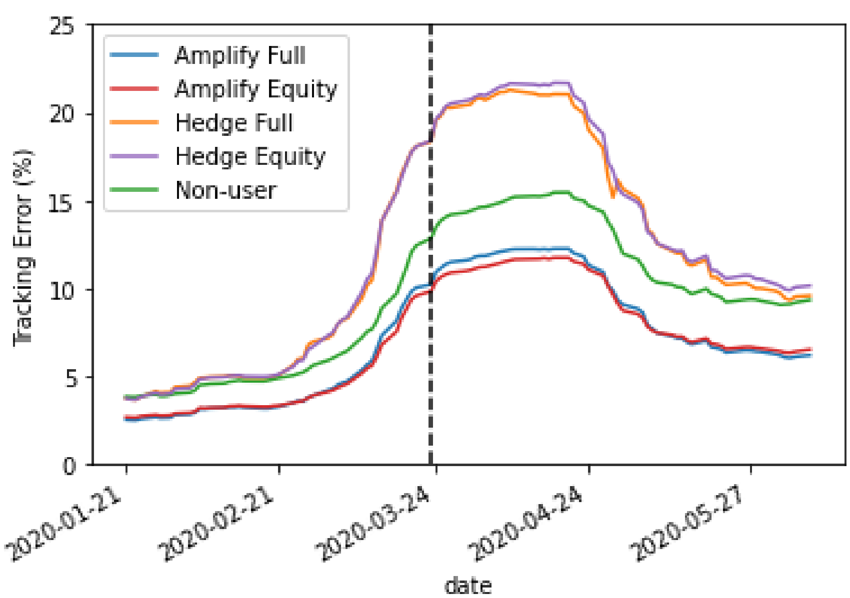


Table 1
Overview of Derivative Use

The table shows the summary of derivative use in equity domestic active funds. The sample includes all equity domestic active funds that use derivatives from September 2019 to June 2020. 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 notional amount of derivative positions, normalized by the fund size and shown in percentage points. TNA is the total net assets in million dollar. 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 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 signed derivative relative contribution. All variables are winsorized at 1% level. Panel C shows the transition matrix of derivative use by category quarter by quarter.

Panel A: Breakdown of Derivative Usage

	No. of Funds	Absolute Weight	Gross Notional Exposure
All Derivatives	756	2.05	20.91
Future/Forward	432	0.70	10.16
Swap	124	0.64	9.07
Option	317	0.43	1.09
Foreign Exchange	179	0.28	0.60

Panel B: Summary Statistics of Key Variables

Variable	Mean	StdDev	Min	10%	20%	30%	40%	50%	60%	70%	80%	90%	Max
Absolute Derivative Weight (%)	2.05	4.32	0	0.01	0.02	0.05	0.1	0.21	0.55	1.29	2.78	5.98	29.86
Gross Notional Exposure (%)	20.91	50.99	0	0	0	0.17	0.79	1.6	2.89	6.23	23.31	70.45	448.52
Derivative Relative Contribution	2.39	25.4	0	0	0	0.01	0.02	0.05	0.13	0.33	0.78	2.27	1261
Signed Derivative Relative Contribution	-0.37	25.51	-1261	-0.64	-0.11	-0.01	0	0	0.01	0.03	0.14	0.98	1193
Derivative Induced Return (bps)	-8.99	127.13	-923.76	-63.53	-15.16	-4.55	-0.67	0.08	1.57	4.58	18.31	36.58	865.98
Non-derivative Induced Return (bps)	4.11	690.31	-2228.11	-917.88	-428.40	-122.08	15.44	109.59	194.08	276.74	377.56	692.83	1641.42
TNA ($ mil.)	1761.51	8108.99	1.16	37.41	92.23	177.23	290.11	486.64	732.68	1130.83	1827.38	4655.26	198652.18

Panel C: Transition Matrix of Derivative Use

	Future		Swap		Option		Foreign Exchange	
Use^t_{t-1}	N	Y	N	Y	N	Y	N	Y
N	0.94	0.06	0.98	0.02	0.91	0.09	0.99	0.01
Y	0.05	0.95	0.03	0.97	0.12	0.88	0.06	0.94

Table 2
Derivative Weight and Notional Exposure by the Extent of Use

The table shows fund-level derivative weight (Panel A) and gross notional exposure (Panel B), grouped by the extent of derivative use. The sample includes equity domestic active funds that use derivatives from September 2019 to June 2020. For each quarter, funds are sorted by the absolute derivative weight into deciles. Token users are the funds in the bottom five deciles, medium users between the sixth and eighth deciles, and Heavy users in the top two deciles. Panel C shows the transition matrix of the user type quarter by quarter.. The table further shows the composition of long and short positions within each derivative type. For option positions, a purchased call or a written put is counted as a long position, and a written call or a purchased put is counted as a short position. If a fund receives equity returns and pays a fixed or floating rate to its counterparty in a swap position, it is counted as a long position.

Panel A: Absolute Derivative Weight (%)

	All Users	Token Users	Non-token Users	
			Medium	Heavy
All Derivative	2.05	0.06	1.11	8.36
Future	0.70	0.03	0.64	2.44
% in Long	68.2	88.8	69.5	67.0
Swap	0.64	0.00	0.12	3.02
% in Long	73.0	44.6	65.5	73.5
Option	0.43	0.01	0.23	1.75
% in Long	26.5	69.5	29.9	25.0
Foreign Exchange	0.28	0.02	0.12	1.15
% in Long USD	60.0	89.4	67.5	57.9

Panel B: Gross Notional Exposure (%)

	All Users	Token Users	Non-token Users	
			Medium	Heavy
All Derivative	20.91	2.03	19.59	69.64
Future	10.16	1.44	12.62	28.11
% in Long	62.0	76.0	54.9	64.8
Swap	9.07	0.30	5.06	36.73
% in Long	69.3	88.0	65.6	69.7
Option	1.09	0.08	1.57	2.86
% in Long	48.2	52.4	39.9	54.6
Foreign Exchange	0.60	0.20	0.34	1.94
% in Long USD	89.7	89.3	82.1	91.8

Panel C: Transition Matrix of User Types

$UserType_{t-1}^{t}$	Token	Non-token	
		Medium	Heavy
Token	0.82	0.17	0.01
Medium	0.21	0.61	0.18
Heavy	0.12	0.16	0.72

Table 3
Derivative Weight by Amplifying/Hedging Funds

The table shows fund-level derivative usage, grouped by whether the fund uses derivatives for amplifying or hedging. The sample includes equity domestic active funds that use derivatives. For each fund, we calculate the correlation between *DIR* and *non-DIR* from July 2019 to January 2020. Funds are sorted by the correlation into terciles. A fund is classified as an amplifying (hedging) fund if its correlation is in the top (bottom) tercile. For each quarter, funds are sorted by the absolute derivative weight into deciles. Token users are the funds in the bottom five deciles. Medium users are the funds between the sixth and eighth deciles. Heavy users are the funds in the top two deciles. The table further shows the percentage of long and short positions for each derivative type. For option positions, a purchased call or a written put is counted as a long position, and a written call or a purchased put is counted as a short position. If a fund receives equity returns and pays a fixed or floating rate to its counterparty in a swap position, it is counted as a long position.

Panel A: Absolute Derivative Weight (%)

	Amplifying Funds				Hedging Funds			
			Non-token				Non-token	
	All	Token	Medium	Heavy	All	Token	Medium	Heavy
All Derivative	1.31	0.06	1.14	6.69	2.75	0.08	1.03	8.04
Future	0.79	0.06	0.99	3.22	0.56	0.01	0.25	1.58
% in Long	84.9	92.0	84.3	84.9	45.7	71.3	55.9	43.7
Swap	0.33	0.00	0.05	2.31	0.67	0.01	0.15	2.10
% in Long	87.1	100	87.9	87.1	49.4	31.5	40.7	50.1
Option	0.04	0.01	0.09	0.05	1.03	0.02	0.41	3.00
% in Long	46.4	77.9	41.3	51.3	17.8	66.7	14.6	18.0
Foreign Exchange	0.16	0.00	0.02	1.11	0.49	0.05	0.22	1.36
% in Long USD	47.1	84.8	61.6	46.6	67.3	89.7	66.9	66.2

Panel B: Gross Notional Exposure (%)

	Amplifying Funds				Hedging Funds			
			Non-token				Non-token	
	All	Token	Medium	Heavy	All	Token	Medium	Heavy
All Derivative	13.99	2.59	13.76	61.79	20.47	1.17	21.17	42.84
Future	7.46	2.35	9.41	23.97	7.54	0.48	10.87	12.57
% in Long	70.5	85.5	59.9	74.4	55.0	70.5	59.7	50.1
Swap	5.85	0.21	2.89	36.41	10.44	0.23	6.91	26.27
% in Long	78.7	96.4	85.2	77.0	49.8	66.1	39.7	52.4
Option	0.55	0.01	1.38	0.81	2.05	0.09	3.03	3.38
% in Long	58.7	53.6	57.9	62.2	38.3	56.9	27.1	48.1
Foreign Exchange	0.12	0.02	0.08	0.60	0.44	0.37	0.36	0.62
% in Long USD	92.2	98.8	91.5	91.4	63.1	79.8	60.3	53.0

Table 4
Composition of Underlying Assets

The table shows the composition of underlying assets and the return correlation with non-derivative positions. In panel A, for each fund and quarter, we calculate the composition of derivatives' underlying assets, and then average across funds and quarters. In panel B, for each fund and each derivative type, we calculate the correlation between *DIR* and *non-DIR* from July 2019 to January 2020. We then show the average correlation across funds.

Panel A: Composition of Underlying Assets (%)

Composition	All	Amplify	Hedging
Stock	19.1	0.6	31.4
Benchmark Index	22.3	32.9	17.1
Non-benchmark Index	27.3	41.1	24.1
Foreign Exchange	13.6	12.2	17.6
Interest Rate	7.9	3.7	8.7
Commodity	7.5	8.0	0.2
CDS	1.1	0.2	0.1
Others	1.3	1.4	0.9
Total	100.0	100.0	100.0

Panel B: Correlation with Non-derivative Returns

Correlation	All	Amplify	Hedging
All Derivatives	0.20	0.94	-0.61
Future	0.51	0.92	-0.43
Swap	0.03	0.91	-0.37
Option	-0.12	0.32	-0.52
Foreign Exchange	-0.19	0.28	-0.43

Table 5
Performance of Derivative Users

The table shows the performance of derivative users between 2010 and 2019. The sample includes equity domestic active funds. We backfill the derivative use data for periods before September 2019 using the fund's derivative use data in September 2019. Panel A shows the factor loading of users and nonusers. Panel B breaks down derivative users by the extent of derivative use. Panel C shows the factor loading of hypothetical equity returns, assuming reported equity positions are held throughout the quarter. All returns and alphas are annualized and in percentage points.

Panel A: Derivative Users vs Nonusers

Users	Return	Benchmark	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	11.52***	-2.52***	-1.80***	0.99***	-0.96**	0.94***	0.18***	-0.04**	-0.05**	-0.03
	(2.84)	(-8.40)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Users	9.72***	-3.00***	-2.16***	0.88***	-1.44***	0.85***	0.12***	-0.02	-0.08**	0.05
	(2.68)	(-10.68)	(-3.51)	(68.40)	(-2.82)	(71.14)	(5.88)	(-0.79)	(-2.57)	(1.24)
Users - Non	-1.80***	-0.48***	-0.36	-0.11***	-0.48	-0.09***	-0.06***	0.02*	-0.02	0.08***
	(-3.31)	(-3.60)	(-1.04)	(-14.82)	(-1.65)	(-14.52)	(-5.83)	(1.70)	(-1.48)	(3.99)

Panel B: By Derivative Usage

Users	Return	Benchmark	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	11.52***	-2.52***	-1.80***	0.99***	-0.96**	0.94***	0.18***	-0.04**	-0.05**	-0.03
	(2.84)	(-8.40)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Token Users	11.28***	-2.16***	-1.92***	0.98***	-0.96**	0.93***	0.17***	0.00	-0.07***	-0.02
	(2.81)	(-8.24)	(-3.26)	(79.33)	(-2.57)	(113.17)	(12.35)	(0.09)	(-3.48)	(-0.75)
Medium Users	8.52**	-3.72***	-2.40***	0.81***	-2.04***	0.79***	0.07**	-0.03	-0.07*	0.07
	(2.51)	(-10.27)	(-3.36)	(52.02)	(-2.84)	(47.21)	(2.47)	(-0.87)	(-1.68)	(1.34)
Heavy Users	6.96**	-4.44***	-2.28***	0.69***	-2.28***	0.68***	0.04	-0.06	-0.06	0.16***
	(2.39)	(-12.39)	(-3.02)	(41.59)	(-2.91)	(38.03)	(1.36)	(-1.64)	(-1.25)	(2.86)
NonToken - Nonusers	-3.58***	-1.56***	-0.58	-0.22***	-1.08**	-0.19***	-0.12***	-0.00	-0.02	0.14***
	(-3.39)	(-7.67)	(-1.05)	(-17.46)	(-2.16)	(-16.13)	(-6.16)	(-0.11)	(-0.74)	(3.78)
Heavy - Nonusers	-4.56***	-1.92***	-0.48	-0.30***	-1.32**	-0.26***	-0.14***	-0.02	-0.00	0.19***
	(-3.31)	(-6.19)	(-0.80)	(-20.25)	(-2.13)	(-19.35)	(-6.12)	(-0.66)	(-0.08)	(4.56)

Panel C: Hypothetical Equity Returns

Users	Return	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	13.44***	-0.60	1.05***	0.24	1.00***	0.21***	-0.04**	-0.05**	-0.04
	(3.12)	(-0.95)	(73.41)	(0.65)	(105.80)	(13.43)	(-2.17)	(-2.14)	(-1.30)
Token Users	13.32***	-0.96	1.06***	0.24	1.00***	0.20***	0.01	-0.08***	-0.03
	(3.06)	(-1.47)	(77.87)	(0.63)	(127.39)	(15.20)	(0.54)	(-3.97)	(-1.28)
Medium Users	12.48***	-0.48	0.97***	0.02	0.93***	0.17***	-0.03	0.00	0.02
	(3.11)	(-0.67)	(57.01)	(0.06)	(56.07)	(6.07)	(-0.91)	(0.09)	(0.48)
Heavy Users	11.88***	-0.96	0.95***	-0.48	0.92***	0.10***	-0.04	-0.07	0.01
	(3.01)	(-1.29)	(60.31)	(-0.71)	(56.01)	(3.62)	(-1.34)	(-1.54)	(0.22)
NonToken - Nonusers	-0.96*	0.06	-0.08***	-0.26	-0.06***	-0.05***	0.01	0.04	0.05
	(-1.81)	(0.08)	(-7.48)	(-0.58)	(-5.48)	(-2.84)	(0.64)	(1.54)	(1.61)
Heavy - Nonusers	-1.56**	-0.36	-0.10***	-0.72	-0.07***	-0.11***	-0.00	-0.01	0.05
	(-2.25)	(-0.50)	(-7.16)	(-1.26)	(-4.99)	(-4.70)	(-0.12)	(-0.37)	(1.12)

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Performance of Amplifying/Hedging Funds

The table shows the performance of amplifying and hedging funds between 2010 and 2019. We backfill the derivative use data for periods before September 2019 using the funds' information in September 2019. Panel A shows the factor loading of real returns. Panel B shows the factor loading of hypothetical equity returns, assuming reported equity positions are held throughout the quarter. All returns and alphas are annualized and in percentage points.

Panel A: Realized Fund Returns

Users	Return	Benchmark	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	11.52***	-2.52***	-1.80***	0.99***	-0.96**	0.94***	0.18***	-0.04**	-0.05**	-0.03
	(2.84)	(-8.40)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Amplify	10.92***	-2.52***	-2.28***	0.98***	-1.44***	0.93***	0.18***	0.01	-0.03	-0.01
	(2.70)	(-9.84)	(-3.99)	(78.91)	(-3.92)	(110.71)	(12.85)	(0.38)	(-1.29)	(-0.26)
Hedge	10.08***	-2.51***	-1.44***	0.86***	-0.96**	0.84***	0.06***	-0.02	-0.11***	0.05
	(2.87)	(-8.02)	(-2.84)	(79.01)	(-2.08)	(78.60)	(3.15)	(-1.16)	(-4.08)	(1.63)
Hedge - Amplify	-0.72	0.01	0.84**	-0.12***	0.48*	-0.10***	-0.13***	-0.03**	-0.08***	0.06***
	(-1.21)	(0.03)	(2.15)	(-13.92)	(1.66)	(-14.65)	(-11.42)	(-2.38)	(-4.98)	(2.99)
Hedge - Nonusers	-1.44**	0.01	0.36	-0.13***	0.00	-0.10***	-0.12***	0.02	-0.06***	0.09***
	(-2.02)	(0.51)	(0.94)	(-14.11)	(0.26)	(-15.02)	(-11.50)	(0.84)	(-3.57)	(4.14)
Amplify - Nonusers	-0.60**	-0.01	-0.48**	-0.00	-0.48*	-0.01	-0.00	0.05***	0.03*	0.02
	(-2.34)	(0.57)	(-1.98)	(-0.83)	(-1.85)	(-0.93)	(-0.05)	(4.41)	(1.88)	(1.64)

Panel B: Hypothetical Equity Returns

Users	Return	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	13.44***	-0.60	1.05***	0.24	1.00***	0.21***	-0.04**	-0.05**	-0.04
	(3.12)	(-0.95)	(73.41)	(0.65)	(105.80)	(13.43)	(-2.17)	(-2.14)	(-1.30)
Amplify	13.08***	-0.96	1.05***	-0.04	0.99***	0.22***	-0.00	-0.01	-0.02
	(3.04)	(-1.61)	(77.72)	(-0.16)	(124.40)	(16.17)	(-0.12)	(-0.70)	(-0.77)
Hedge	13.32***	-0.60	1.04***	0.12	1.00***	0.11***	0.01	-0.08***	-0.01
	(3.13)	(-1.38)	(103.28)	(0.46)	(129.89)	(8.64)	(0.93)	(-4.14)	(-0.29)
Hedge - Amplify	0.24	0.36	-0.01	0.16	0.01	-0.10***	0.02	-0.07***	0.01
	(0.72)	(0.93)	(-0.86)	(0.63)	(1.32)	(-8.23)	(1.07)	(-3.49)	(0.52)
Hedge - Nonusers	-0.12	0.00	-0.014	-0.12	0.01	-0.11***	0.05***	-0.03**	0.03
	(-0.32)	(0.07)	(-1.29)	(-0.37)	(1.21)	(-9.08)	(3.40)	(-2.07)	(1.46)
Amplify - Nonusers	-0.36*	-0.36	-0.01	-0.28	-0.01	0.00	0.04***	0.04**	0.02
	(-1.67)	(-1.38)	(-0.73)	(-1.34)	(-0.47)	(0.07)	(2.91)	(2.21)	(1.17)

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Fund Flows

The table 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 then regress net flows on fund types dummy. In columns (1) - (3), we split funds into nonusers, token users, and non-token users. In columns (4) - (6), we further split non-token users into non-token amplifying funds, neutral funds, and hedging funds. In columns (1) - (6), flows to nonusers serve as the baseline. In columns (7) - (9), we run regressions on the share-class level and interact fund types dummy with retail share class dummy, and institutional flows to nonusers serve as the baseline. 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.

	(1) netflow	(2) netflow	(3) netflow	(4) netflow	(5) netflow	(6) netflow	(7) netflow	(8) netflow	(9) netflow
Token	0.0970	0.113	0.111	0.0965	0.113	0.110	0.0298	0.0407	0.0392
	(1.39)	(1.63)	(1.59)	(1.39)	(1.62)	(1.58)	(0.53)	(0.73)	(0.70)
NonToken	0.241**	0.219**	0.215**						
	(2.56)	(2.34)	(2.29)						
AmplifyNonToken				0.400***	0.387***	0.377***	0.266***	0.258***	0.250***
				(2.85)	(2.74)	(2.67)	(2.83)	(2.75)	(2.67)
NeutralNonToken				0.302*	0.251	0.246	0.302***	0.263**	0.256**
				(1.87)	(1.57)	(1.54)	(2.84)	(2.51)	(2.42)
HedgeNonToken				-0.0205	-0.0238	-0.0205	-0.0596	-0.0642	-0.0609
				(-0.16)	(-0.19)	(-0.17)	(-0.53)	(-0.58)	(-0.55)
retail							-0.437***	-0.436***	-0.437***
							(-6.87)	(-6.80)	(-6.82)
Token X retail							0.0143	0.0157	0.0158
							(0.24)	(0.26)	(0.26)
AmplifyNonToken X retail							-0.173*	-0.181*	-0.176*
							(-1.69)	(-1.76)	(-1.71)
NeutralNonToken X retail							-0.429***	-0.404***	-0.398***
							(-3.18)	(-2.99)	(-2.93)
HedgeNonToken X retail							-0.0803	-0.0691	-0.0746
							(-0.49)	(-0.42)	(-0.46)
Level	Fund	Fund	Fund	Fund	Fund	Fund	Share	Share	Share
Perf	Return	CAPM	FF5	Return	CAPM	FF5	Return	CAPM	FF5
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StyleFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0714	0.0729	0.0714	0.0715	0.0730	0.0715	0.133	0.135	0.133
N	284207	280421	280421	284207	280421	280421	408664	404284	404284

t statistics in parentheses

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

Table 8
Change in Portfolio Allocation During COVID-19

The table shows the change in portfolio allocation of derivative users during the COVID-19 pandemic, from 2019 Q4 to 2020 Q1. Panel A shows the change in derivative use, proxied by absolute derivative weight and gross notional exposure. Panel B shows the change in portfolio weight of non-derivative positions. STIV stands for short-term investment vehicle. Repo stands for repurchase agreement. The percentage numbers in parenthesis show the relative change from the previous quarter.

Panel A: Derivative Positions

	Absolute Derivative Weight	Gross Notional Exposure
All Derivatives	1.22*** (87.83%)	5.44* (38.41%)
Long Positions	0.68*** (76.44%)	0.32 (3.48%)
Short Positions	0.54*** (108.16%)	4.65*** (129.02%)

Panel B: Non-Derivative Positions

	Portfolio Weight
Equity	-1.67*** (-2.05%)
Debt	0.20 (2.93%)
STIV/Repo	1.07*** (14.63%)
Cash	0.66*** (35.06%)

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

Table 9
COVID Exposure and Change in Notional Exposure
The table shows the change in notional exposure of funds in high and low COVID exposure group. 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 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 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 in 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 10
Notional Exposure of Derivative Positions
The table shows the notional exposure of new derivative positions, and the difference between 2019 Q4 and 2020 Q1. Funds are grouped by the correlation between *DIR* and *non-DIR* into terciles. Amplifying (hedging) funds are in the top (bottom) tercile. We only report the statistical significance for the "Dif" columns.

Group	Long Positions			Short Positions		
	2019/Q4	2020/Q1	Dif	2019/Q4	2020/Q1	Dif
Amplify	9.24	8.13	-1.11	1.34	6.90	5.56***
Hedging	6.80	7.40	0.60***	4.36	5.25	0.89**
Amplify - Hedge			-1.71**			4.67**

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

Table 11
Fund Return Decomposition

The table shows the monthly fund return decomposition for the outbreak period and recovery period. For each fund-month observation, fund return is decomposed into two parts: *DIR* and *non-DIR*. We also calculate the monthly hypothetical equity return based on the most recent equity holdings. Columns 1-4 show monthly averages of *DIR*, *non-DIR*, fund return, and hypothetical equity return, respectively. Column 5 shows the average return of active equity trading, which is the difference between *non-DIR* and hypothetical equity returns. Column 6 shows the hypothetical derivative returns. Column 7 shows the return of active derivative trading. All numbers are at monthly frequency and are in basis points. The outbreak period is between February 2020 and March 2020. The recovery period is between April 2020 and June 2020. The statistical significance is only shown for rows "Amplify - Hedging".

Panel A: Outbreak Period

Group	Derivative	Non-derivative	Fund	Hypo Equity	Active Equity Trading	Hypo Derivative	Active Derivative Trading
Nonusers			-1177.9	-1153.9	-24.0		
Amplify	-37.8	-1089.7	-1127.4	-1153.1	63.5	-51.4	13.7
Hedging	58.6	-763.4	-704.8	-1135.4	372.0	22.7	35.9
Amplify - Hedging	-96.3***	-326.3***	-422.6***	-17.7	-308.6***	-74.1***	-22.2

Panel B: Recovery Period

Group	Derivative	Non-derivative	Fund	Hypo Equity	Active Equity Trading	Hypo Derivative	Active Derivative Trading
Nonusers			688.5	682.3	6.1		
Amplify	4.9	678.4	683.3	753.7	-75.3	4.4	0.5
Hedging	-63.5	480.2	416.6	689.3	-209.1	-10.0	-53.5
Amplify - Hedging	68.4***	198.3***	266.7***	64.5*	133.8***	14.4*	54.0

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

Table 12
Performance During the COVID-19 Pandemic

The table shows the performance of derivative users From January 1, 2019, to June 8, 2020. Daily alphas are estimated using fund daily returns with a one-year rolling window. All dependent variables are in annualized percentage points. The dummy variable *outbreak* is equal to one between January 20, 2020, and March 23, 2020. The dummy variable *recovery* is equal to one between March 24, 2020, and June 8, 2020. The sample includes all derivative users and nonusers. Derivative users are grouped by the pre-crisis correlation between *DIR* and *non-DIR* into terciles. Funds in the top (bottom) tercile are classified as amplifying (hedging) funds. The performance of nonusers is served as the baseline in all regressions. We only report coefficient estimates of amplifying funds and hedging funds due to page space. We also report the performance difference between hedging/amplifying funds and nonusers throughout the crisis, which spans outbreak and recovery periods. All regression specifications include fund controls (expense ratio, turnover ratio, natural logarithm of fund size), and time fixed effect. All standard errors are clustered at fund level.

	(1) Ret	(2) $Ret^{BenchAdj}$	(3) α^{CAPM}	(4) α^{FF5}	(5) Ret_hypo	(6) $Ret\_hypo^{BenchAdj}$	(7) α^{CAPM}_hypo	(8) α^{FF5}_hypo
Amplify	-1.078*	0.204	-0.702**	-0.283	-1.219***	-0.0791***	-1.720***	-4.634
	(-1.95)	(0.69)	(-2.03)	(-0.90)	(-2.80)	(-2.68)	(-5.76)	(-0.92)
Hedge	-5.065***	-1.429***	-0.250	-0.453	-1.025*	0.162***	-0.756**	6.176
	(-6.76)	(-3.31)	(-0.59)	(-1.08)	(-1.93)	(3.52)	(-2.18)	(1.16)
Amplify × outbreak	3.681	-6.262***	0.871	6.970***	2.242	0.0779	1.748	-0.0419
	(0.76)	(-3.18)	(0.24)	(2.70)	(0.54)	(1.12)	(0.50)	(-0.00)
Hedge × outbreak	52.30***	4.364*	9.157***	10.48***	4.004	-0.0851	2.532	-3.507
	(8.01)	(1.76)	(2.77)	(4.28)	(0.85)	(-1.21)	(0.77)	(-0.31)
Amplify × recovery	-8.865**	2.970**	-3.740***	-5.227***	-2.033	0.546***	0.0195	10.38
	(-2.35)	(2.09)	(-2.61)	(-4.35)	(-0.85)	(3.23)	(0.02)	(0.90)
Hedge × recovery	-41.62***	-7.500***	-6.431***	-2.695*	-6.259**	1.797***	-0.979	-11.32
	(-8.87)	(-4.00)	(-3.50)	(-1.67)	(-2.22)	(6.51)	(-0.71)	(-0.92)
Amplify × (outbreak + recovery)	-3.149***	-1.226	-1.643	0.317	-0.0841	0.333***	0.807	5.634
	(-2.64)	(-1.60)	(-1.09)	(0.29)	(-0.08)	(4.19)	(0.62)	(0.60)
Hedge × (outbreak + recovery)	1.108	-2.104**	0.661	3.300***	-1.576	0.938***	0.623	-7.755
	(0.86)	(-2.41)	(0.44)	(2.81)	(-1.29)	(6.86)	(0.44)	(-0.86)
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0840	0.0598	0.139	0.0924	0.0873	0.0518	0.203	0.000524
F	15.07	5.822	4.222	4.881	2.552	12.69	5.731	0.514
N	976496	976496	976496	976496	897533	897533	897268	897268

t statistics in parentheses

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

Table 13
High and Low CTE Amplifying Funds
The table examines flow and gross notional exposure of high and low CTE amplifying funds. For each amplifying fund, we calculate the change in tracking error (CTE) between the end of 2019 and the start of recovery in 2020. We then sort amplifying funds into high and low CTE group. 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 fund types dummy with retail share class dummy. We only report the coefficient estimates of High (Low) CTE dummy and its interaction with 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 new derivative positions and the difference between 2019 Q4 and 2020 Q1 for high and low CTE amplifying funds. We only report the statistical significance for the "Dif" columns.

Panel A: Flow Regression

	(1) netflow	(2) netflow	(3) netflow
Amplify Low CTE	0.241	0.211	0.199
	(1.15)	(1.03)	(0.97)
Amplify High CTE	0.504***	0.488***	0.476***
	(3.48)	(3.40)	(3.35)
Amplify Low CTE × retail	-0.0519	-0.0483	-0.0460
	(-0.21)	(-0.20)	(-0.19)
Amplify High CTE × retail	-0.423**	-0.400**	-0.392**
	(-2.60)	(-2.45)	(-2.41)
retail	-0.438***	-0.436***	-0.437***
	(-6.87)	(-6.79)	(-6.82)
Perf	Return	CAPM	FF5
Controls	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes
StyleFE	Yes	Yes	Yes
Adjusted R^2	0.134	0.136	0.134
N	398952	395100	395100

Panel B: Notional Exposure

Group	Long Positions			Short Positions		
	2019/Q4	2020/Q1	Dif	2019/Q4	2020/Q1	Dif
High CTE	10.77	9.08	-1.69	1.51	9.19	7.68***
Low CTE	6.72	6.48	-0.24	0.96	3.39	2.43
High - Low			-1.45			5.25*

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14
Tracking Error during COVID-19 Crisis

The table shows the monthly tracking error during the COVID-19 crisis. The dependent variables in column (1)-(3) are funds' tracking error, hypothetical tracking error, and the difference between hypothetical and realized tracking error, all in annualized percentage point. The dependent variable in column (4) is scaled difference in tracking errors by benchmark volatility. The (hypothetical) tracking error is calculated as the within-month standard deviation of the difference between fund (hypothetical equity) returns and benchmark returns. Benchmark volatility is the within-month standard deviation of daily benchmark returns. The sample includes all derivative users and nonusers. Derivative users are grouped by the pre-crisis correlation between *DIR* and *non-DIR* into terciles. Funds in the top (bottom) tercile are classified as amplifying (hedging) funds. The tracking errors of nonusers are served as the baseline in all regressions. We only report amplifying funds and hedging funds due to page space. The fund controls include expense ratio, turnover ratio, and the natural logarithm of fund size. We also include time fixed effects. The standard errors are clustered at fund level. The sample spans from January 2019 to June 2020. The outbreak period is between February 2020 and March 2020. The recovery period is between April 2020 and June 2020.

	(1) TE	(2) HTE	(3) TE-HTE	(4) $(\text{TE} - \text{HTE})/\text{Vol}^{\text{Bench}}$
Amplify	-0.738***	-0.945***	-0.137	-0.0103
	(-3.59)	(-3.87)	(-1.03)	(-0.63)
Hedge	-0.377**	0.361	-0.807***	-0.146***
	(-2.27)	(1.19)	(-3.21)	(-4.48)
Amplify × crash	-1.079***	-0.929**	-0.550	-0.0116
	(-2.75)	(-2.11)	(-1.60)	(-1.21)
Hedge × crash	1.131**	4.454***	-3.294***	-0.00227
	(2.34)	(4.77)	(-3.43)	(-0.18)
Amplify × recovery	-1.800***	-1.640***	-0.656***	-0.0225
	(-6.17)	(-4.67)	(-2.78)	(-1.55)
Hedge × recovery	-0.182	1.955***	-2.069***	-0.00863
	(-0.56)	(3.16)	(-3.32)	(-0.45)
Controls	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
Adjusted R^2	0.312	0.273	0.0589	0.0875
F	21.09	17.40	6.165	6.061
N	48645	44720	44720	44720

t statistics in parentheses

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

Internet Appendix

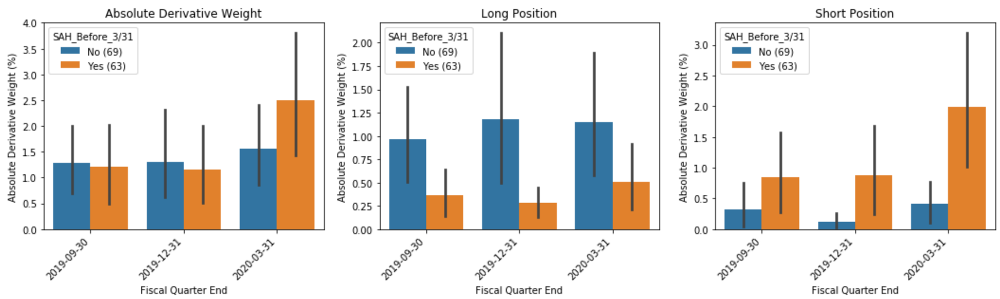
In the appendix, we show managers' reaction to SAH in neighboring states in Figure A1, histogram of *DIR* for each derivative instrument in figure A2, heavy users' performance and tracking error in Figures A3 and A4, and a map of SAH order in Figure A5. We also focus on the performance comparison of heavy users during the pandemic in Tables A1, A2, and A3.

Figure A1

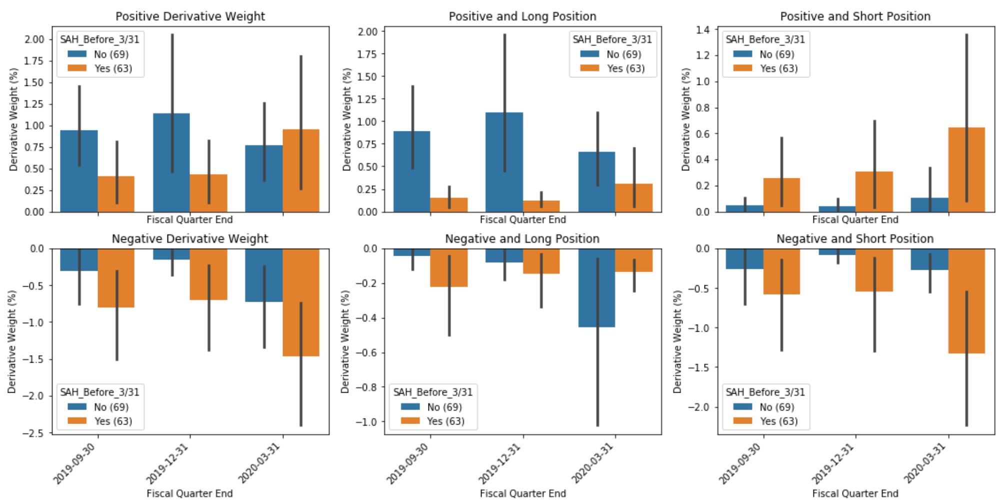
Stay-at-home Around the Border

The figure shows the change in derivative use in response to Stay-at-home order around borders. Different from Figure 4, the sample only includes funds in the following states: CO, OH, MN, WI, KS, TX, PA, MO, IA, NE. The first five states have SAH before March 31, 2020.

(a) Absolute Derivative Weight and SAH



(b) Derivative Weight Decomposition



(c) Notional Exposure

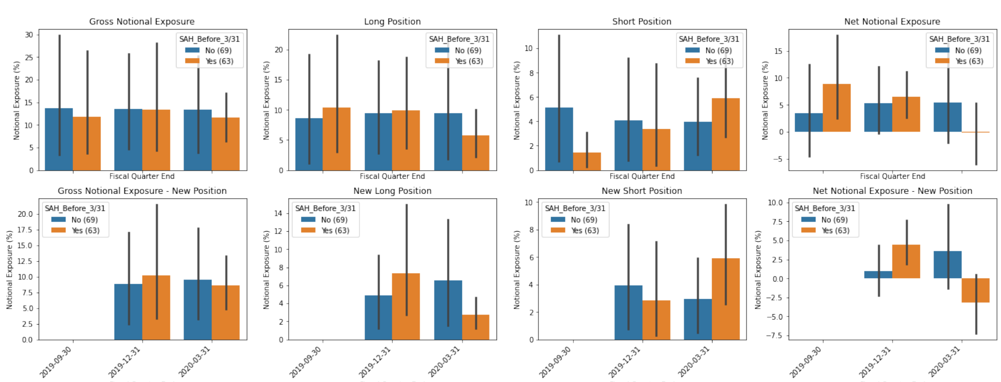
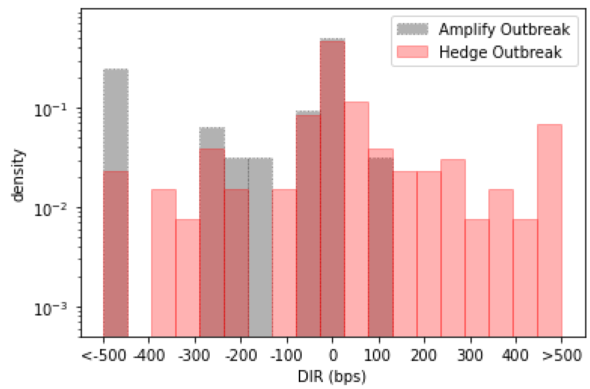


Figure A2

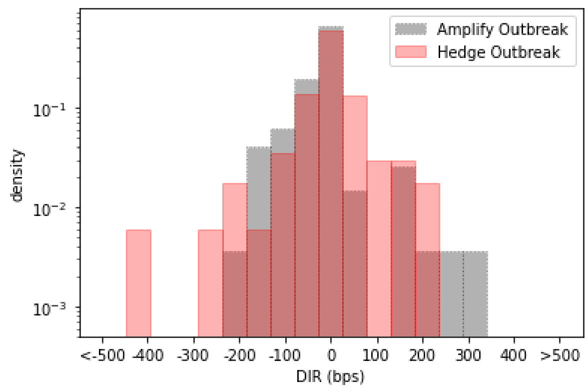
Distribution of Derivative Instrument Return in COVID-19 Outbreak

The figure shows the return distribution of derivative instruments. For all instruments, *DIR* are plotted between -5% and 5%, with a bandwidth of 50 bps. Densities of returns that are greater (smaller) than 5% (-5%) are stacked at the boundary for the ease of presentation. Outbreak period is defined as February 2020 and March 2020. The y-axis is in log-scale.

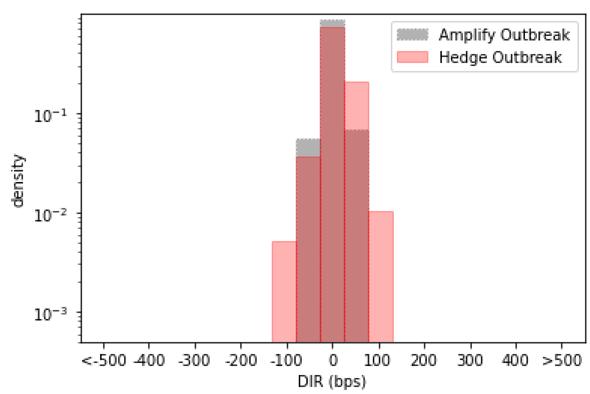
(a) Swaps



(b) Futures



(c) Options



(d) Foreign Exchange Contracts

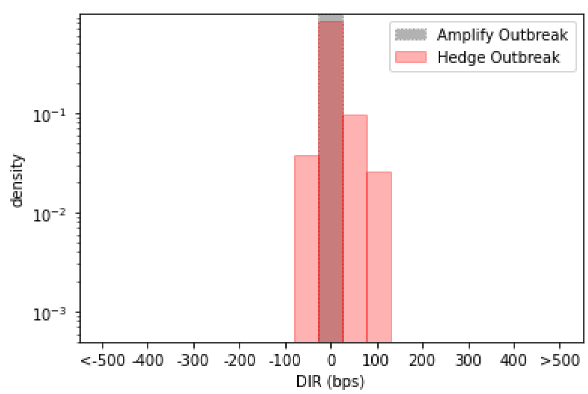
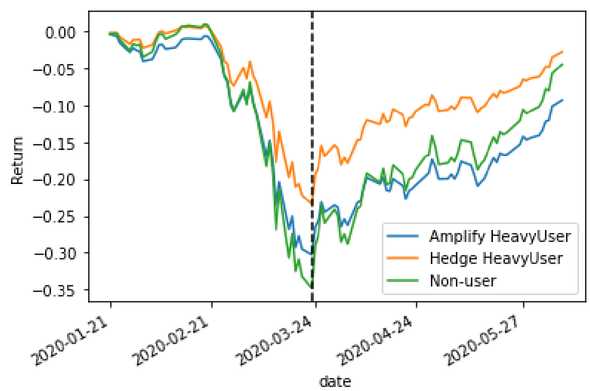


Figure A3

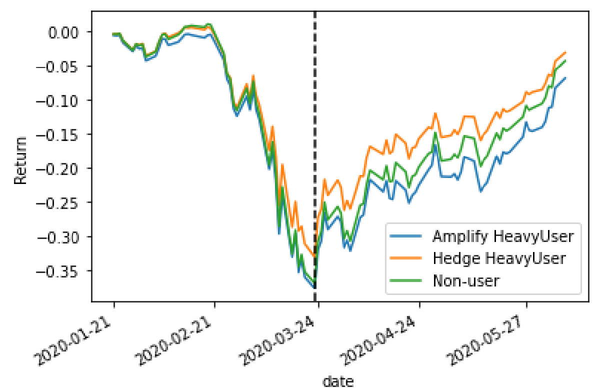
Fund Performance in COVID-19 Pandemic - Heavy Users

The figure shows the cumulative returns and alphas for active funds starting from the outbreak on January 20, 2020. Nonusers are the funds without derivative positions. For derivative users, funds are sorted by the absolute derivative weight into deciles. Token users are the funds in the bottom five deciles. Medium users are the funds between the sixth and eighth deciles. Heavy users are the funds in the top two deciles. Derivative users are further partitioned by the correlation between derivative and non-derivative returns prior to February 2020 into three terciles. Amplifying funds are in the top tercile, and hedging funds are in the bottom tercile. The figure shows the performance of nonusers, heavy amplifying users, and heavy hedging 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).

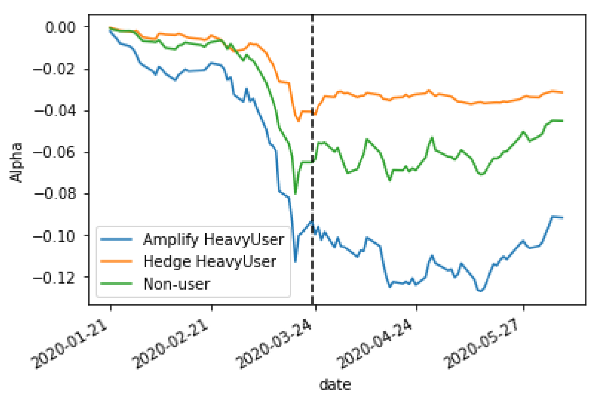
(a) Return



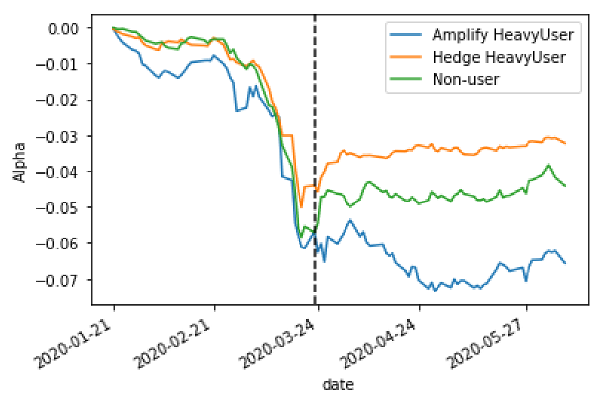
(b) Hypothetical Return



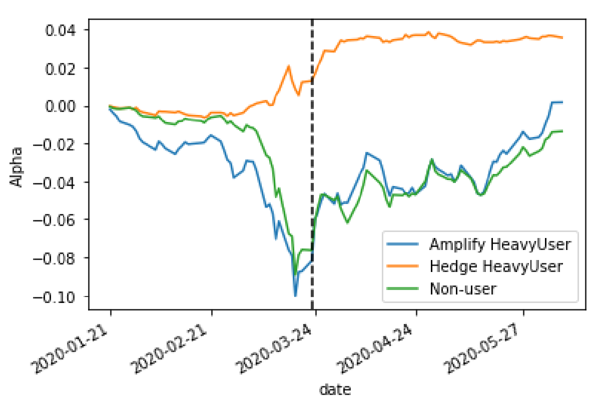
(c) CAPM Alpha



(d) FF5 Alpha



(e) Down-market Alpha



(f) Hypothetical Down-market Alpha

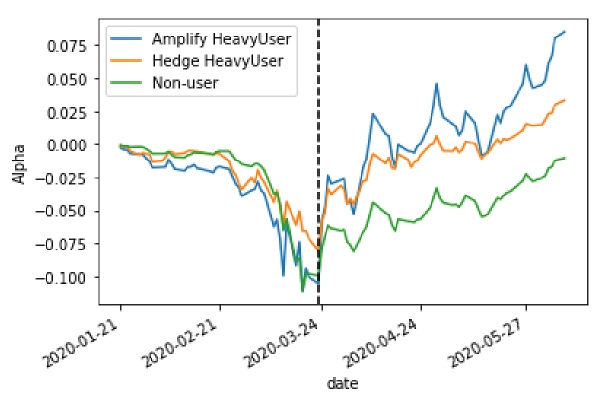
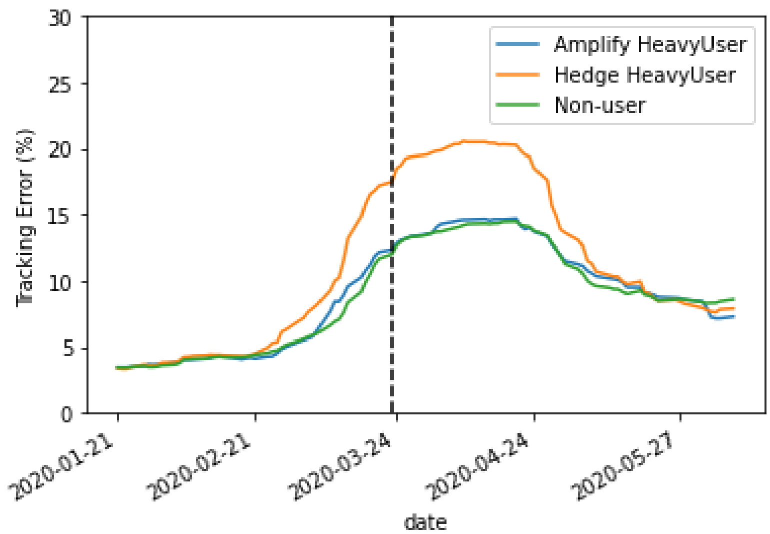


Figure A4
Fund Risk in COVID-19 Pandemic - Heavy Users
The figure shows the tracking error and volatility of active funds starting from the outbreak on January 20, 2020. Nonusers, heavy amplifying users, and heavy hedging users are defined as in Figure A3. Panel (a) shows the annualized tracking error, which is the 30-day rolling standard deviation of the difference between fund returns and benchmark returns. Panel (b) shows the annualized hypothetical tracking error, which is the 30-day rolling standard deviation of the difference between fund hypothetical returns and benchmark returns.

(a) Tracking Error



(b) Hypothetical Tracking Error

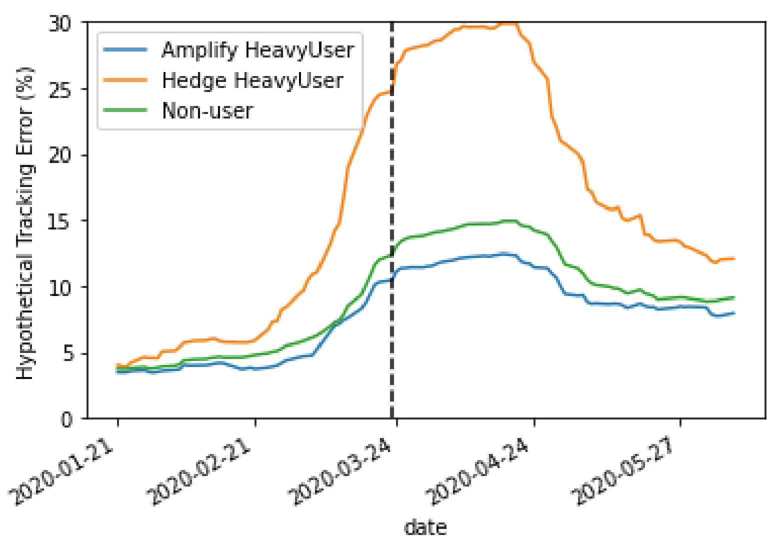


Figure A5

Map of Stay-at-home Order

The figure plots the status of 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.

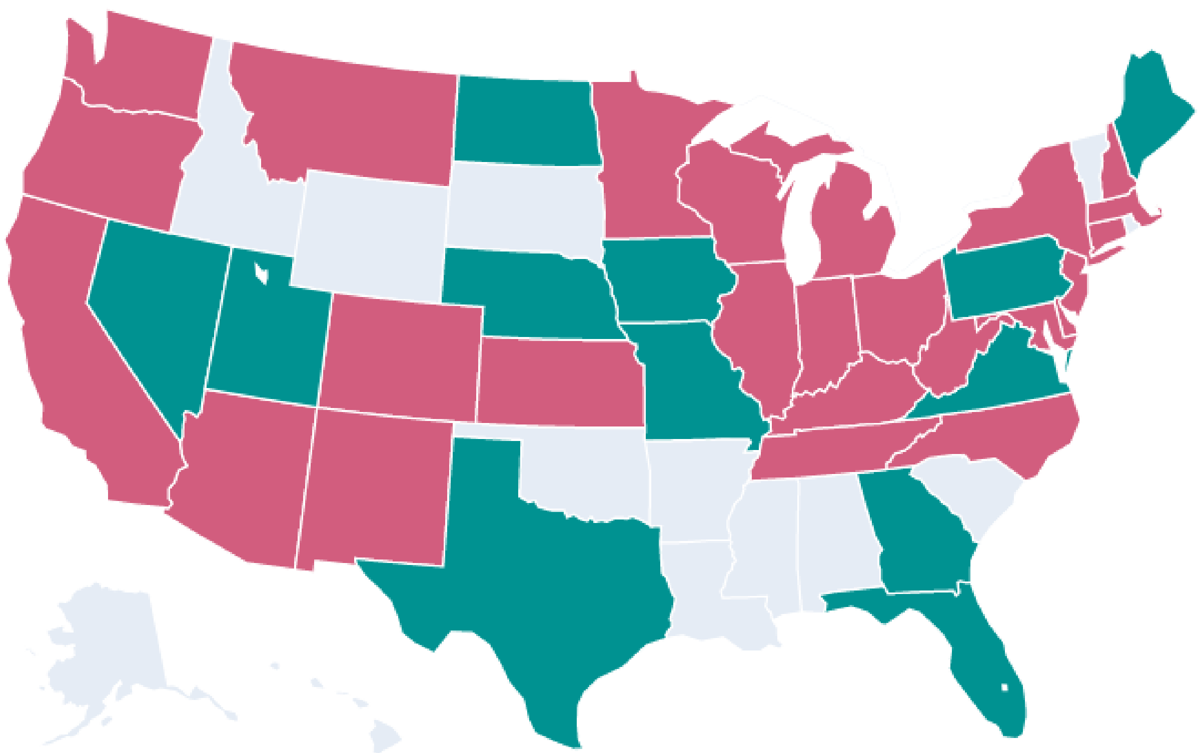


Table A1

Performance During the COVID-19 Pandemic - Non-token Users

The table shows the performance of derivative users From January 1, 2019, to June 8, 2020. Daily alphas are estimated using fund daily returns with a one-year rolling window. All dependent variables are in annualized percentage points. The dummy variable *outbreak* is equal to one between January 20, 2020, and March 23, 2020. The dummy variable *recovery* is equal to one between March 24, 2020, and June 8, 2020. The sample includes all derivative users and nonusers. Among derivative users, funds are further classified by the extent of derivative use in the last quarter of 2019 into token and non-token users. The performance of nonusers is served as the baseline in all regressions. We also report the performance difference between heavy hedging/amplifying funds and nonusers throughout the crisis, which spans outbreak and recovery periods. We only report non-token funds due to page space. All regression specifications include fund controls (expense ratio, turnover ratio, natural logarithm of fund size), and time fixed effect. All standard errors are clustered at fund level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret	$Ret^{BenchAdj}$	α^{CAPM}	α^{FF5}	Ret_hypo	$Ret\_hypo^{BenchAdj}$	α^{CAPM}_hypo	α^{FF5}_hypo
NonToken	-6.452***	-0.743**	0.120	-0.118	-1.412***	0.190***	-0.658**	-1.019
	(-10.17)	(-2.18)	(0.34)	(-0.33)	(-3.08)	(4.58)	(-2.13)	(-0.22)
NonToken × outbreak	58.56***	-6.230***	0.378	-1.460	12.74***	-0.264***	1.962	-1.656
	(11.20)	(-2.80)	(0.12)	(-0.55)	(3.29)	(-3.70)	(0.72)	(-0.15)
NonToken × recovery	-51.13***	-2.406	-5.944***	-1.985	-9.585***	2.157***	-1.183	-0.611
	(-12.83)	(-1.55)	(-3.84)	(-1.38)	(-3.84)	(8.92)	(-1.00)	(-0.06)
NonToken × (outbreak + recovery)	-1.165	-4.148***	-3.065**	-1.746	0.621	1.050***	0.255	-1.088
	(-0.95)	(-5.26)	(-2.26)	(-1.55)	(0.62)	(9.16)	(0.21)	(-0.13)
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0838	0.0597	0.139	0.0923	0.0861	0.0519	0.203	0.000520
F	28.30	8.303	3.333	3.560	3.795	18.58	2.498	0.0744
N	976496	976496	976496	976496	897533	897533	897268	897268

t statistics in parentheses

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

Table A2

Performance During the COVID-19 Pandemic - Heavy Users

The table shows the performance of derivative users From January 1, 2019, to June 8, 2020. Daily alphas are estimated using fund daily returns with a one-year rolling window. All dependent variables are in annualized percentage points. The dummy variable *outbreak* is equal to one between January 20, 2020, and March 23, 2020. The dummy variable *recovery* is equal to one between March 24, 2020, and June 8, 2020. The sample includes all derivative users and nonusers. Among derivative users, funds are further classified by the extent of derivative use in the last quarter of 2019 into token, medium, and heavy users. Derivative users are also grouped by the pre-crisis correlation between derivative and non-derivative returns into terciles. Funds in the top (bottom) tercile are classified as amplifying (hedging) funds. The performance of nonusers is served as the baseline in all regressions. We also report the performance difference between heavy hedging/amplifying funds and nonusers throughout the crisis, which spans outbreak and recovery periods. We only report heavy amplifying funds and heavy hedging funds due to page space. All regression specifications include fund controls (expense ratio, turnover ratio, natural logarithm of fund size), and time fixed effect. All standard errors are clustered at fund level.

	(1) Ret	(2) $Ret^{BenchAdj}$	(3) α^{CAPM}	(4) α^{FF5}	(5) Ret_hypo	(6) $Ret\_hypo^{BenchAdj}$	(7) α^{CAPM}_hypo	(8) α^{FF5}_hypo
AmplifyHeavy	-5.023**	0.631	0.582	1.788	-4.840***	-0.261***	-2.123***	-16.10
	(-2.47)	(0.96)	(0.48)	(1.37)	(-2.81)	(-3.13)	(-3.00)	(-1.09)
HedgeHeavy	-8.972***	-2.172**	-0.690	-2.000*	-1.723	0.234**	-0.978	9.313
	(-5.49)	(-2.28)	(-0.69)	(-1.90)	(-1.44)	(2.12)	(-1.51)	(0.98)
AmplifyHeavy × outbreak	15.95	-23.13***	-23.10**	-12.45	19.31	-0.0960	4.443	25.79
	(1.40)	(-3.46)	(-1.99)	(-1.57)	(1.13)	(-0.34)	(0.42)	(0.46)
HedgeHeavy × outbreak	95.37***	4.906	19.87***	15.96***	24.83***	-0.259*	12.37**	-17.32
	(8.45)	(0.91)	(3.80)	(3.15)	(2.90)	(-1.81)	(2.40)	(-0.91)
AmplifyHeavy × recovery	-41.62***	2.110	-9.902**	-8.265**	-10.55	0.191	0.349	41.67
	(-3.14)	(0.42)	(-2.15)	(-2.10)	(-0.96)	(0.46)	(0.09)	(1.36)
HedgeHeavy × recovery	-75.80***	-12.32***	-15.59***	-8.163**	-19.09***	2.460***	-3.299	-23.90
	(-10.06)	(-3.36)	(-4.21)	(-2.46)	(-3.30)	(3.56)	(-1.25)	(-0.96)
AmplifyHeavy × (outbreak + recovery)	-15.27***	-9.457***	-15.95***	-10.19***	3.076	0.0598	2.217	34.42
	(-3.13)	(-3.35)	(-2.90)	(-2.72)	(0.99)	(0.29)	(0.53)	(1.00)
HedgeHeavy × (outbreak + recovery)	2.560	-4.429**	0.645	2.884	1.106	1.211***	3.907*	-20.87
	(0.85)	(-2.25)	(0.21)	(0.98)	(0.61)	(3.53)	(1.91)	(-1.25)
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0837	0.0602	0.139	0.0926	0.0852	0.0523	0.203	0.000536
F	9.915	4.672	3.755	3.937	2.527	6.361	2.986	0.603
N	976496	976496	976496	976496	897533	897533	897268	897268

t statistics in parentheses

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

Table A3

Fund Return Decomposition - Heavy Users

The table shows the monthly fund return decomposition for outbreak and recovery periods. Similar to Table A2, the table presents heavy amplifying funds, heavy hedging funds, and nonusers. For each fund-month observation, fund return is decomposed into two parts: *DIR* and *non-DIR*. We also calculate the monthly hypothetical equity return based on the most recent equity holdings. Columns 1-4 show monthly averages of *DIR*, *non-DIR*, fund return, and hypothetical return, respectively. Column 5 shows the average return of active equity trading, which is the difference between non-derivative returns and hypothetical equity returns. Column 6 shows the hypothetical derivative returns. Column 7 shows the return of active derivative trading. All numbers are at monthly frequency and are in basis points. The outbreak period is between February 2020 and March 2020. The recovery period is between April 2020 and June 2020. The statistical significance is only shown for rows "Amplify - Hedging".

Panel A: Outbreak Period

Group	Derivative	Non-derivative	Fund	Hypo Equity	Active Equity Trading	Hypo Derivative	Active Derivative Trading
Nonusers			-1177.9	-1153.9	-24.0		
Heavy Amplify	-137.7	-990.6	-1128.3	-781.3	-209.3	-226.6	88.9
Heavy Hedging	139.8	-663.4	-523.6	-907.4	244.0	69.9	69.9
Amplify - Hedging	-277.6***	-327.2***	-604.7***	126.2	-453.3***	-296.6**	19.0

Panel B: Recovery Period

Group	Derivative	Non-derivative	Fund	Hypo Equity	Active Equity Trading	Hypo Derivative	Active Derivative Trading
Nonusers			688.5	682.3	6.1		
Heavy Amplify	99.1	466.2	565.4	547.4	-81.1	273.2	-174.1
Heavy Hedging	-165.2	514.8	349.6	591.8	-77.0	-84.8	-80.4
Amplify - Hedging	264.3***	-48.5	215.8**	-44.4	-4.1	358.0***	-93.6

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