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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Pingle Wang - pingle.wang@utdallas.edu
The University of Texas at Dallas

Ron Kaniel - ron.kaniel@simon.rochester.edu
University of Rochester Simon School and CEPR

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Unmasking Mutual Fund Derivative Use

Ron Kaniel* Pingle Wang†

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Abstract

Using new SEC data, 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. Contrary to prior research concluding derivatives are used for hedging, we find most derivative users buy index derivatives to amplify market exposure. Surprisingly, they underperform nonusers yet receive more flows. Using COVID-19 pandemic as a shock to evaluate explanations, we find they suffered a double whammy: failed to outperform nonusers by suffering losses from long derivative positions during the crash and from newly opened short positions when markets unexpectedly rebounded.

*Ron.Kaniel@simon.rochester.edu, Simon Business School , University of Rochester; FISF, Fudan; IDC Herzliya; and CEPR.

†Pingle.Wang@utdallas.edu, Jindal School of Management, University of Texas at Dallas.
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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 the lack of appropriate data. A central limitation of data used in prior work attempting to tackle this topic is that it did not enable recovering reasonable estimates for funds' derivative positions and derivative portfolio returns, since the data typically provided only flags identifying derivative use at a semiannual frequency. This is especially limiting when trying to understand dynamic relations between derivative and equity positions. The most direct evidence so far comes from a survey of mutual funds by Koski and Pontiff (1999), which suggests most mutual fund managers use derivatives for hedging, and only a small minority use them for amplification and speculation.

Using a novel dataset extracted from SEC's Form N-PORT, which became available only in September 2019, we infer the performance of fund derivative positions, evaluate the impact of derivatives on fund returns, and empirically test whether derivatives are used for hedging or amplification among US domestic active equity mutual funds.[1] We show that, contrary to the common belief that derivatives are used for hedging, most (63%) of the derivative using funds use derivatives to amplify market exposure, and reveal that filtering out funds that use a 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), Frino, Lepone, and Wong (2009)). Despite potential performance enhancement through derivatives, we find that amplifying 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, the evidence

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

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.

Derivative users represent a substantial proportion of active equity funds in our sample, 26% in terms of the number of funds and 27% in terms of total net assets. Examining detailed derivative holding, we find substantial cross-sectional variation and high persistence in the extent of derivative usage, which can explain differences in fund returns and risk exposure. We measure the extent of derivative use by absolute derivative weight and gross notional exposure. Among derivative users, 50% are *token* users, which have derivative weights of less than 0.2% and perform similarly to nonusers. 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), Fong, Gallagher, and Ng (2005), and Cao, Ghysels, and Hatheway (2011)). In contrast, the other 50% of derivative users (*non-token* users), which represent 14% of total net assets among all active equity funds, invest substantial amounts in derivatives, with a median absolute derivative weight of more than 2% and a gross notional exposure of 16%. Given the non-negligible amount of non-token derivative users and their large derivative exposure, it is important to understand how derivatives affect their overall fund performance and flows. Furthermore, prior work on derivative use by funds focuses almost exclusively on options and futures, but has overlooked an important derivative class: swaps. The omission was due to the fact that Form N-SAR, the main data source used in these papers to identify users, asks whether the fund uses options and futures, but does not ask about other derivatives.[2] 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 utilize 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 the component of fund returns stemming from derivative positions based on realized and unrealized Profit-and-Loss (PnL) of derivatives, and to directly calculate the 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.

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. Even though these amplifying funds

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

[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.

have a high correlation between derivative and non-derivative returns, they do not take excess risk in the market, as their market betas are close to nonusers. In fact, they tend to hold 7% less in equity than nonusers and use equity index derivatives as a cheap way to re-gain equity exposure. 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 rationale 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 occurred 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]

We find that funds' derivative use doubled when entering into the pandemic, and the increase was concentrated in short positions. The increased usage came from the intensive margin, as the number of funds using derivatives remained almost unchanged. 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 a high level of expertise, so that it is not easy for a

[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 (2021) that focus on financial fragility in corporate bond funds.

nonuser to suddenly become a derivative user in the midst of the pandemic. The measured increase in derivative use is not simply due to shrinkage in funds' total net assets, as we find that the increase came almost entirely from an increase in short derivative positions during the crisis, and that funds did not fully unwind their increased positions when the market fully recovered from the crash.

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 in 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 they provide to 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, as the unrealized PnL on their short positions were negative by the end of the outbreak when the market had already started to rebound.

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 to these funds? Does derivative use attract flows, or do flows induce derivative use? To answer these questions, we propose two potential channels. The first is through a risk-taking channel, in which derivative use attracts flows. Specifically, institutional investors, who provide extra flows, are able to, ex-ante, identify funds that will use derivatives to increase their risk-taking and deviate from benchmarks, which is a necessary but not sufficient condition for outperformance in a crisis period. Alternatively, there could be a reverse causality explanation through a flow-management channel, where these 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 captures managers' deviation from benchmarks. Our evidence supports the risk-taking channel, as funds that substantially increased their tracking error during the COVID period received abnormally high flows from institutional investors in normal times, prior to the crisis. Moreover, these funds indeed shifted their strategies by betting on short derivative positions during the crisis. While consistent with the risk-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 amplifying and hedging 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 reduce the tracking error that would otherwise explode.

Finally, we take advantage of differential salience of the severity of the pandemic to shed light on the role of salience in impacting fund managers' derivative allocation decisions. 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 at the start of the pandemic 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.

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. Section 5 discusses potential reasons for derivative use and considers whether they can explain our findings. Section 6 considers the role of salience in impacting derivative use during the crisis. Finally, section 7 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. Funds belonging to fund families with net assets of $1 billion or more were required to start reporting from June 1, 2019. Others were required to start reporting on March 1, 2020. Most (89%) funds started to report in 2019. Although funds report filings monthly, the holding parts of the reports are available to the public only at a quarterly frequency, corresponding to fiscal quarter-ends.

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

The quarterly-level data include funds' total net assets and portfolio holdings. The holding data cover not only equity and debt positions, but also detailed descriptions of over-the-counter and exchange-traded derivative positions. We extract derivative instruments, names of underlying assets, portfolio weight, notional amount, expiration date, and unrealized appreciation or depreciation for each derivative position. The value of these derivative positions is marked to market as they are reported. The derivative instrument not only includes forwards/futures and options, which are indicated by flags in N-SAR, but also covers swaps, swaptions, warrants, and foreign exchange contracts, all of which have not been documented in prior studies.[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. Note that CRSP switched its data provider to Lipper in late 2010 and started to also provide information on derivative holdings.[6] However, not all derivative positions are listed in CRSP holding. There exists a catch-all category, often named "other assets" or "other assets less liabilities", which may include derivative positions. For example, Guggenheim Style-Plus Large Core Fund reported in N-PORT a swap position on S&P 500 index with counterparty Wells Fargo and a portfolio weight of 3.7%, but this position is not reflected in the CRSP holdings and is grouped into "other assets less liabilities".

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 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 the outbreak and recovery periods. For analyses with only monthly frequency available, we denote the outbreak period as February 2020 and March 2020, and the recovery period as the months between April 2020 and June 2020.[7] 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

[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.

[6]There is very little coverage of derivative holding before it switched to Lipper.

[7]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.

20, 2020.[8] 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.[9] We choose June 8, 2020, as the recovery ending date because it is the first time S&P 500 index closed higher than its December 31, 2019 close since the crash.

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 how, or how much, derivative positions contribute to fund returns or risks. Specifically, it has limited use for testing whether funds use derivatives to hedge or amplify returns, an important part of our analysis. This section addresses these unanswered questions.

In Section 3.1, we show there is 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 the portfolio weight and notional amount of each derivative position from N-PORT. To proxy for the extent of derivative use, we use two measures. The first, keeping in mind that funds can increase exposure by trading derivatives on both long and short sides, is the sum of *absolute derivative weights* in the portfolio. The second is *gross notional exposure*, which is the sum of notional amounts of derivative

[8] 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

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

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 27% 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, we find that 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. Although 2% seems small in absolute terms, derivatives provide funds ample market exposure because of the embedded leverage. Specifically, the average gross notional exposure is 21% relative to a fund's total net assets. 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 a 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 quarters. Second, our evidence suggests that these derivatives have a fairly long time-to-maturity. For example, the median time-to-maturity of futures is 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 three years. Furthermore, the use of 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 the remaining half using derivatives heavily. Such a pattern is also documented in Cao et al. (2011) but has received little attention in subsequent studies. Figure 1 visualizes the cross-sectional variations in derivative use. On the one hand, 50% of funds have derivative weights (gross notional exposure) of less than 0.2% (0.3%). On the other hand, the remaining 50% of funds have a median derivative weight (gross notional exposure) of more than 2% (16%). In fact, over 35% (27%) of derivative users have a derivative weight (gross notional exposure) of more than 5% (10%), so that derivatives are a large part of funds' asset allocation.

To gain deeper insight into how funds use derivative positions, 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.[10] 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 omitted 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%).

[10]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 study has systematically examined 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 funds' non-derivative performance, and test the central hypothesis of whether derivatives are used for hedging or amplification.[11]

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

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

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

We find that *DIR* is a large component of overall fund returns. 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 the importance of derivative positions to fund returns.

The blue curve in Figure 2 shows the CDF of (signed) derivative relative contribution. Signed derivative relative contribution is 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

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

returns among medium and heavy users, which is shown by the blue curve in Figure 2(c).[12]

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 the median contribution are all highly significant.[13] The substantial differences in contributions further buttress the importance of including swaps users when examining funds' derivative use.

3.2.1 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 is not affected by the COVID-19 crisis. Panel (a) of 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.

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 a highly positive correlation, some hedging funds have a relatively weak negative correlation between *DIR* and *non-DIR*.[14] Amplifying and hedging funds have similar sizes as nonusers.

[12] To alleviate the concern that our measure of derivative relative contribution may not be stable when the denominator is small, for robustness in Appendix Figure A2 we require the absolute value of *non-DIR* to be greater than or equal to 10 bps. Conclusions are similar.

[13] 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.

[14] We have examined the alternative cutoff of correlations by assigning amplifying funds with a correlation above 0.5 and

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.

One may be concerned that we only have seven months of derivative returns to calculate the correlation, which may lead to a noisy estimation. To alleviate such concern, we construct an alternative measure, *net exposure ratio*, which is based on the notional exposure of derivative positions rather than returns. Specifically, for each fund, *net exposure ratio* is the ratio between the total amount of net and gross notional exposure. If a fund mainly uses derivatives to gain exposure to the market, net exposure ratio will be close to one. If a fund holds short derivative positions, or dynamically shifts between long and short positions, net exposure ratio will be close to zero or negative. Our measure of net exposure ratio has a correlation of 0.7 with the derivative return correlation. Appendix Figure A1 plots the histogram of *net exposure ratio*. Consistent with the correlation histogram, we find a large number of funds clustering at the right tail, suggesting that the majority of funds mainly use derivatives to gain market exposure.[15]

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 the 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 the 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 on 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 index, and non-benchmark index, based on security names.

Amplifying funds and hedging funds differ not only by the composition of long and short positions, but

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.

[15] Our subsequent results are robust to this alternative classification and available upon request.

also by the types of underlying assets their derivative positions build on. First, most amplifying funds' derivatives are in long positions, so that their derivative positions are unlikely to be used to circumvent short-selling constraints. For example, 85% (87%) of heavy users' futures (swaps) positions are long, as shown in Panel A of Table 3.[16] Second, they hold very few 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 indexes. Moreover, we also hand-collect returns of non-benchmark indices and examine the return correlation between the non-benchmark index and the benchmark. We find that most of the 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 substitutes to their benchmark, which allows them to cheaply maintain low 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, on the contrary, hold a balanced derivative portfolio of long and short positions. For example, 46% (49%) of their futures (swaps) are in long positions. Therefore, they too do not use derivatives solely as a way to relax short-selling constraints. They also differ from amplifying funds by investing relatively more in 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 a large proportion in single stock derivatives.[17] 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

[16] 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.

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

non-benchmark index derivatives, the median (average) return correlation between benchmark and non-benchmark index is 0.84 (0.61), which is considerably lower than that of amplifying funds.

Around 36% of hedging funds' single stock derivative positions are built without holding the 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 utilize information better. For example, a manager can use derivatives to trade on a negative signal more efficiently. Also, a manager can better exploit firm-specific information by using derivatives to hedge away the systematic risk. Second, derivatives can reduce transaction costs if a manager wants to quickly increase or decrease market exposure. So far, there is fairly little empirical evidence on the performance difference between derivative using funds and nonusers. We revisit this question by taking into account the extent of derivative use and regressing equal-weighted fund returns on various asset pricing models between 2010 and 2019, where portfolios are formed based on the extent of derivative use.

We use two approaches to identify derivative users. The first approach is to use CRSP mutual fund holdings that contain derivative positions since late 2010 when CRSP switched data provider to Lipper. Specifically, in each year, we group funds by the extent of derivative use based on security names and portfolio weight in CRSP holdings, form the equal-weighted portfolios, and hold them throughout the subsequent year.[18] Detailed identification of derivative positions is discussed in Appendix A.1. The second approach is to use the classification of derivative users in September 2019 based on N-PORT

[18] The persistence of derivative use and the breakdown of derivative weight by instruments are similar to what we report in Table 2.

and back-fill the classification. The advantage of the first approach over the second is that there is no look-ahead bias, in which a fund may later change its derivative strategy because of its past fund performance, nor is there an issue of classification of funds that dropped from the latter part of the sample. The disadvantage is that not all derivative positions are listed in the CRSP holdings. As we discussed in Section 2, there exists a catch-all category, often named "other assets" or "other assets less liabilities", which may include derivative positions. Moreover, the median portfolio weight for such a catch-all category is not trivial, over 0.5%, especially considering that the weight cutoff between token users and non-token users is around 1%. In other words, the first approach of using CRSP data rules out the survivorship bias, while the second approach of using N-PORT data offers a more accurate estimation of funds' extent of derivative use.

Tables 5 and 6 show the performance of derivative users by CRSP and N-PORT classifications, respectively, and the results are largely consistent under the two approaches. As shown in Panel A, after controlling for common risk factors, there is no significant difference in performance between derivative users and nonusers, which is consistent with Koski and Pontiff (1999). However, they do differ slightly in terms of factor loading. Derivative users have lower market beta than nonusers in both tables, and lower SMB beta in Table 6.

Even though derivative users on average have similar performance to nonusers, we show that the extent of use can explain substantial cross-sectional differences in performance. In Panel B of both tables, we split derivative users by their extent of derivative use into three groups. Nonusers and token users perform similarly after adjusting for risks, consistent with the fact that token users hold a tiny fraction of derivatives. In contrast, non-token users significantly underperform nonusers by 0.72% per year in Fama-French five-factor (FF5) alpha under the CRSP classification and by 1.08% per year under the N-PORT classification. The magnitude of the underperformance widens between heavy users and nonusers.[19] One distinction in Panel B between Table 5 and Table 6 is that the magnitude of derivative users' underperformance monotonically increases with the extent of use under the N-PORT classification, but not so under the CRSP classification. Note that funds need to report every position separately to SEC through N-PORT filings. As a result, there is little measurement error in the extent of derivative

[19] In untabulated analysis, we find that the underperformance of heavy users and nonusers 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.

use. However, in terms of CRSP holdings, as noted above some funds report a catch-all category for part of their holdings, which may contain derivative positions, leading to an inaccurate estimation of the extent of use.

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 a lower market beta, whereas a fund that uses derivatives to gain cheap exposure to the market or to utilize information better should have a similar market beta to nonusers. We find that derivative users' market beta and SMB beta monotonically decrease with the extent of use, suggesting that some derivative users, especially non-token users, use derivatives to manage overall fund exposure. Moreover, token users have similar market beta and SMB beta as nonusers, which is consistent with their negligible derivative usage.

The use of derivatives can further impact a fund's risk-taking in equity positions, which could in turn 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.[20] We then form portfolios based on hypothetical equity returns and regress them on factor returns. Panel C of Tables 5 and 6 reports results. Derivative users hypothetical market betas and SMB beta are lower than nonusers, where differences are most pronounced for heavy users. Although, these differences only partially explain the corresponding differences in exposures in Panel B. For example, under the N-PORT classification, 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 overall performance, but also its equity trading strategy more broadly. In later Section 4.2.4, we investigate how derivative positions affect fund risks and equity selection in detail.

[20] 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.

3.3.1 Under-performance of Amplifying funds

After documenting the extent to which derivative use has implications on fund performance, we then examine whether derivatives used for amplifying or hedging impact fund performance. Similar to the previous subsection, we use two approaches to identify amplifying and hedging funds. The first approach is to use the correlation between *DIR* and *non-DIR*, as shown earlier. Even though the correlation measure is only based on the most recent data, it is the most accurate to capture the relation between a fund's derivative strategy and equity strategy. The downside is that the classification is based on recent data and may be subject to survivorship bias. To ensure that our classification of amplifying and hedging funds are persistent over time, for each non-token funds, we then hand-collect two snapshots of their derivative holding from N-Q back in 2010 and 2015, respectively.[21] We find that, even back in 2010 (2015), 73.4% (78.7%) of amplifying funds were using long-only futures and swaps on major equity indices, while 70.9% (82.1%) of hedging funds were trading either single stock derivatives through swaps and options, or short derivative positions on equity indices.[22] Therefore, it is reassuring that funds' derivative using styles are highly persistent over time, which greatly alleviates the concern of back-filling.

The second approach is to utilize CRSP derivative holdings since 2010. We assign a value of 1 (-1) for each long (short) derivative position, and then calculate the average value for each fund-year pair, denoted as the *net position*. This measure shares the same range as the correlation measure, between -1 and 1, and its distribution is shown in Panel (b) of Figure 3. Consistent with the correlation measure, most derivative users have long positions, and the right tail is more clustered than the one in Panel (a). Given the clustering of funds in the right tail, we classify a derivative user as an amplifying fund if its *net position* measure is equal to one, and a hedging fund if its *net position* measure is negative. The classification is highly persistent over the years. Specifically, the probability of an amplifying (hedging) fund still being classified as an amplifying (hedging) fund in the next year is 90% (76%). The holding-based classification from CRSP rules out survivorship bias, but it has three disadvantages. First, CRSP holdings on derivatives can be incomplete, so that there is measurement error in derivative use. Second, assuming

[21] 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.

[22] The use of derivatives is also persistent. 79% (85%) of derivative users in 2019 are users in 2010 (2015), and 94% (97%) of nonusers in 2019 are nonusers in 2010 (2015).

all positions are identified perfectly, a long derivative position may not necessarily enhance equity returns. For example, the return of a variance swap is often negatively correlated with equity returns. Third, the holding-based measure is based on snapshots at quarter-end and is subject to managers' window dressing incentives.

We present the performance of amplifying and hedging funds under two approaches in Table 7. Amplifying funds, on average, underperform hedging funds and nonusers, regardless of whether we use return-correlation-based classification or holding-based classification. In Panel A of Table 7, 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. The difference in performance is not driven by fees, as they all have an average expense ratio of 1%.[23] The gap in performance widens when we zoom in onto non-token users. In untabulated results, we find that non-token amplifying funds significantly underperform nonusers by FF5 alpha of 1.5% per year. Panel B presents the result using CRSP holding-based classification, which helps rule out the survivorship bias. Amplifying funds significantly underperform nonusers by 0.84% (0.48%) per year in CAPM (FF5), consistent with the results in Panel A.

Despite the fact that amplifying funds use index derivatives to amplify equity returns, they have similar market exposure as nonusers. To test why this is the case, we look into funds' cash and cash equivalent holdings, equity holdings, and the notional exposure of derivatives. A fund's realized beta should be the average beta of each component, where the beta of cash is zero. We find that amplifying funds hold 6% less equity but more cash than nonusers. Given their similar equity betas estimated from hypothetical equity returns, if there were no derivatives, amplifying funds would have lower realized beta than nonusers. Note that amplifying funds' derivative positions are invested mostly in equity index derivatives, and these funds have a beta close to one. Therefore, amplifying funds' equity index derivatives fill the gap in beta.[24] Moreover, we find that there is a strong positive correlation of 0.28 between a fund's change in cash position and change in notional exposure, consistent with them using cash as collateral in derivative markets, and a strong negative correlation of -0.43 (-0.65) between a fund's change in equity weights and change in notional exposure (cash).

A potential explanation for the difference in fund performance is that the equity holdings of amplifying

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

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

funds perform worse than nonusers. We test and rule out this explanation. Appendix Table A1 shows the factor loading and alpha of hypothetical equity returns, assuming equity positions are held throughout the quarter. Amplifying funds have the same hypothetical market beta, and they perform similarly to nonusers. Our results suggest that the difference in ex-post performance is due to their different strategies of derivative use and active equity trading.

One may be concerned whether factor regressions can correctly measure the performance of derivative users, as certain contracts, such as options, have non-linear payoffs. First of all, amplifying funds mainly invest in futures and swaps that have linear payoffs, and they hold very few options. Second, we also test whether amplifying funds have lower value-added than nonusers, following Berk and Van Binsbergen (2015). The value-added measure is constructed using a set of tradeable Vanguard index funds instead of factors. Amplifying funds underperform nonusers in terms of value-added by $0.16 million per month.

Hedging funds, on the other hand, have similar risk-adjusted returns to nonusers, a lower market beta than nonusers suggesting they use derivatives to hedge against market risk, and have similar value-added as nonusers.

3.3.2 Amplifying Funds Receive More Flows

Having documented amplifying funds' underperformance, we next examine 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 8.

First, token users receive similar flows to nonusers, as shown by the insignificant coefficient estimates of token user dummy in columns (1) to (3). Second, 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, institutional, or both share classes, we estimate regressions on the share-class level in columns (4)-(6) of Table 8. We find that amplifying funds receive more flows than nonusers within institutional share classes, but statistically indistinguishable flows to nonusers within retail share classes.[25] Similar to

[25] We also examine whether different types of funds have differential flow-performance sensitivity (FPS), in untabulated

the previous section, we also repeat our analyses using CRSP holding-based classification of derivative users, and the results are qualitatively similar and shown in columns (7) to (12).

The abnormal flow to amplifying funds is puzzling, given that they significantly underperform nonusers after adjusting for common risk factors. An explanation could be that amplifying funds are concentrated in very different style categories from nonusers. To rule out this explanation, we tabulate the relative frequency of the Lipper style category for derivative users and nonusers in Panel A of Appendix Table A3, and amplifying funds do not differ from nonusers in style distribution. Hedging funds, in contrast, have more long/short equity funds, which is consistent with their short derivative positions. In Panel B, we match each derivative user to nonusers using propensity score matching and estimate the flow regression. Funds are matched by total net assets, expense ratio, turnover ratio, and past year performance in each year and Lipper style category. The regression results are qualitatively similar to Table 8.

Another 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 (2022), we construct the 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: they have a lower maximum daily return measure than nonusers. We also construct the maximum daily hypothetical return based on their reported equity holding. The rationale for this measure is that investors may react to lottery stocks reported in their holdings. We find that amplifying funds also have a 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.

Lastly, investors may react to attention-grabbing keywords related to derivatives in the prospectus, which can explain the abnormal flows. 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 analyses.[26] We find that 21.2% of derivative users 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

results. Although non-token funds on aggregate have similar FPS to nonusers, amplifying (hedging) funds have higher (lower) FPS than nonusers.

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

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 contains risk-related keywords or speculation-related keywords.[27] 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. Furthermore, given the low frequency of mentions of speculative related keywords, it is unlikely they are the catalyst for amplifier funds receiving more flows than nonusers.

Given that we classify derivative users into amplifying and hedging funds using recent derivative performance data, one might be concerned whether our classification might capture something else back in 2010 either due to changes in the fund universe (entry or exit) or changes in fund strategies, which could drive our findings of fund performance and flows. To alleviate the concern, we further check the robustness of the performance and flow difference between amplifying funds and nonusers using two alternative time windows that are close to the window we use to classify funds: 2017 - 2019, and 2015 - 2019. Our classification will be more accurate in recent time windows. The results are reported in Table A2. In both alternative time windows, amplifying funds significantly underperform nonusers by more than 84 (about 50) bps per year measured by CAPM (Fama-French five-factor) alpha, the magnitude of which is even higher (very comparable) than the one documented in Table 7. Moreover, despite the underperformance, amplifying funds receive more flows than nonusers in both time windows, consistent with our finding in Table 8.

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, one could hypothesize,

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

following the argument in Glode (2011), that amplifying funds underperform in normal times because their strategy is 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 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 hypothesis. We undertake this 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 with 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 the 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.[28] 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 reduce their trading activity.

On the other hand, derivative positions allow funds to take short positions, which is especially important in downturns because funds' equity holdings are predominantly long positions. Such flexibility

[28]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.

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 9 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. Column (1) shows that the absolute derivative weight increased by 1.22%, from 1.39% in pre-crisis to 2.61% during the outbreak, a relative increase of 88%. Moreover, the increased derivative use was driven by funds increasing their bets on short positions. On a relative scale, the weight on short derivative positions increased by 108%, almost doubling the 76% increase in long positions. When we measure derivative use by notional exposure, short notional exposure increased by 4.65%; an increase of 129% 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 a high level of 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 Derivative Performance During the Crisis

4.2.1 Distribution of *DIR*

Having identified increased derivative use during the COVID-19 outbreak, a natural follow-up is to investigate how funds' derivative positions perform and how they contribute to funds' returns. 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 4 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 in 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. As is shown in Figure 7(b), the dispersion in portfolio weights of short derivative positions increases significantly during the crisis. 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 smaller 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 4 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.[29] 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 a 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 the major equity index, a negative PnL suggests that they were late to trade and lost on short derivative positions when the market unexpectedly rebounded. Moreover, amplifying funds barely changed their long derivative positions during the outbreak, which rules out the explanation that they simply increased short positions to reduce equity exposure. The evidence we find suggests that amplifying funds might have tried to exploit the market crash but got hit by the unexpected Fed intervention and market rebound.

4.2.2 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 due to active derivative trading, hypothetical equity holding returns, and returns stemming from active equity trading. The sum of the first two components is *DIR*, and the sum of the latter two components is *non-DIR*.

To examine the active trading and holding components of monthly *DIR*, we hand-collect security returns for each derivative position using security names provided in Form N-PORT. For each fund, similar to hypothetical equity holding return, we create its hypothetical *DIR*, assuming derivative positions are held throughout the following quarter. Specifically, hypothetical *DIR* are the sum of products between

[29] The histograms of *DIR* by derivative instruments are shown in Appendix Figure A4.

derivative return and its notional exposure. The return of active derivative trading is the difference between *DIR* and hypothetical *DIR*.

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, derivatives 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.

For the derivative part, 77% (-74.1/(-96.3)) of the difference in *DIR* between amplifying and hedging funds stemmed from their derivative holding differences, whereas there was no significant return difference in active derivative trading. In contrast, for the equity part the key driver of the differences was active equity trading, with 94% (-308.6/(-326.3)) of the return difference due to the difference in their active equity trading. It could be that hedging funds' derivative positions in place provided insurance against a market crash and facilitated better execution of equities, as these funds can be more patient and engage less in fire sales than amplifying funds or nonusers.

Panel B shows the decomposition for the recovery period. 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, further challenging the hypothesis that they perform better around crisis periods. Hedging funds took losses from derivative positions (-0.64%) and active equity trading (-2.09%), consistent with their hedging strategy.

4.2.3 Fund Performance

One caveat of the previous analysis in Section 4.2.2 is that we only have monthly-level *DIR*, which does not facilitate an estimation of risk-adjusted returns; an estimation that would require a longer sample. To complement the analysis, in this section, we examine their risk-adjusted performance.[30]

[30] Risk-adjusted performance is estimated using a one-year rolling window. For each fund at date t, we regress its net returns in excess of risk-free rate on either market excess returns or FF5-factor returns in the past year between $t-252$ and

Figure 5 shows the cumulative performance of funds starting from the beginning of the crisis. During the outbreak period, amplifying funds performed very similarly to nonusers, losing almost 35% in returns and 5% in risk-adjusted alphas. The fact that mutual funds as a group earned negative alpha during the outbreak is also documented in Pástor and Vorsatz (2020). One potential explanation is that they lost to other institutions, such as hedge funds.

Amplifying funds underperformed nonusers by the CAPM and FF5 models in the first half of the 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 outperformance 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 as 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.[31]

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, consistent with our previous finding of underperformance in normal times using a longer historical window. Similar to Figure 5, the evidence of their performance in the outbreak is mixed. They significantly underperformed in benchmark-adjusted return, did not differ in either return

$t-1$, estimate the factor loading, and predict the alpha at date t. The results are very similar and available upon request if we add lags of factor returns in the estimation, following Lewellen and Nagel (2006).

[31] In the appendix, we zoom in on heavy derivative users and examine their performance (Table A7 and Figure A5, and the results are qualitatively similar.).

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. Importantly, 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 A6, 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, it is important to keep in mind that swaps and futures, which are the majority of derivatives used by funds, have a linear payoff structure. Although options have a 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 5 shows the cumulative alpha since the beginning of the crisis. Amplifying funds perform similarly to nonusers, casting further doubt on the hypothesis that their underperformance in normal times is compensated by superior performance in times of 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 the 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 the crisis.

4.2.4 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 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 errors.

The regression results are shown in Table 13. First, we show that both amplifying funds and hedging funds have lower tracking errors 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.[32] 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 similarly to nonusers in pre-crisis period, which can be seen from the insignificant coefficient estimate of "Hedge" dummy in column (2). During the crash, their 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 holdings behave similarly to their benchmark in normal times but very differently during the crisis.

Although most interaction terms between fund type dummies and crash/recovery dummies are negative and significant in column (3), suggesting derivatives may further reduce tracking error during the crisis, this result could be driven mechanically 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 there was no additional reduction in tracking error during the 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 6 focuses on the daily rolling tracking error, which allows us to examine the difference among

[32]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.

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 wedges in Panels (a) and (b).[33] On 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 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 Discussion on Derivative Use

5.1 Reverse Causality: Do Flows Affect Derivative Use?

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. Does derivative use attract flows, or do flows induce derivative use? 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 the benchmark during the crisis, which is a necessary but not a sufficient condition for superior performance. Due to the

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

Fed's unanticipated intervention and sharp market rebound, these funds failed to deliver superior performance on the realized price path. Alternatively, there could be a reverse causality explanation through a flow-management channel.[34] 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 (Frino et al. (2009)).

To test which of these two explanations holds 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, which captures the increased or decreased deviation of a fund from its benchmark. Tracking error is calculated as the annualized 30-day rolling standard deviation of return difference between a fund and its benchmark. If institutional investors indeed provide extra flows in normal times to amplifying funds that will shift their strategy during a crisis, then we should expect only the funds in the high change-in-tracking-error (CTE) group to be the ones that experienced abnormally high flows to begin with. If, on the other hand, the result is driven by the flow-management explanation, then both high and low CTE funds would have received abnormally high flows in the pre-crisis period.

We first show that amplifying funds in the high change-in-tracking-error (CTE) group received abnormally higher institutional flows than nonusers in the past decade, and amplifying funds in the low CTE group did not. The result is shown in Panel A of Table 14. The regression model is exactly the same as the one in columns (4) to (6) of Table 8, 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 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 that significantly increased short notional exposure during the crash. As shown in Panel B of Table 14, their short notional exposure increased by

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

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%).[35] 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 derivative strategies during the crash by increasing short notional exposure, but such a shift did not yield superior performance on the realized price path exhibited during the pandemic due to the unexpected FED announcement that likely led to the quick market rebound.

5.2 Alternative Reasons for Derivative Use

In this section, we briefly discuss several alternative reasons for derivative use by these equity mutual funds. The first is the cash equitization channel proposed by Frino et al. (2009), who use data from Australia and find funds using index futures perform better than nonusers when there are significant fund flows and perform similarly to nonusers otherwise. Although we do find most amplifying funds simply invest in index futures or swaps, the cash equitization channel is unlikely to explain our finding, as we also find amplifying funds underperform both in normal times and in crisis, which is in contrast to Frino et al. (2009) model's prediction that they should weakly outperform. The cash equitization channel will also predict that, in the time series, a fund's derivative use correlates with the flows. To test this channel, we regress quarterly fund flows on the number of derivative contracts from the CRSP data and control for fund fixed-effects and time fixed-effects. The coefficient estimate on the number of derivatives is insignificant, which does not support the cash equitization channel.

Second, funds may use derivatives to circumvent short-selling constraints. Using funds' most recent N-SAR data, we identify whether a fund is permitted to short-sell stocks and whether it engages in short-

[35] In untabulated results, we also find that high and low CTE amplifying funds have similar characteristics, such as expense ratio, turnover ratio, and fund size. They also have very similar performance and factor exposures in the past decade.

selling. The fraction of funds permitting short-selling is quite high, as 74.5% (83%) of nonusers (users) in our data were permitted to short-sell stocks. Consistent with the dominant role of long positions in amplifying funds' derivative positions, their likelihood to engage in short-selling is fairly low and similar to that of nonusers. Specifically, 8.5% of amplifying funds and 7% of nonusers engage in short-selling. Therefore, circumventing short-selling constraints is unlikely a central reason for amplifying funds' derivative use. Hedging funds' likelihood to engage in short-selling of stocks is higher, at 16.7%. Furthermore, among funds that do not permit short-selling, only 15% of them are derivative users, which is lower than 26%, the unconditional fraction of derivative users in the sample.

Third, funds may use derivatives to gain exposure to risks that cannot be easily achieved using equities. For example, funds may purchase VIX futures if they want to hedge against a volatile market, or purchase CDS to hedge against firms' credit risks. They could also purchase commodity contracts to gain exposure to commodity markets. We find that these three alternative channels combined represent only around 9.6% of derivative positions, and as such are unlikely to play an important role in explaining the amplifying funds' results that we uncover.

Fourth, funds may use derivatives to arbitrage mispricing of individual securities, for example, violations of put-call parity. This channel is unlikely to be of first-order importance for amplifying funds, as only 0.6% of their derivative positions are single stock derivatives. Hedging funds, on the contrary, invest 31.4% of their positions in single stock derivatives. We further use derivative names to match with underlying security names, and find that around 35% of single stock derivatives of hedging funds have underlying stocks directly held by the fund.

Fifth, funds may use derivatives to time the market. Using the Principal Investment Strategy section from the fund prospectus, we find that only 0.8% of funds mention either "*market timing*" or "*time the market*". When we manually check those mentions, most funds advertise that they do not attempt to time the market. One could argue that funds may not walk their talk, but formally testing this hypothesis requires more high-frequency data on derivative holdings, which can be explored by future research.

Lastly, funds may use futures contracts for tax benefits. In the US, futures contracts are subject to the 60/40 rule. That is, 60% of profits are taxed as a long-term capital gain rate, while 40% of the gains are subject to a short-term rate. This is likely one of the reasons futures are heavily used among equity funds, as the majority of futures contracts in our sample have a 3-month maturity date so that futures users benefit from the tax perspective. However, the tax benefit channel would predict that derivative users, especially amplifying funds, should slightly outperform nonusers, which is different from our finding that amplifying funds underperform nonusers.

Overall, our finding suggests that most derivative users in our sample purchase equity index futures and swaps to gain market exposure, which is different from the hedging motives documented in prior studies. Such a strategy cannot simply be explained by cash-equitization or tax motives, as those two motives would predict these funds would outperform rather than underperform nonusers. One potential explanation is that amplifying funds dynamically adjust their exposure, trying to profit from market timing. This channel is also consistent with our finding during the COVID-19 crisis, where amplifying funds bet significantly on the opposite side of the market by opening short derivative positions.

6 Salience in Derivative Use During the Crisis

Section 4.1 shows an increase in derivative use associated with the Covid-19 outbreak. In this section, we explore cross-sectional variation in derivative use during the initial outbreak. We hypothesize that the change in derivative use was likely to be greater for fund managers who faced a more salient risk of recession. We explore three potential channels of variation in risk related to the pandemic. The first, staggered Stay-at-home orders implemented at the state level. The second, pre-crisis concentration in funds' industry holdings and differential exposure of industries to the pandemic crisis. For example, the airline industry was more severely hit by COVID-19 disruptions than the utility industry. The third, pre-crisis concentration in funds' equity holdings of firms with headquarters in outbreak areas.

6.1 Stay-at-home Order

As the number of COVID-19 cases rose in the US, many states imposed state-level Stay-at-home Order (SAH) to reduce COVID-19 spread. The staggering SAH introduction at the state level allows us to test, in the cross-section, how the pandemic influenced funds' trading strategies on derivative positions. By the end of March, 25 states implemented SAH in place, and 11 states did not.[36] 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 7 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 7, 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 reveals 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) 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 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) shows how derivative notional exposure changes quarter-by-quarter. The top (bottom) row

[36] We only study states with at least one mutual fund. Figure A7 shows a map of states with SAH status by March 31, 2020.

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 there was no response for non-SAH funds. The first column of Panel A in Table 15 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 15, SAH funds reduced short notional exposure by only 2.68% in the recovery phase, compared with an increase of 6.55% in the outbreak phase.

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

Figure A3 shows the 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.[37]

[37]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 4.2.

6.2 Fund-level COVID-19 Exposure

Funds equity holdings' exposure to the pandemic may also impact funds' derivative trading decisions. We explore variations in equity exposure through two channels. The first is funds' concentration of industry holdings. As the nationwide business activities started to shrink, certain industries, such as the airline industry, experienced larger shocks than others. Our identification takes advantage of the ex-ante fund-level industry concentration. We use the Fama-French 30-industry classification and returns. For each industry, we measure the CAPM-adjusted 10-day cumulative abnormal returns starting from February 20, the beginning of the market crash. For each fund i, we then use its latest equity holdings before February 2020 to construct the following variable, $\textit{Industry Exposure}_i$,

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

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. There was a significant increase in short notional exposure by 5.3% among funds in high COVID industry-exposure group, but no changes for low exposure funds, which is shown in Panel A of Table 15.

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

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

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

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

where $w_{s,i}$ is the portfolio weight of firm s in fund i, and $severity_s$ is the number of cases per population of the state where firm s is headquartered. The greater the measure $HQ\ Exposure_i$ is, the more exposed fund i's ex-ante holdings could be to the pandemic. However, we find no evidence that fund managers reacted to *HQ Exposure*. One explanation could be that headquarter may not necessarily capture locations of business activity.

7 Conclusion

Research on derivative use by mutual funds and the impact of derivative trades on funds' performance has been hampered by the lack of sufficiently granular data. Taking advantage of data that has become available only recently, we are able to shed new light on questions that were hard to evaluate earlier and overturn some prior conclusions.

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 between derivative users and nonusers. Our analysis starts by showing 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. In contrast, and somewhat surprisingly, Non-token users underperform nonusers.

Importantly, our data allow us to estimate funds' derivative performance, so that we can test how derivative positions correlate and contribute to funds' overall return; the main focus of our paper. 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. In normal times, these amplifying funds significantly underperform nonusers while having similar market beta, but receive abnormally high flows stemming mostly from institutional investors.

Utilizing the COVID-19 pandemic as an exogenous shock to the 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, 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 holdings behave similarly to the benchmark in normal times but differently during the crisis. Having short derivative positions in place as protection against the market crash, hedging funds significantly reduced 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 in non-crisis times and fail to outperform in the crisis period. Nevertheless, they receive more flows than nonusers. As a result, fund managers benefit at the expense of investors.

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 past interim 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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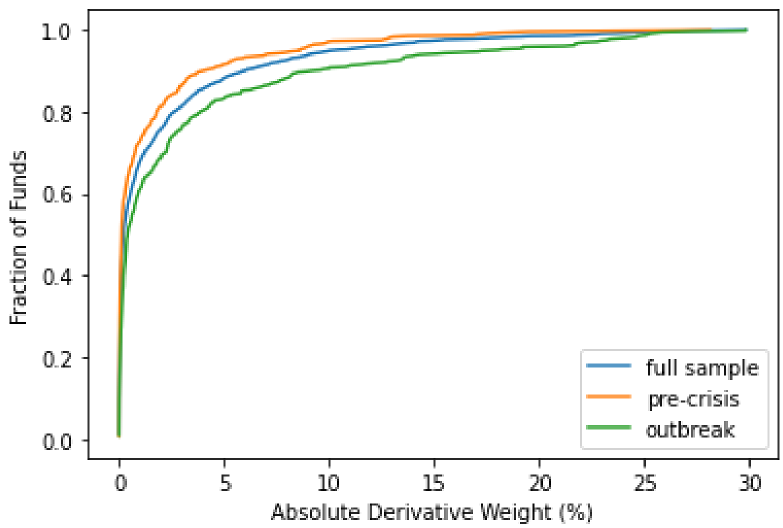
Figure 1
The Extent of Derivative Use
The figure shows the cumulative distribution functions of the fund-level derivative use. The extent of derivative use is proxied by absolute derivative weight in Panel (a), and by gross notional exposure in Panel (b). The absolute derivative weight is the sum of the absolute value of portfolio weights of all derivative positions for a fund. The gross notional exposure is the sum of notional amount of derivative positions scaled by the fund's total net assets. The numbers on the 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

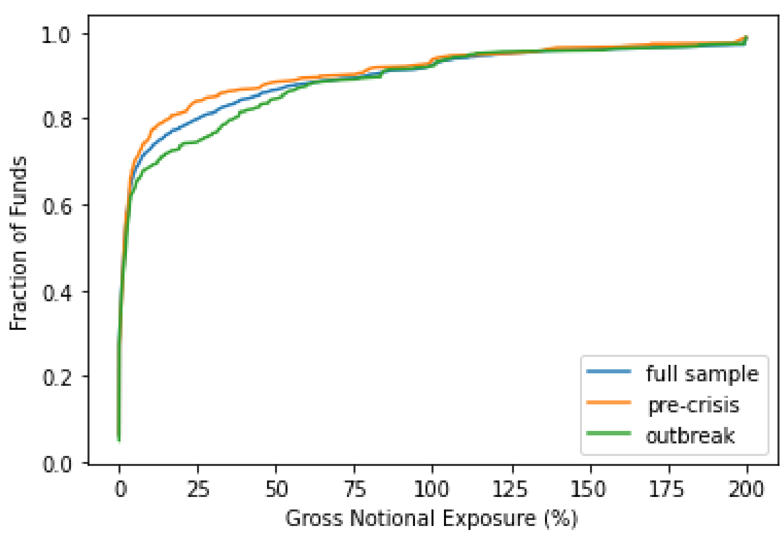
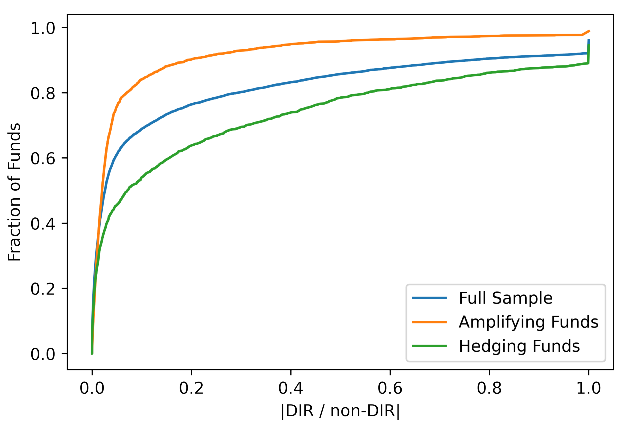


Figure 2

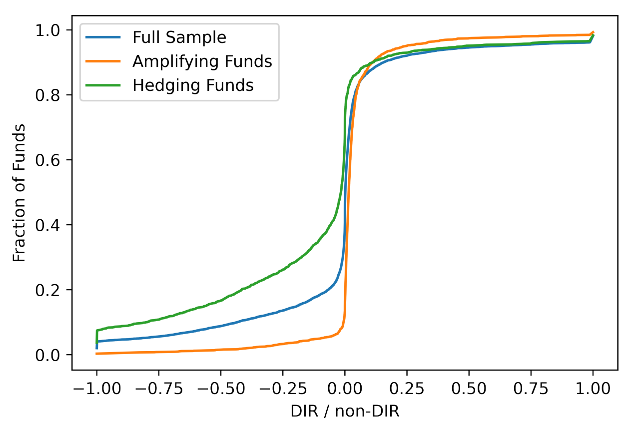
Derivative Contribution to Fund Return

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 the 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.

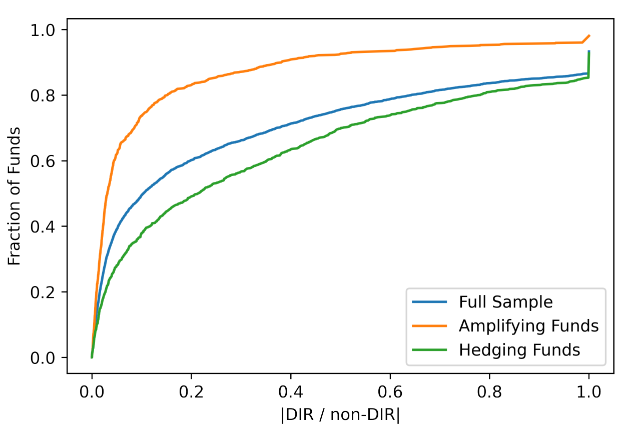
(a) Derivative Relative Contribution for All Funds



(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

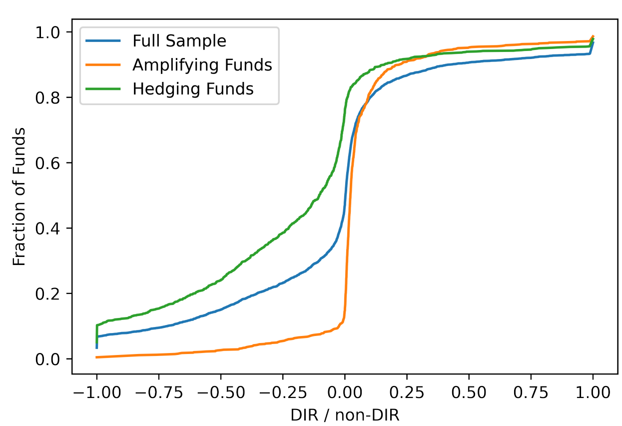
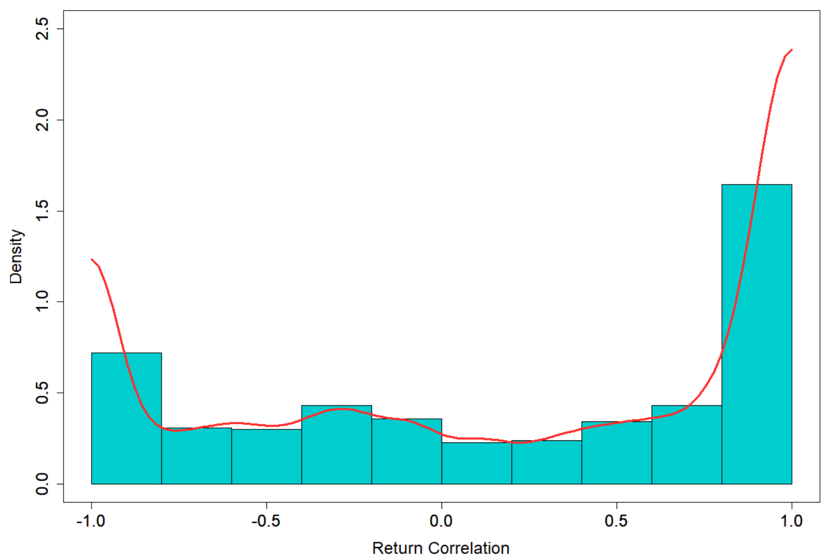


Figure 3

Distributions of Amplifying and Hedging Funds

The figure shows the histogram and fitted kernel of the correlation between *DIR* and *non-DIR* in panel (a), and the net position in panel (b). *DIR* in month t is calculated as the sum of realized PnL and change of unrealized PnL in month t, normalized by the fund total net assets in month $t-1$. *Non-DIR* is the difference between the fund return and *DIR*. The correlation is calculated based on the availability of N-PORT data between July 2019 and January 2020. Net position is calculated as the average of long and short positions of a fund in a year between 2010 and 2019, where a long (short) position receives a value of 1 (-1).

(a) Histogram of Return Correlation



(b) Histogram of Net Position

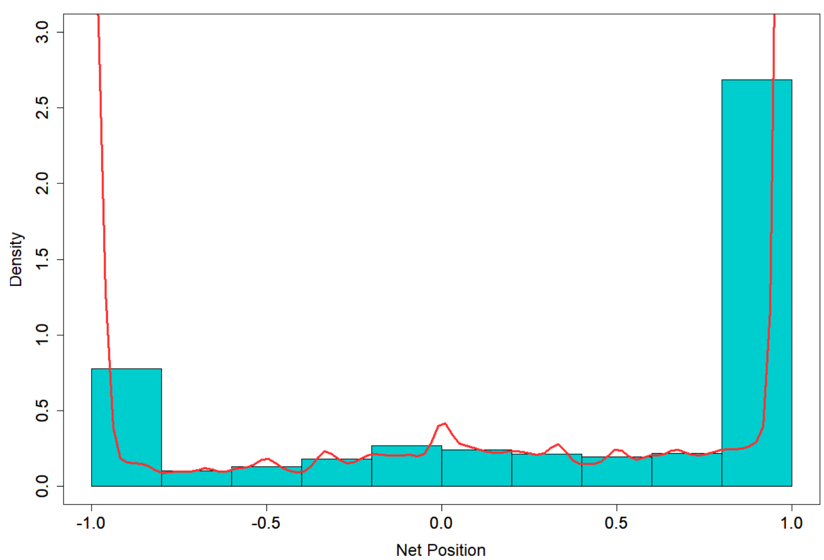
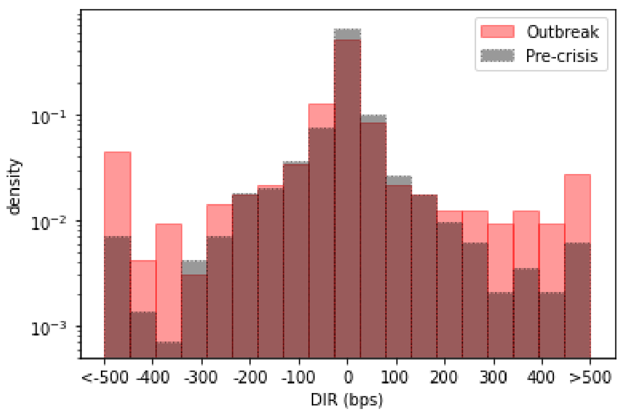


Figure 4

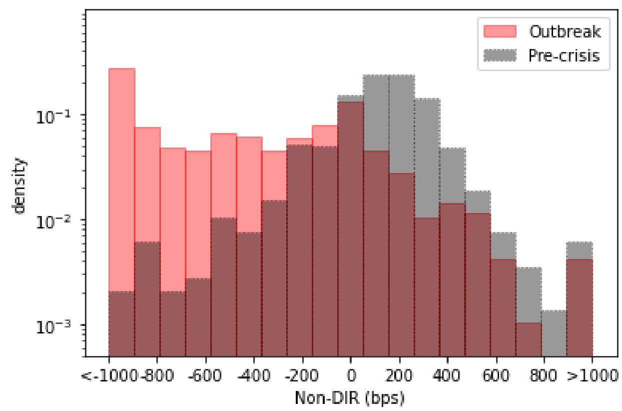
Distribution of *DIR* in Crisis

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 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. The outbreak period is defined as February 2020 and March 2020. The pre-crisis period is between July 2019 and January 2020. The y-axis is in the log-scale.

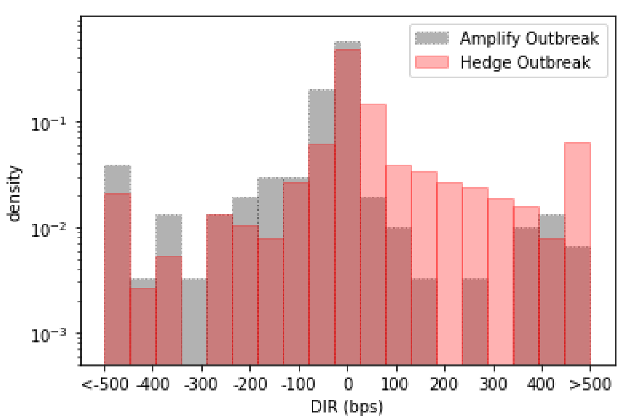
(a) *DIR*



(b) *Non-DIR*



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



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

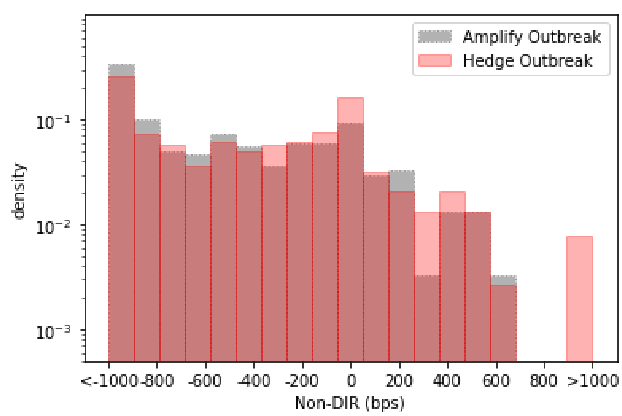
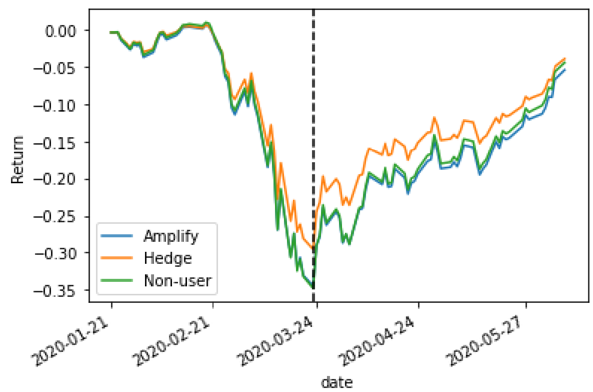


Figure 5

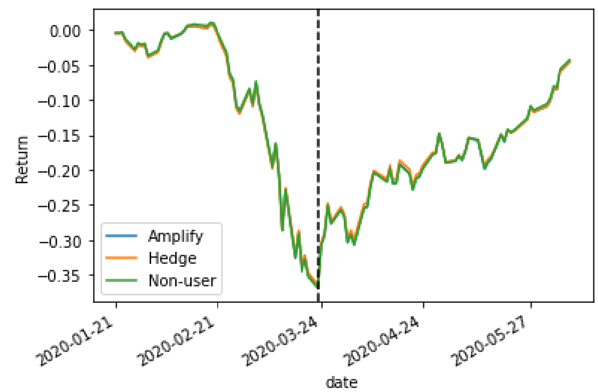
Fund Performance in COVID-19 Pandemic

The figure shows the cumulative returns and alphas for funds starting from the outbreak on January 20, 2020. Nonusers are 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).

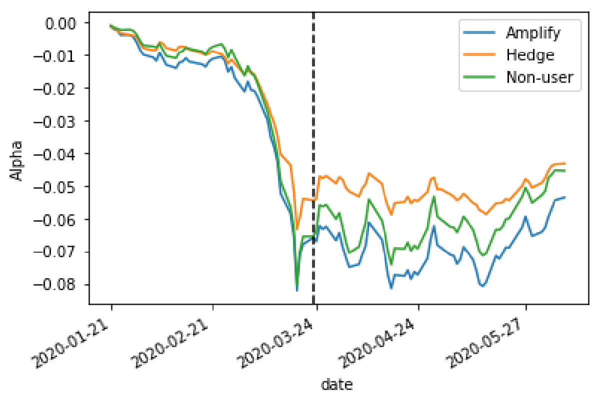
(a) Return



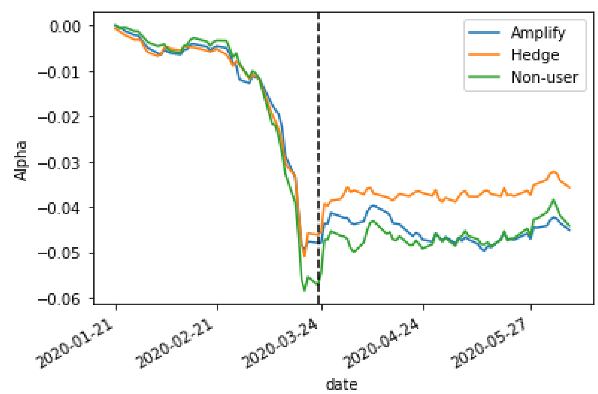
(b) Hypothetical Return



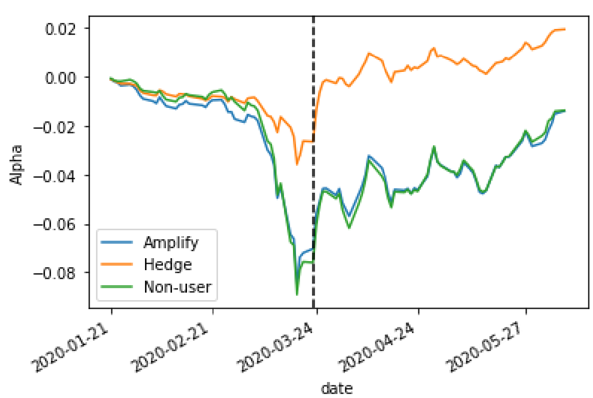
(c) CAPM Alpha



(d) FF5 Alpha



(e) Down-market Alpha



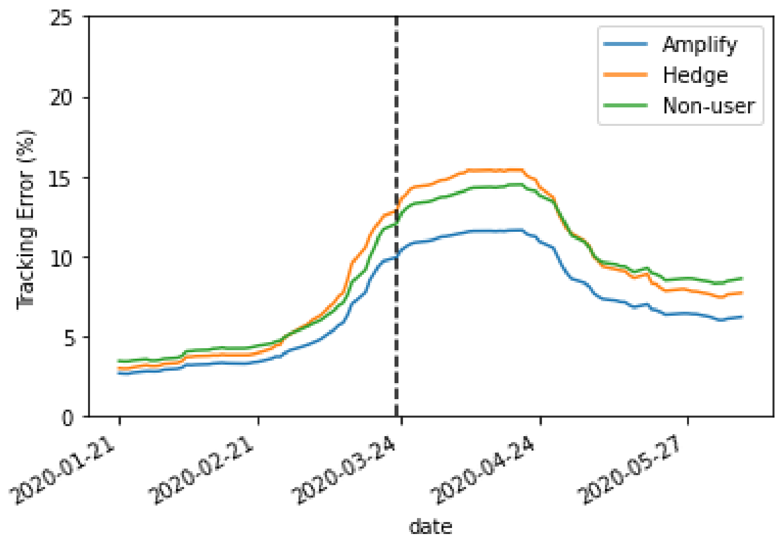
(f) Hypothetical Down-market Alpha

Figure 6

Tracking Error in COVID-19 Pandemic

The figure shows funds' tracking error starting from the COVID-19 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 errors. 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

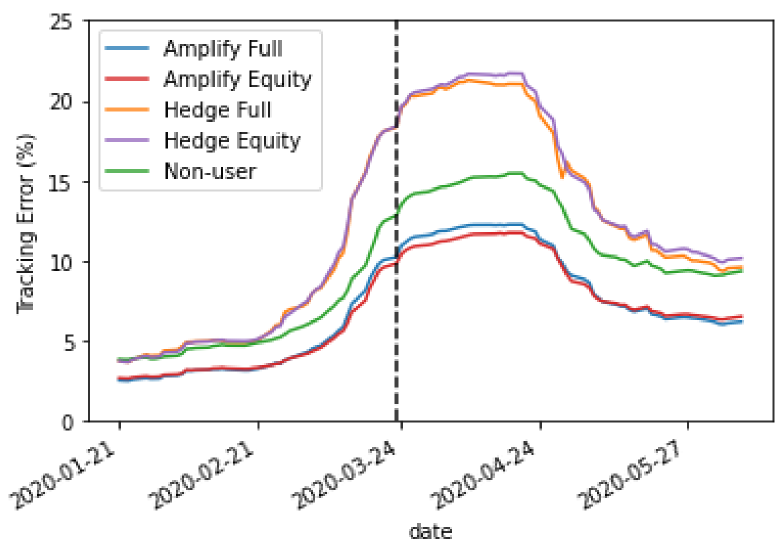
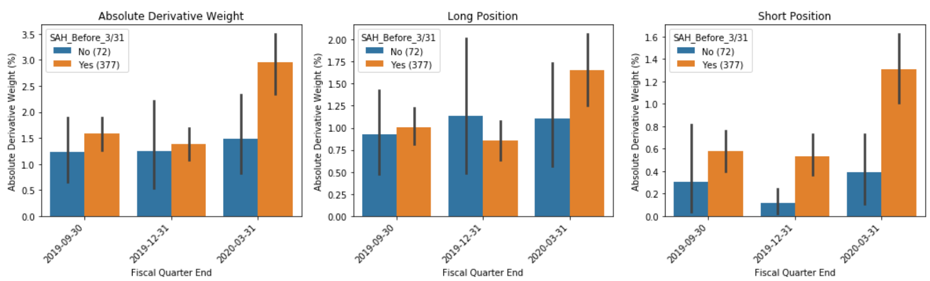


Figure 7

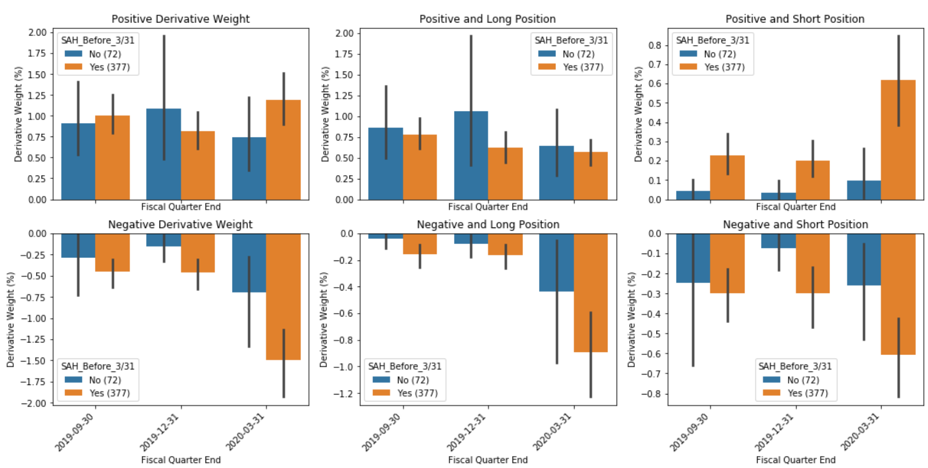
Derivative Use and Stay-at-home Orders

The figure shows funds' derivative use before and during the COVID-19 pandemic. The sample includes funds that report holdings in September 2019, December 2019, and March 2020. The orange (blue) bars show the average derivative use of funds residing in states with (without) the Stay-at-home order in place before the end of March 2020. The solid black lines represent the corresponding 95% confidence interval. The number in the parenthesis shows the number of funds in each group. Panel (a) shows the 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

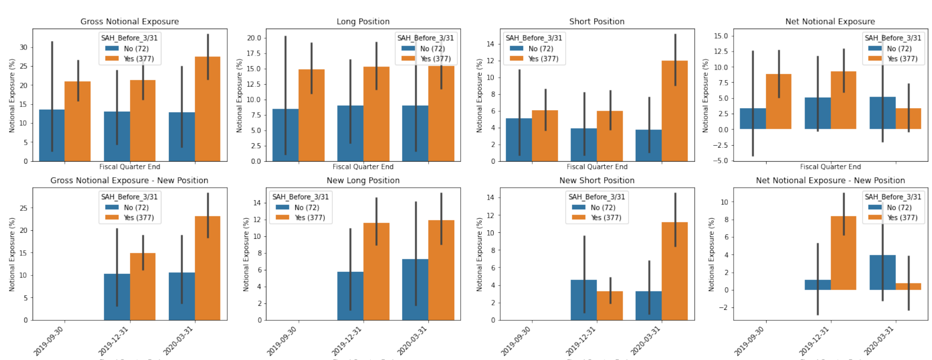


Table 1

Overview of Derivative Use

The table shows the summary of derivative use. The sample includes all actively managed domestic equity funds that use derivatives from September 2019 to 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's total net assets (TNA) and shown in percentage points. TNA is the total net assets in million dollars. 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 the fund-level derivative weight (Panel A) and gross notional exposure (Panel B), grouped by the extent of derivative use. 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	Non-token Users 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	Non-token Users 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

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

Table 3
Types of Derivatives by Amplifying/Hedging Funds
The table shows fund-level derivative usage, grouped by whether the fund uses derivatives for amplifying or hedging. 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	Hedge
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	Hedge
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 Using CRSP Holdings

The table shows the performance of derivative users between 2010 and 2019. Derivative users and their extent of derivative use are identified every year using CRSP holdings in the previous year. 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

		Benchmark	CAPM		FF5					
Users	Return	Adjusted	Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	CMA
Nonusers	10.48**	-2.16***	-2.04***	0.99***	-1.32***	0.94***	0.16***	-0.01	-0.05*	-0.06*
	(2.23)	(-6.75)	(-3.18)	(66.43)	(-3.05)	(86.26)	(9.28)	(-0.65)	(-1.76)	(-1.69)
Users	9.04**	-4.32***	-2.64***	0.91***	-1.80**	0.86***	0.14***	-0.05	-0.14***	-0.04
	(2.03)	(-9.99)	(-3.09)	(46.56)	(-2.56)	(50.24)	(5.12)	(-1.44)	(-3.27)	(-0.84)
Users - Nonusers	-1.44***	-2.16***	-0.60	-0.08***	-0.48	-0.08***	-0.02	-0.04*	-0.09***	0.02
	(-2.74)	(-8.98)	(-1.32)	(-7.03)	(-1.01)	(-7.26)	(-1.27)	(-1.71)	(-3.49)	(0.31)

Panel B: By Derivative Usage

		Benchmark	CAPM		FF5					
Users	Return	Adjusted	Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	CMA
Nonusers	10.48**	-2.16***	-2.04***	0.99***	-1.32***	0.94***	0.16***	-0.01	-0.05*	-0.06*
	(2.23)	(-6.75)	(-3.18)	(66.43)	(-3.05)	(86.26)	(9.28)	(-0.65)	(-1.76)	(-1.69)
Token Users	9.64**	-4.44***	-2.64**	0.96***	-1.56**	0.89***	0.17***	-0.08**	-0.17***	-0.06
	(2.06)	(-8.45)	(-2.6)	(41.82)	(-2.03)	(47.67)	(5.76)	(-2.08)	(-3.82)	(-1.05)
Medium Users	9.52**	-3.00***	-1.92***	0.90***	-1.44***	0.86***	0.12***	-0.02	-0.03	0.00
	(2.21)	(-8.55)	(-3.28)	(65.75)	(-2.93)	(69.84)	(6.23)	(-0.93)	(-0.87)	(0.11)
Heavy Users	5.68	-6.72***	-4.08***	0.74***	-3.24***	0.70***	0.05	0.02	-0.17***	-0.08
	(1.41)	(-13.02)	(-3.72)	(29.87)	(-3.07)	(26.74)	(1.06)	(0.43)	(-2.71)	(-0.96)
NonToken - Nonusers	-2.16***	-1.92***	-0.60*	-0.13***	-0.72*	-0.12***	-0.07***	0.00	-0.03	0.03
	(-3.12)	(-8.14)	(-1.74)	(-14.36)	(-1.92)	(-12.4)	(-4.28)	(0.17)	(-1.16)	(1.16)
Heavy - Nonusers	-4.80***	-4.56***	-2.04**	-0.25***	-1.92**	-0.24***	-0.11***	0.03	-0.12***	-0.02
	(-3.73)	(-10.54)	(-2.43)	(-12.82)	(-2.44)	(-11.75)	(-3.73)	(0.93)	(-2.64)	(-0.4)

Panel C: Hypothetical Equity Returns

		CAPM		FF5					
Users	Return	Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	CMA
Nonusers	11.52**	-0.96	1.06***	-0.12	1.01***	0.20***	-0.01	-0.04	-0.05*
	(2.51)	(-1.37)	(66.34)	(-0.29)	(97.91)	(11.81)	(-0.69)	(-1.57)	(-1.71)
Token Users	10.80**	-1.56	1.06***	-0.48	0.98***	0.22***	-0.08**	-0.15***	-0.04
	(2.33)	(-1.56)	(44.5)	(-0.62)	(54.33)	(7.62)	(-2.25)	(-3.31)	(-0.7)
Medium Users	11.40**	-0.72	1.04***	-0.12	0.99***	0.17***	-0.01	-0.01	-0.01
	(2.56)	(-1.12)	(71.78)	(-0.16)	(89.6)	(9.3)	(-0.64)	(-0.42)	(-0.21)
Heavy Users	9.84**	-2.16**	1.02***	-1.44	0.97***	0.11***	0.01	-0.08	-0.06
	(2.22)	(-2.33)	(49.04)	(-1.66)	(46.0)	(3.18)	(0.16)	(-1.62)	(-0.96)
Non-token - Nonusers	-0.48	-0.12	-0.03***	-0.36	-0.02*	-0.05***	0.01	0.01	0.03
	(-1.44)	(-0.47)	(-3.71)	(-1.02)	(-1.9)	(-3.33)	(0.32)	(0.27)	(1.05)
Heavy - Nonusers	-1.68**	-1.20*	-0.04***	-1.32*	-0.04*	-0.09***	0.02	-0.04	-0.01
	(-2.5)	(-1.69)	(-2.97)	(-1.92)	(-1.88)	(-3.31)	(0.65)	(-1.09)	(-0.23)

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

Table 6
Performance of Derivative Users Using N-PORT Holding

The table shows the performance of derivative users between 2010 and 2019. We backfill the derivative use data for periods before September 2019 using the fund's derivative use data from N-PORT 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 Adjusted	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 Adjusted	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 7
Performance of Amplifying/Hedging Funds

The table shows the performance of amplifying and hedging funds between 2010 and 2019. Panel A uses the return-correlation-based classification from N-PORT data. Panel B uses holding-based classification from CRSP data. All returns and alphas are annualized and in percentage points.

Panel A: Return-correlation-based classification

Users	Return	Benchmark Adjusted	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 - 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 - Hedge	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)
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: Holding-based classification

Users	Return	Benchmark Adjusted	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Nonusers	10.48**	-2.16***	-2.04***	0.99***	-1.32***	0.94***	0.16***	-0.01	-0.05*	-0.06*
	(2.23)	(-6.75)	(-3.18)	(66.43)	(-3.05)	(86.26)	(9.28)	(-0.65)	(-1.76)	(-1.69)
Amplify	9.88**	-4.44***	-2.88***	1.00***	-1.80**	0.93***	0.23***	-0.04	-0.11**	-0.07
	(2.01)	(-9.93)	(-2.93)	(43.53)	(-2.58)	(53.11)	(8.2)	(-1.16)	(-2.53)	(-1.4)
Hedge	7.96**	-3.96***	-1.92***	0.76***	-1.44**	0.73***	0.01	-0.02	-0.14***	-0.01
	(2.1)	(-7.87)	(-2.78)	(47.11)	(-2.2)	(43.29)	(0.35)	(-0.63)	(-3.26)	(-0.18)
Hedge - Nonusers	-2.52**	-1.80***	0.12	-0.23***	-0.12	-0.21***	-0.15***	-0.01	-0.09***	0.05
	(-2.3)	(-4.8)	(0.24)	(-18.01)	(-0.39)	(-19.36)	(-9.23)	(-0.37)	(-3.45)	(1.41)
Amplify - Hedge	1.92	-0.48	-0.96*	0.24***	-0.36	0.20***	0.22***	-0.02	0.03	-0.06
	(1.46)	(-0.94)	(-1.83)	(13.33)	(-0.53)	(13.4)	(9.51)	(-0.66)	(0.77)	(-1.48)
Amplify - Nonusers	-0.60	-2.28***	-0.84**	0.01*	-0.48*	-0.01	0.07***	-0.03	-0.06*	-0.01
	(-1.18)	(-7.95)	(-1.99)	(1.77)	(-1.85)	(-0.39)	(3.49)	(-1.08)	(-1.97)	(-0.56)

t statistics in parentheses

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

Table 8
Fund Flows

The table shows the monthly fund flows between 2010 and 2019. The dependent variable is the monthly fund net flows in percentage points. In columns (1) - (3), we regress net flows on fund types dummy, where we split derivative users into token users, non-token amplifying funds, neutral funds, and hedging funds. Flows to nonusers serve as the baseline. In columns (4) - (6), 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 types are classified by the N-PORT return correlation measure. In columns (7) to (12), we repeat the analysis but use CRSP holding-based measure. 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.

	Return-correlation-based Classification						Holding-based Classification					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Flow	Flow	Flow	Flow	Flow	Flow	Flow	Flow	Flow	Flow	Flow	Flow
Token	0.097	0.113	0.11	0.030	0.041	0.039	0.067	0.070	0.059	0.076	0.081	0.073
	(1.39)	(1.62)	(1.58)	(0.53)	(0.73)	(0.70)	(1.10)	(1.17)	(0.99)	(1.24)	(1.32)	(1.17)
AmplifyNonToken	0.400***	0.387***	0.377***	0.266***	0.258***	0.250***	0.307**	0.293**	0.267*	0.248**	0.232**	0.221**
	(2.85)	(2.74)	(2.67)	(2.83)	(2.75)	(2.67)	(2.10)	(1.99)	(1.82)	(2.41)	(2.30)	(2.19)
NeutralNonToken	0.302*	0.251	0.246	0.302***	0.263**	0.256**	0.083	0.068	0.054	0.051	0.032	0.025
	(1.87)	(1.57)	(1.54)	(2.84)	(2.51)	(2.42)	(0.60)	(0.50)	(0.40)	(0.51)	(0.33)	(0.26)
HedgeNonToken	-0.021	-0.024	-0.021	-0.060	-0.064	-0.061	0.022	0.037	0.036	0.033	0.036	0.037
	(-0.16)	(-0.19)	(-0.17)	(-0.53)	(-0.58)	(-0.55)	(0.27)	(0.46)	(0.45)	(0.50)	(0.56)	(0.58)
retail				-0.437***	-0.436***	-0.437***				-0.448***	-0.446***	-0.447***
				(-6.87)	(-6.80)	(-6.82)				(-7.25)	(-7.22)	(-7.25)
Token X retail				0.014	0.016	0.016				-0.114	-0.117	-0.118
				(0.24)	(0.26)	(0.26)				(-1.53)	(-1.57)	(-1.59)
AmplifyNonToken X retail				-0.173*	-0.181*	-0.176*				-0.303**	-0.293**	-0.294**
				(-1.69)	(-1.76)	(-1.71)				(-2.06)	(-1.99)	(-2.00)
NeutralNonToken X retail				-0.429***	-0.404***	-0.398***				-0.062	-0.049	-0.045
				(-3.18)	(-2.99)	(-2.93)				(-0.54)	(-0.43)	(-0.40)
HedgeNonToken X retail				-0.080	-0.069	-0.075				-0.126	-0.130	-0.134
				(-0.49)	(-0.42)	(-0.46)				(-1.07)	(-1.10)	(-1.14)
Level	Fund	Fund	Fund	Share	Share	Share	Fund	Fund	Fund	Share	Share	Share
Performance	Return	CAPM	FF5	Return	CAPM	FF5	Return	CAPM	FF5	Return	CAPM	FF5
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 9

Change in Portfolio Allocation during the COVID-19 Outbreak

The table shows the change in portfolio allocation of derivative users during the COVID-19 outbreak, 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 vehicles. 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*** (87.8%)	5.44* (38.4%)
Long Positions	0.68*** (76.4%)	0.32 (3.5%)
Short Positions	0.54*** (108.2%)	4.65*** (129.0%)

Panel B: Non-Derivative Positions

	Portfolio Weight
Equity	-1.67*** (-2.1%)
Debt	0.20 (2.9%)
STIV/Repo	1.07*** (14.6%)
Cash	0.66*** (35.1%)

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

Table 10

Change in Notional Exposure during the COVID-19 Outbreak

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***
Hedge	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 during the COVID-19 Pandemic

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 the 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
Hedge	58.6	-763.4	-704.8	-1135.4	372.0	22.7	35.9
Amplify - Hedge	-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
Hedge	-63.5	480.2	416.6	689.3	-209.1	-10.0	-53.5
Amplify - Hedge	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 daily fund 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 the 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
Amplify	-1.078*	0.204	-0.702**	-0.283	-1.219***	-0.079***	-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	0.078	1.748	-0.042
	(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	-0.085	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***	0.020	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	-0.084	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)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.084	0.060	0.139	0.092	0.087	0.052	0.203	0.000
N	976496	976496	976496	976496	897533	897533	897268	897268

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

Table 13
Tracking Error during the COVID-19 Pandemic

The table shows the monthly tracking error during the COVID-19 crisis. The dependent variables in columns (1)-(3) are funds' tracking error, hypothetical tracking error, and the difference between hypothetical and realized tracking error, all in annualized percentage points. The dependent variable in column (4) is the 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 the 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	-0.010
	(-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	-0.012
	(-2.75)	(-2.11)	(-1.60)	(-1.21)
Hedge × crash	1.131**	4.454***	-3.294***	-0.002
	(2.34)	(4.77)	(-3.43)	(-0.18)
Amplify × recovery	-1.800***	-1.640***	-0.656***	-0.023
	(-6.17)	(-4.67)	(-2.78)	(-1.55)
Hedge × recovery	-0.182	1.955***	-2.069***	-0.009
	(-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	0.059	0.088
N	48645	44720	44720	44720

t statistics in parentheses

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

Table 14
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 the recovery in 2020. We then sort amplifying funds into high and low CTE groups. Panel A shows the monthly fund flows between 2010 and 2019. The sample includes all derivative users and nonusers. The dependent variable is the monthly fund net flows in percentage points. We run regressions of monthly flows on the share-class level and interact the fund types dummy with the retail share class dummy. We only report the coefficient estimates of High (Low) CTE dummy and its interaction with the retail share-class in the table. The fund controls include past quarter performance, past quarter performance squared, expense ratio, turnover ratio, the natural logarithm of fund size, past-year return volatility, and lagged flows. Past quarter performance measures include fund returns, CAPM alpha, and FF5 alpha. We also include time fixed effects and fund style fixed effects. The standard errors are two-way clustered at fund and time levels. Panel B shows the notional exposure of 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) Flow	(2) Flow	(3) Flow
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	-0.052	-0.048	-0.046
	(-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)
Performance	Return	CAPM	FF5
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

Panel B: Notional Exposure

Group	Long Positions			Short Positions		
	2019/Q4	2020/Q1	Dif	2019/Q4	2020/Q1	Dif
High CTE	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 15
COVID Exposure and Change in Notional Exposure

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

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

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

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

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

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

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

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

Internet Appendix

A.1 CRSP Derivative Positions

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

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

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

A.2 Robustness Checks

In this section, we show the fund-level distribution of *net exposure ratio* in Figure A1, the distribution of derivative contribution in Figure A2 on a subsample where the denominator *non-DIR* is far away from zero, managers' reaction to SAH in neighboring states in Figure A3, histogram of *DIR* for each derivative instrument in figure A4, heavy users' performance and tracking error in Figures A5 and A6, and a map of SAH order in Figure A7.

Table A1 shows the hypothetical equity returns of derivative users. Table A2 replicates past performance and flows of derivative users using alternative time windows. Table A3 shows the distribution of Lipper style category and flows of derivative users using a propensity-score-matched sample. Tables A4 and A5 replicate past performance and flows of derivative users using *net exposure ratio* rather than return correlation. Tables A6, A7, and A8 present the performance comparison of heavy users during the pandemic.

Figure A1

Distribution of the Net Exposure Ratio

The figure shows the histogram of the net exposure ratio. For each fund, we sum up the net notional exposure and gross notional exposure between July 2019 and January 2020. The net exposure ratio is the ratio between net and gross notional exposure.

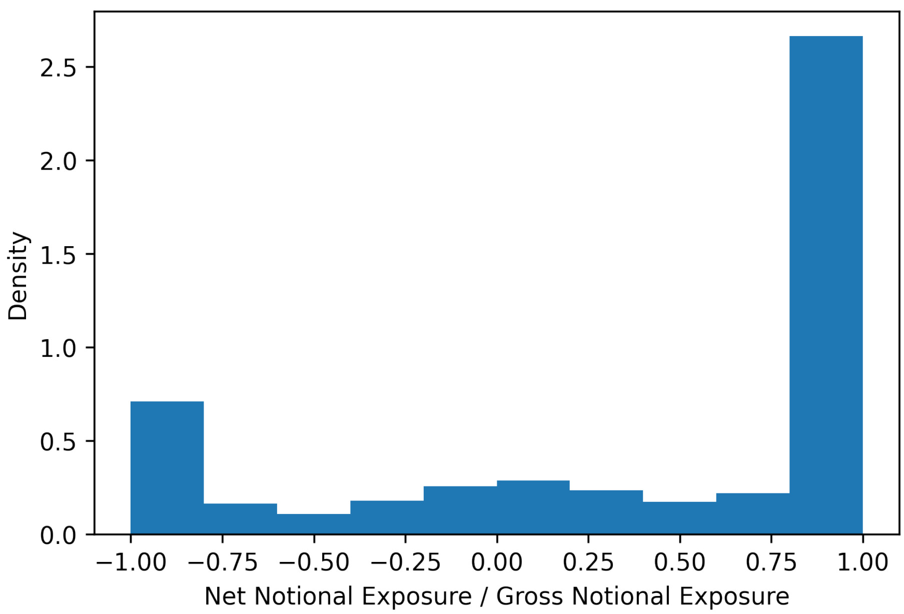
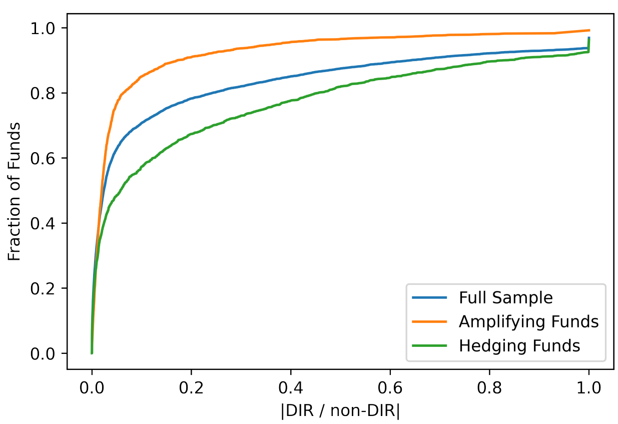


Figure A2

Derivative Contribution to Fund Return - Subsample: $|\ \textit{non-DIR}\ | \geq 10bps$

The figure shows the cumulative distribution function of the fund-level derivative relative contribution. To alleviate the potential concern of unstable measure, we require the denominator $|\ \textit{non-DIR}\ |$ to be greater than or equal to 10 bps. 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) Derivative Relative Contribution for non-Token Users

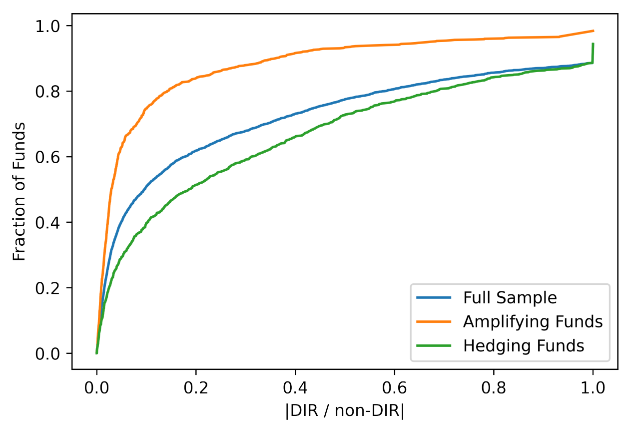
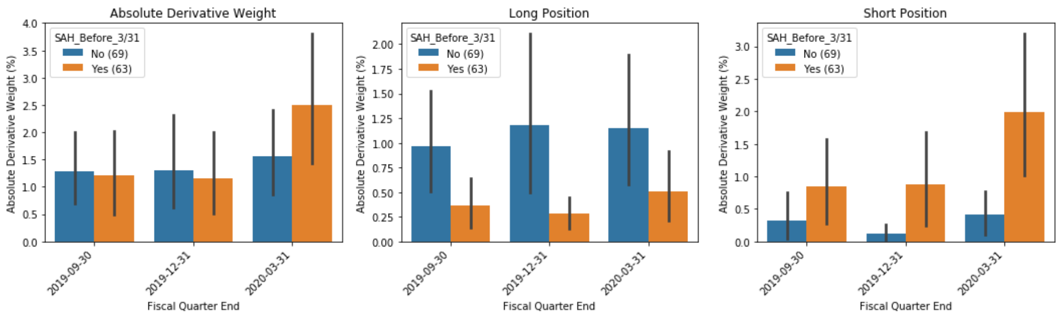


Figure A3

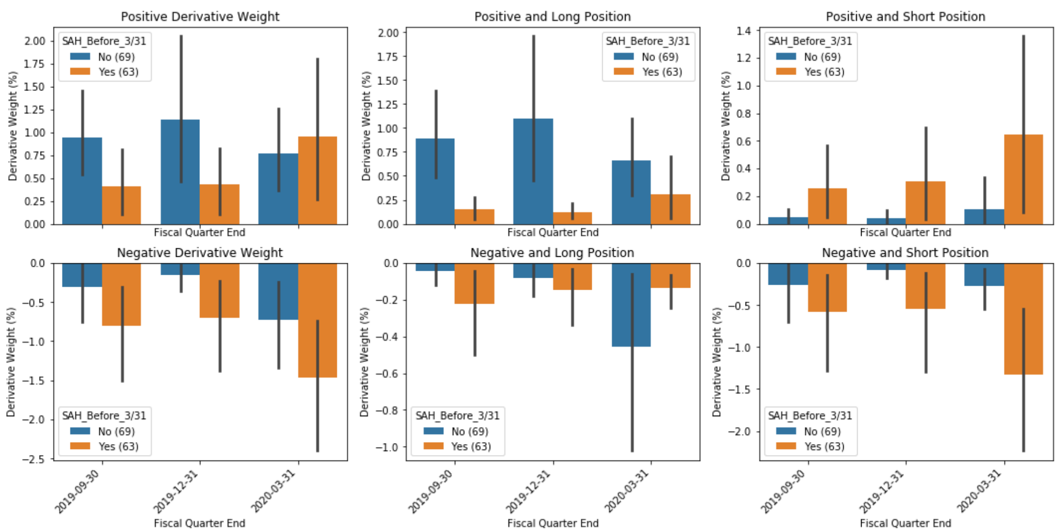
Stay-at-home Around the Border

The figure shows the change in derivative use in response to the Stay-at-home order around borders. Different from Figure 7, 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

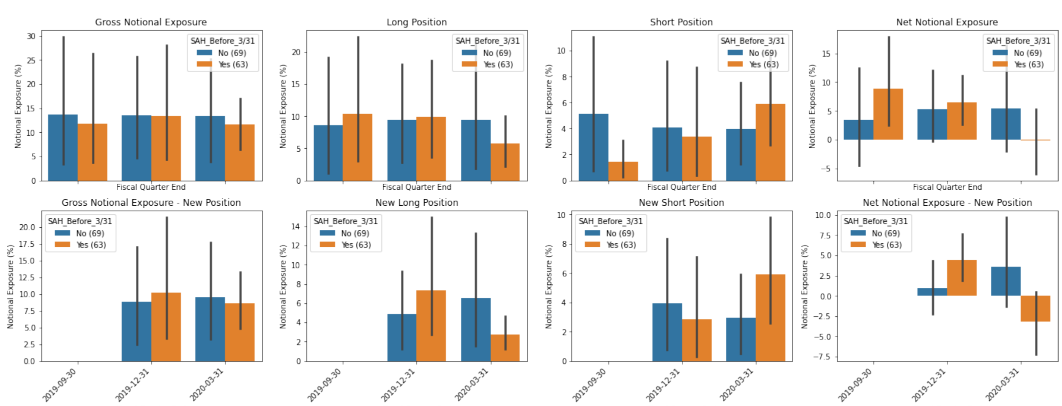
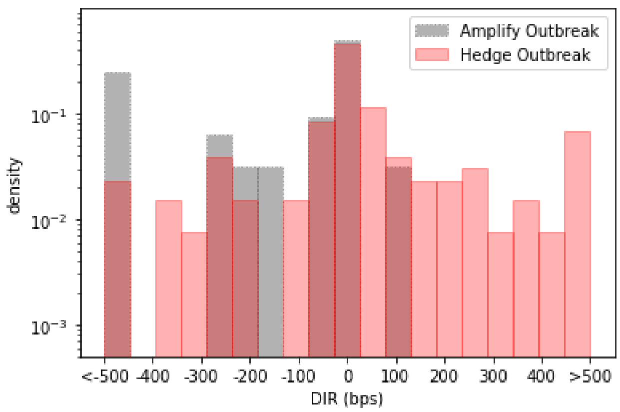


Figure A4

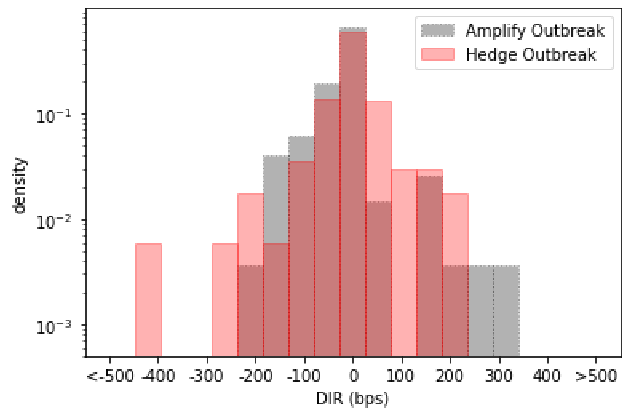
Distribution of Derivative Instrument Return in COVID-19 Outbreak

The figure shows the return distribution of derivative instruments. For all instruments, *DIR* is 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 ease of presentation. The outbreak period is defined as February 2020 and March 2020. The y-axis is in the log-scale.

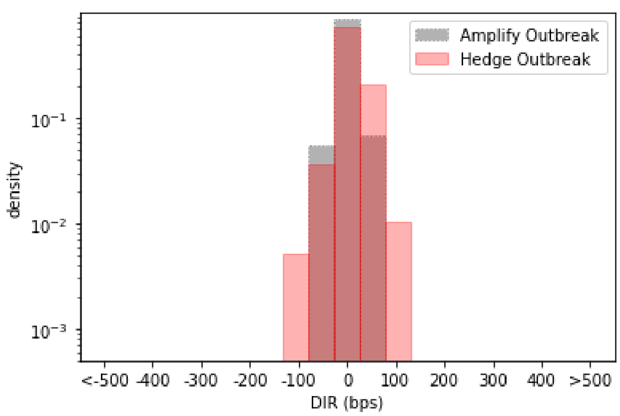
(a) Swaps



(b) Futures



(c) Options



(d) Foreign Exchange Contracts

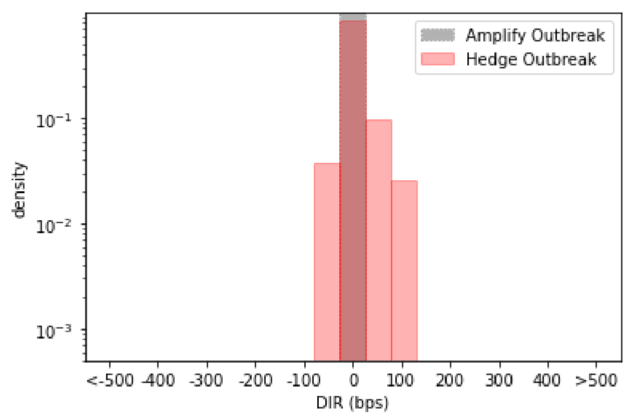
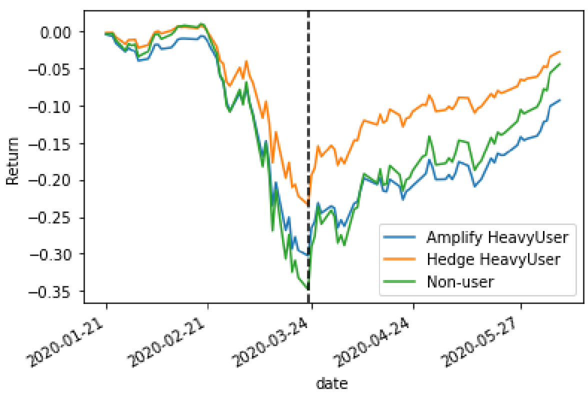


Figure A5

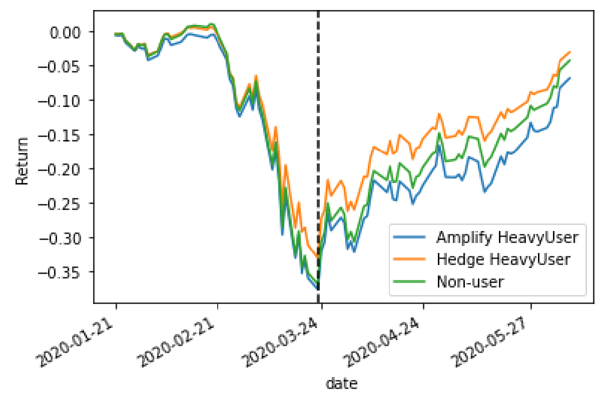
Fund Performance during the COVID-19 Pandemic - Heavy Users

The figure shows the cumulative returns and alphas for funds starting from the COVID-19 outbreak on January 20, 2020. Nonusers are 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).

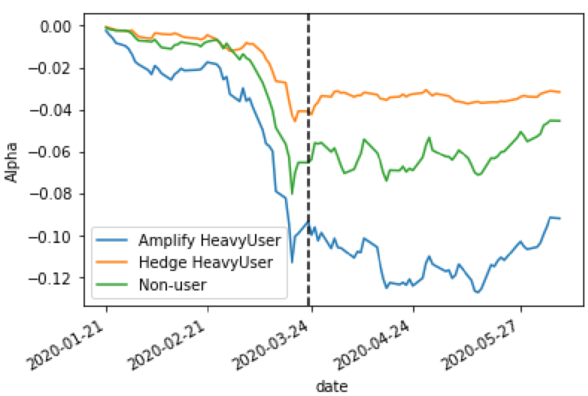
(a) Return



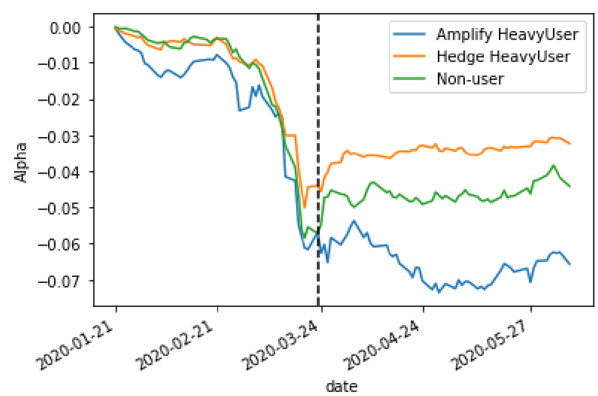
(b) Hypothetical Return



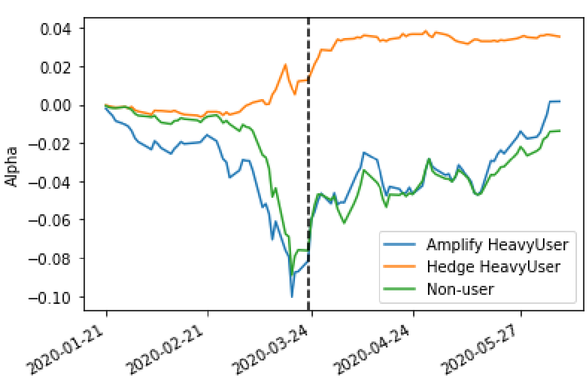
(c) CAPM Alpha



(d) FF5 Alpha



(e) Down-market Alpha



(f) Hypothetical Down-market Alpha

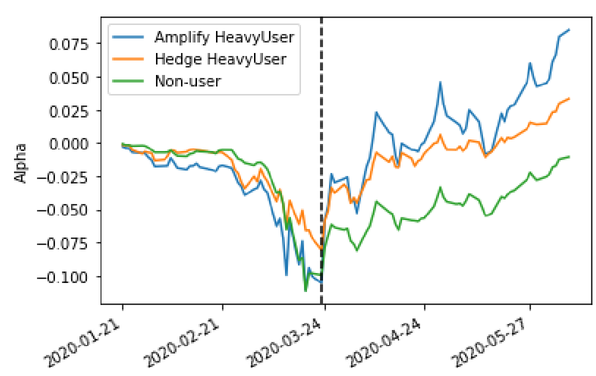
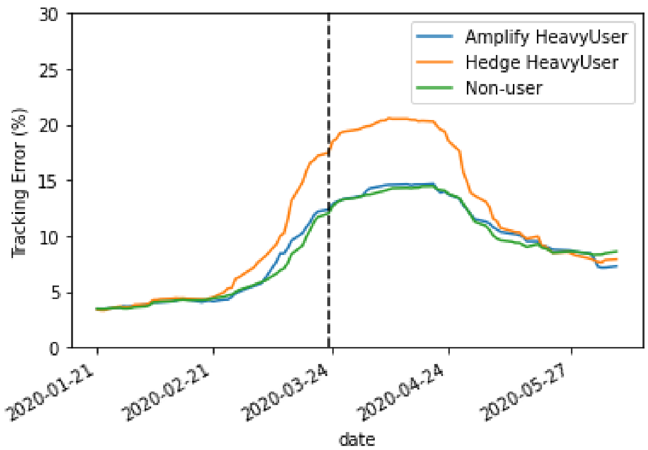


Figure A6

Tracking Error during the COVID-19 Pandemic - Heavy Users

The figure shows funds' tracking error starting from the COVID-19 outbreak on January 20, 2020. Nonusers, heavy amplifying users, and heavy hedging users are defined in Figure A5. 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

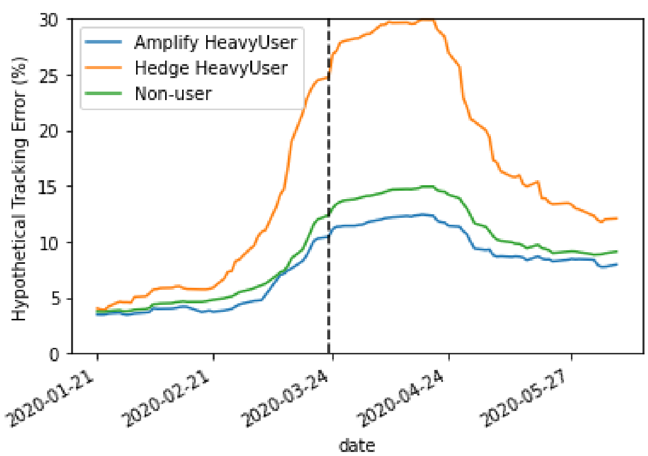


Figure A7

Map of Stay-at-home Order

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

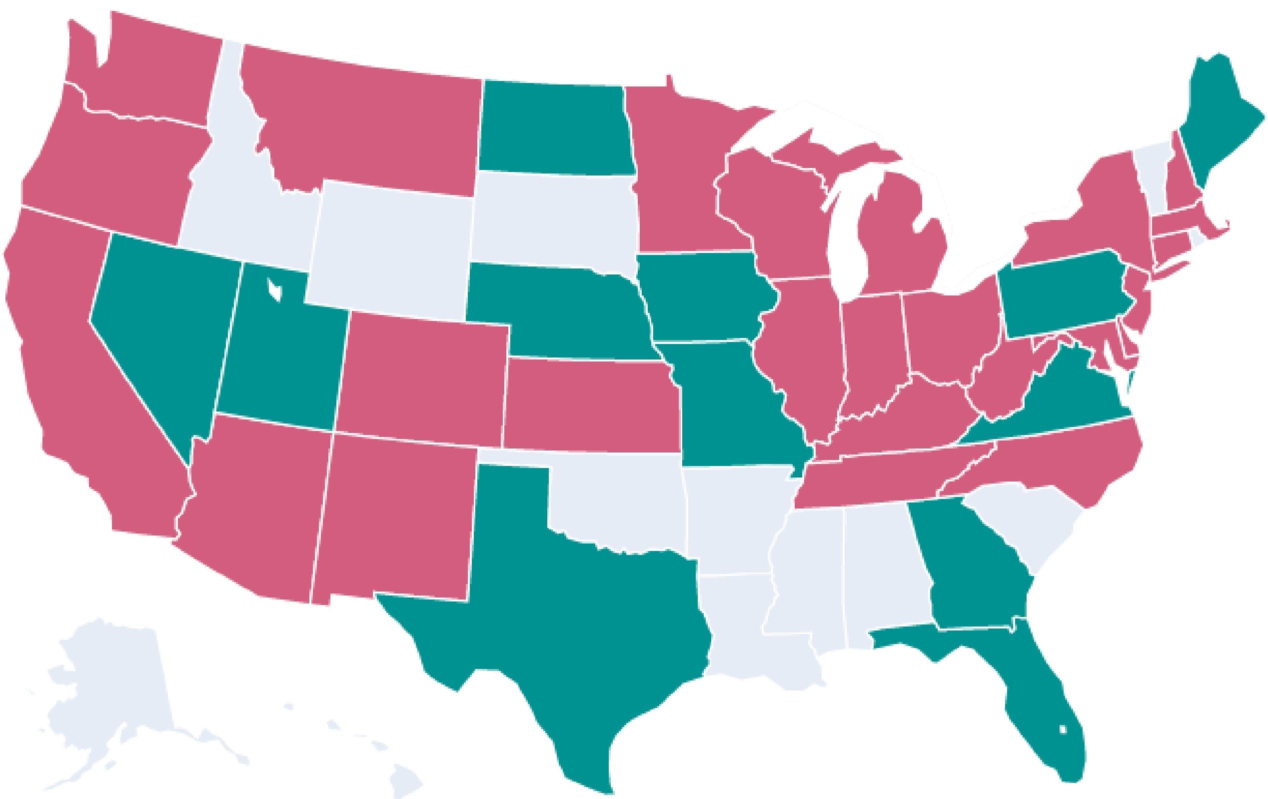


Table A1
Hypothetical Equity Performance of Amplifying/Hedging Funds

The table shows the hypothetical equity 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 fund 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: Return-correlation-based classification

Users	Return	CAPM		FF5					
		Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	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 - 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 - Hedge	-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)
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)

Panel B: Holding-based classification

Users	Return	CAPM		FF5					
		Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	CMA
Nonusers	11.52**	-0.96	1.06***	-0.12	1.01***	0.20***	-0.01	-0.04	-0.05*
	(2.51)	(-1.37)	(66.34)	(-0.29)	(97.91)	(11.81)	(-0.69)	(-1.57)	(-1.71)
Amplify	10.80**	-1.80*	1.07***	-0.48	0.99***	0.28***	-0.05	-0.10**	-0.06
	(2.3)	(-1.66)	(43.32)	(-0.75)	(57.42)	(9.95)	(-1.35)	(-2.38)	(-1.18)
Hedge	10.68**	-1.08*	1.00***	-0.72	0.98***	0.06**	-0.03	-0.07**	-0.00
	(2.47)	(-1.89)	(75.24)	(-1.29)	(70.66)	(2.48)	(-1.09)	(-2.07)	(-0.01)
Hedge - Nonusers	-0.84	-0.12	-0.06***	-0.60	-0.03***	-0.14***	-0.02	-0.03	0.05*
	(-1.53)	(-0.23)	(-5.32)	(-1.65)	(-3.09)	(-10.0)	(-0.88)	(-1.41)	(1.86)
Amplify - Hedge	0.12	-0.72	0.07***	0.24	0.01	0.22***	-0.02	-0.03	-0.06
	(0.18)	(-0.87)	(3.91)	(0.39)	(0.69)	(10.81)	(-0.65)	(-0.96)	(-1.59)
Amplify - Nonusers	-0.72	-0.84	0.01	-0.36	-0.02	0.08***	-0.04	-0.06*	-0.01
	(-1.26)	(-1.41)	(0.76)	(-0.72)	(-1.4)	(3.71)	(-1.21)	(-1.86)	(-0.29)

t statistics in parentheses

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

Table A2

Performance and Flows in Alternative Time Windows

The table shows the performance and flows of amplifying and hedging funds relative to nonusers in alternative time windows: 2017 - 2019, and 2015 - 2019. Panel A compares the annualized CAPM alpha and Fama-French five-factor alpha between amplifying (hedging) funds and nonusers. Panel B estimates the same regression as in Table 8 and reports the flow difference between amplifying (hedging) funds and nonusers. All numbers are in percentage points.

Panel A: Performance Difference

	2017 - 2019		2015 - 2019		2010 - 2019	
	CAPM Alpha	FF5 Alpha	CAPM Alpha	FF5 Alpha	CAPM Alpha	FF5 Alpha
Amplify - Nonusers	-1.03**	-0.41**	-0.84**	-0.49**	-0.48**	-0.48*
	(-2.52)	(-2.05)	(-2.31)	(-1.99)	(-1.98)	(-1.85)
Hedge - Nonusers	0.35	-0.16	0.27	0.05	0.36	0.00
	(0.91)	(-0.66)	(0.50)	(0.21)	(0.94)	(0.26)

Panel B: Flow Difference After Controlling for Performance

	2017 - 2019		2015 - 2019		2010 - 2019	
	Flow	Flow	Flow	Flow	Flow	Flow
Amplify - Nonusers	0.29*	0.34*	0.39***	0.38***	0.39***	0.38***
	(1.85)	(1.84)	(2.87)	(2.76)	(2.74)	(2.67)
Hedge - Nonusers	0.10	0.09	0.12	0.12	-0.02	-0.02
	(0.83)	(0.80)	(1.00)	(1.02)	(-0.19)	(-0.17)
Performance Measure	CAPM	FF5	CAPM	FF5	CAPM	FF5

t statistics in parentheses

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

Table A3

Flows of Amplifying/Hedging Funds - Matched Sample

Panel A of this table shows the distribution of the Lipper style category among nonusers, amplifying funds, and hedging funds. Panel B of this table shows the flow regression result on the propensity score matched sample. In each year and Lipper style category, derivative users are matched with nonusers by total net assets, expense ratio, turnover ratio, and past year performance. Similar to Table 8, we then regress flows on the fund type dummies. 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 A: Lipper Style Distribution

Lipper Style	Nonusers	Amplify	Hedge
Growth	34.6%	30.0%	24.9%
Growth and Income	16.9%	22.6%	23.3%
Small-Cap	16.2%	22.2%	14.5%
Mid-Cap	11.8%	11.7%	11.2%
Equity Income	6.5%	9.7%	8.8%
Capital Appreciation	3.1%	1.9%	0.8%
Long/Short Equity	1.2%	0.8%	12.0%
Others	9.8%	1.2%	4.4%
Total	100.0%	100.0%	100.0%

Panel B: Propensity Score Matched Sample

	(1) Flow	(2) Flow	(3) Flow	(4) Flow	(5) Flow	(6) Flow
Token	0.0948	0.110*	0.111*	0.0726	0.0778	0.0793
	(1.51)	(1.76)	(1.77)	(1.30)	(1.40)	(1.42)
AmplifyNonToken	0.332**	0.327**	0.318**	0.286***	0.280***	0.270**
	(2.57)	(2.56)	(2.50)	(2.70)	(2.67)	(2.59)
NeutralNonToken	0.0448	0.0377	0.0287	0.223*	0.211	0.199
	(0.31)	(0.26)	(0.20)	(1.71)	(1.62)	(1.53)
HedgeNonToken	-0.102	-0.0865	-0.0775	-0.109	-0.103	-0.0924
	(-0.85)	(-0.73)	(-0.66)	(-0.97)	(-0.92)	(-0.84)
retail				-0.388***	-0.387***	-0.387***
				(-5.02)	(-5.02)	(-5.03)
Token X retail				-0.0180	-0.0206	-0.0221
				(-0.28)	(-0.32)	(-0.34)
AmplifyNonToken X retail				-0.168	-0.166	-0.166
				(-1.38)	(-1.36)	(-1.36)
NeutralNonToken X retail				-0.530***	-0.527***	-0.517***
				(-2.72)	(-2.69)	(-2.63)
HedgeNonToken X retail				-0.127	-0.130	-0.139
				(-0.74)	(-0.76)	(-0.81)
Level	Fund	Fund	Fund	Share	Share	Share
Performance	Return	CAPM	FF5	Return	CAPM	FF5
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

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

Table A4

Performance of Amplifying/Hedging Funds - Classified by Net Exposure Ratio

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. Derivative users are grouped into terciles by the net exposure ratio rather than return correlation. Amplifying (hedging) funds are in the top (bottom) tercile. All returns and alphas are annualized and in percentage points.

Users	Return	Benchmark	CAPM		FF5					
			Alpha	Mktrf	Alpha	Mktrf	SMB	HML	RMW	CMA
Nonusers	13.44***	-2.52***	-1.80***	0.99***	-0.96**	0.94***	0.18***	-0.04**	-0.05**	-0.03
	(3.12)	(-8.40)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Amplify	11.16***	-2.65***	-2.36***	0.99***	-1.56***	0.95***	0.17***	0.02	-0.02	-0.00
	(2.73)	(-9.32)	(-3.51)	(68.4)	(-3.98)	(117.04)	(12.7)	(1.0)	(-0.76)	(-0.18)
Hedge	8.84***	-2.40***	-1.56***	0.74***	-1.04**	0.77***	-0.04*	-0.03	-0.07**	0.05
	(2.64)	(-8.25)	(-2.72)	(51.61)	(-2.26)	(47.41)	(-1.94)	(-1.33)	(-2.07)	(1.15)
Hedge - Nonusers	-4.60***	0.12	0.24	-0.25***	-0.08	-0.17***	-0.23***	0.01	-0.02	0.08***
	(-2.87)	(0.05)	(0.46)	(-26.45)	(-0.65)	(-35.89)	(-15.39)	(0.08)	(-0.81)	(2.88)
Amplify - Hedge	2.32***	-0.52	-0.80*	0.25***	-0.52*	0.18***	0.22***	0.05***	0.05***	-0.05**
	(2.64)	(-0.19)	(-1.87)	(28.20)	(-1.75)	(41.29)	(16.29)	(3.25)	(2.66)	(-2.09)
Amplify - Nonusers	-2.28*	-0.13	-0.56**	-0.00	-0.60*	0.01	-0.01	0.05***	0.04***	0.03*
	(-1.93)	(-0.52)	(-2.09)	(-0.92)	(-1.94)	(0.84)	(-1.09)	(5.39)	(2.85)	(1.75)

t statistics in parentheses

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

Table A5
Flows of Amplifying/Hedging Funds - Classified by Net Exposure Ratio

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. Similar to columns (4)-(6) in Table 8, we then regress net flows on fund types dummy. Non-token derivative users are grouped into terciles by the net exposure ratio rather than return correlation. 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) Flow	(2) Flow	(3) Flow
Token	-0.011	0.005	0.007
	(-0.15)	(0.07)	(0.10)
AmplifyNonToken	0.443***	0.435***	0.431***
	(3.09)	(3.06)	(3.02)
NeutralNonToken	0.352**	0.308**	0.294*
	(2.35)	(2.05)	(1.96)
HedgeNonToken	0.251*	0.226*	0.218*
	(1.95)	(1.76)	(1.69)
Performance	Return	CAPM	FF5
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

t statistics in parentheses

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

Table A6

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 daily fund 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 the 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)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.084	0.060	0.139	0.092	0.086	0.052	0.203	0.001
N	976496	976496	976496	976496	897533	897533	897268	897268

t statistics in parentheses

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

Table A7

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 daily fund 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 the 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
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)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.084	0.060	0.139	0.093	0.085	0.052	0.203	0.001
N	976496	976496	976496	976496	897533	897533	897268	897268

t statistics in parentheses

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

Table A8

Fund Return Decomposition during the COVID-19 Pandemic - Heavy Users

The table shows the monthly fund return decomposition for outbreak and recovery periods. Similar to Table A7, 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 the 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 Hedge	139.8	-663.4	-523.6	-907.4	244.0	69.9	69.9
Amplify - Hedge	-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 Hedge	-165.2	514.8	349.6	591.8	-77.0	-84.8	-80.4
Amplify - Hedge	264.3***	-48.5	215.8**	-44.4	-4.1	358.0***	-93.6

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