Unmasking Mutual Fund Derivative Use During the COVID-19 Crisis

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Abstract

Utilizing newly available data from the SEC on derivative performance and detailed derivative holdings, this paper studies how derivatives impact mutual fund performance, with an emphasis on the COVID-19 pandemic period. In contrast to previous research concluding derivatives are used for hedging, we find that most active equity funds use derivatives to amplify market exposure. Despite the seemingly small weight, derivatives have a significant impact on funds' leverage and contribute largely to fund returns. In response to the initial outbreak of COVID-19, funds trade more heavily on short derivative positions. This behavior is more prevalent among managers residing in states with early state-level Stay-at-home orders, where the risk of recession is likely more salient. Funds that used derivatives for hedging purposes before the crisis significantly outperform nonusers by over 9% during the initial outbreak, as their distribution of derivative returns shifts to the right. By the end of June, they still outperform by 1.6%. On the contrary, funds that used derivatives to amplify market exposure underperform, and their distribution of derivative returns shifts to the left. While they do shift strategies, they are slow to open short positions and remain mostly amplifying funds. Consequently, by the time they shift, the market has already started to recover, so that they lose on their short positions. The shifts in derivative return distributions during the COVID-19 crisis are mostly driven by swap contracts, which have been ignored by prior studies.

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1 Introduction

Around one-third 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. Making 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 the past to tackle this important topic is that it does not enable getting reasonable estimates for the return on a fund's derivative portfolio. The data typically provides only some aggregated balance sheet information at a semi-annual frequency. This is especially limiting in trying to understand dynamics during a concentrated crisis period, such as the crisis in financial markets at the peak of the COVID-19 pandemic.

Using a novel dataset extracted from the SEC's Form N-PORT, we obtain the actual performance of derivative positions at a monthly frequency and provide a detailed examination of derivative use by domestic equity mutual funds in the US. We show that, contrary to the common belief that derivatives are used for hedging and risk management (Koski and Pontiff (1999)), the majority of active equity funds use derivatives to amplify their market exposure, as the median correlation between derivative returns and non-derivative returns is highly positive. Furthermore, despite their seemingly small portfolio weight, derivatives have a significant impact on funds' leverage and a substantial impact on fund returns. In response to the initial outbreak of the COVID-19 pandemic and a market crash of almost 30% in March 2020, fund managers trade more heavily on short derivative positions. Such a trading pattern is more prevalent among managers residing in states with early state-level Stay-at-home order (SAH), where the risk of recession is more salient. Moreover, we find evidence supporting both the hedging channel and amplifying channel. Specifically, the distribution of derivative returns shifts to the right for funds with hedging strategy, and to the left for funds with amplifying strategy. The shift in distributions is mostly driven by swap contracts, which have been ignored by prior studies.

Our paper starts by highlighting that prior research on fund derivative use has overlooked an important derivative class: swaps. Prior work focuses almost exclusively on options and futures, since the data they used did not contain information on other derivatives.[1] The swap contract is one of the largest and most liquid derivative contract classes. Swaps constitute north of 30%.

Our analysis accounts for the variation in the extent of derivative use. We uncover substantial cross-sectional variation in the extent of usage. Taking advantage of the derivative holdings data, we measure the extent of derivative use by the absolute derivative weight and gross leverage and find polarized cross-sectional usage. Within active funds that use derivatives, over 50% are ***Token*** users with derivative weights of less than 0.2%, while 20% of funds have derivative weights of more than 3%. Even though a 3% derivative weight seems small in absolute terms, we show that it represents 36% gross of leverage and provides funds with abundant exposure to the market.

Token users' performance is, not surprisingly, very similar to nonusers. This explains why exiting papers that try to distinguish performance and risk of users and nonusers by using the option/future usage flag in N-SAR to identify users and then compare the two groups could suffer from limited power. To account for different levels of derivative use, we split derivative users by the extent of usage into three groups, token users, medium users, and heavy users, according to a 50/30/20 cut. Our result shows heavy users underperform nonusers by 1.32% per year using Fama-French five-factor alpha and by 1.92% per year using benchmark-adjusted returns. Moreover, contrary to the similar market beta between users and nonusers documented in Koski and Pontiff (1999), the analysis reveals that heavy users have a considerably lower market beta than nonusers. The difference in beta is driven mostly by their derivative positions, but also by lower exposure to market risk of their equity holdings.

[1]Koski and Pontiff (1999), Deli and Varma (2002), Almazan, Brown, Carlson, and Chapman (2004) study options and futures. Frino, Lepone, and Wong (2009) study index futures. Cici and Palacios (2015) and Natter, Rohleder, Schulte, and Wilkens (2016) focus on options alone. An exception is Cao, Ghysels, and Hatheway (2011) that considers total derivative use, but does not consider swaps separately.

An important innovation of our paper is that, in addition to considering fund performance, it is the first paper to directly investigate the performance of derivative positions and how they contribute to fund returns. By obtaining realized and unrealized Profit-and-Loss (PnL) of different derivative classes at a monthly frequency, we are able to estimate the returns of each derivative class separately and together. We define the derivatives' contribution as the ratio between derivative returns and fund returns. Around 20% of the fund-month observations have an absolute derivative contribution of more than 25%. Such a contribution is large, especially considering the relatively small portfolio weight of derivative positions.

Taking advantage of the time-series derivative and non-derivative returns, we study whether fund managers use derivatives for hedging or amplification purposes by calculating their correlation between July 2019 and January 2020. Prior work attempting to answer this question, for example Koski and Pontiff (1999), was forced to tackle it indirectly since the data used in those studies could not facilitate estimating derivative returns. Contrary to the common belief that derivatives are used for hedging, we find that the majority of funds use derivatives to amplify their exposures; the median correlation of 0.34 is large and positive, and 63% of funds have a positive correlation. We further sort funds by the correlation into terciles and define a fund as an amplifying (hedging) fund if its correlation is in the top (bottom) tercile. Over 85% of amplifying funds' derivatives are long positions. Around 50% of hedging funds' derivatives are short positions, which explains the negative correlation between derivative returns and non-derivative returns.

Having demonstrated the importance of derivative positions to both fund holdings and returns, we study how fund managers trade derivatives during the crisis. During the initial outbreak of the COVID-19 pandemic, the S&P 500 index dropped over 30% between 12/31/2019 and 03/23/2020 and fully recovered by the end of July. The sharp market downturn and the unanticipated rebound provide us an ideal laboratory to study managers' trading behavior. Unlike hedge fund managers, most mutual fund managers are restricted from taking short equity positions. Therefore, the flexibility of trading derivatives is crucial to mutual fund managers if they want to deleverage equity positions and outperform their peers. However, the use of derivatives is a double-edged sword, given the high volatile nature of derivative contracts and the uncertain timing of the market rebound. As the employment risk rose significantly around the peak of the pandemic outbreak, derivative users had incentives to be more conservative and decrease derivative holdings so to pool with the nonusers who are the majority.

Empirically, we find fund managers' derivative use almost doubled from December 2019 to March 2020, the outbreak of the crisis. In September and December 2019, absolute derivative weight in managers' portfolios was around 1.5%. Between January and late March, it significantly increased by 1.41%, 0.72% of which is from long and 0.69% from short positions. The leverage on short derivative positions also increases by 8.3% with a p-value of less than 0.001, whereas there is no change in leverage on long positions. The result suggests that the increase in derivative use on short positions is not simply due to market returns. Fund managers actively put more weight in short positions to hedge against the crisis.

The increased usage is not from the extensive margin but from the intensive margin, as the number of users remains flat. The cumulative distribution function (CDF) of derivative use shifts to the right during the initial COVID-19 outbreak, suggesting that the increased derivative use is not driven by a small number of funds heavily building up their derivative positions. Instead, it is a result of a shift in employing more derivatives by the industry as a whole.[2]

We further show that the increase in derivative use comes from managers who face a more salient risk of recession. Prior studies find that agents tend to overreact to salient risk situations (Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978), Dessaint and Matray (2017)). As the number of the COVID-19 cases rose in the US, states gradually implemented Stay-at-home orders (SAH) starting from later March to early April. We utilize the staggered SAH at the state level and conjecture that the COVID-19 risk is more

[2]The two distributions are significantly different from each other, as the p-value of the Kolmogorov-Smirnov test is less than 1%.

salient for fund managers in states with than without SAH in place. By the end of March 2020, among states with at least one registered mutual fund, 25 states have SAH in place, and 11 states do not. The absolute derivative weights significantly increase for funds with SAH in place, but no significant change occurs for funds without SAH. When we decompose derivative weight by long/short positions and positive/negative weights, we find that most of the variation in managers' reactions comes from the short positions. The dispersion between positive and negative weights widens during the pandemic. The result suggests fund managers who face greater risks from COVID-19 bet more in the short positions but open these positions at different times during the pandemic. When the market rebounded unexpectedly and sharply after March 23, funds that entered late suffer loss from these short derivative positions. In the data, we find that the average time-to-maturity of new short positions significantly decreases during the crisis for funds with SAH, and there is no change in long positions.

How does the increased derivative use contribute to fund returns during the crisis? The effect depends on the types of derivative strategies employed by fund managers before the crisis. Specifically, the distribution of derivative returns shifts to the right for hedging funds in March 2020, but to the left for amplifying funds. Swap contracts, which have been ignored by prior research on fund derivative use, contribute the most to derivative returns during the crisis, followed by future contracts. Options and foreign exchange related contracts contribute little. As a result, hedging funds significantly outperform by an annualized Fama-French five-factor alpha of 14% between February 20, 2020, and March 23, 2020. The benefit of hedging during the crisis does not come for free. When the market rebounded sharply after March 23, hedging funds underperform. The outperformance of hedging funds is not due to their equity holdings, as their hypothetical equity returns do not perform differently than other funds.

To gain more insight into the performance of hedging funds during the crisis, we further incorporate the downside risk into the CAPM model and show that hedging funds perform exceptionally well out-of-sample. Specifically, we add a down-market dummy, which is equal to one if the market excess return is negative, the squared market excess return, and the interaction terms between the down-market dummy and the (squared) market excess return into the CAPM model. This model takes into account the market crash (jump) and asymmetric sensitivity of fund returns with respect to the market. Using estimated pre-2020 factor loading, we then calculate out-of-sample factor-adjusted returns for funds in 2020. Our result shows that hedging funds have positive factor-adjusted returns in the crisis period, while amplifying funds and nonusers have negative returns. The cumulative gap in factor-adjusted return is 9.2% by March 23, 2020, and the gap remains as large as 6% by the end of June.

The rest of the paper is organized as follows. Section 2 relates our work to the literature. Section 3 describes the data. Section 4 provides an overview of derivative use. Section 5 analyzes the change in managers' trading behavior during the COVID-19 pandemic. Finally, section 6 concludes.

2 Related Literature

Prior data limitations have confounded the ability to analyze the impact of derivative use on mutual fund performance and risk on a couple of fronts.

First, prior literature has focused exclusively on options and futures when referring to derivatives in equity funds. For example, Koski and Pontiff (1999) investigates the use of options and futures by 679 domestic equity mutual funds between 1992 and 1994.[3] Deli and Varma (2002), Almazan et al. (2004), and Calluzzo, Moneta, and Topaloglu (2017) study the characteristics of funds and fund families that use options and futures. Cici and Palacios (2015) and Natter et al. (2016) study the performance of option users. The restriction to options and futures was due to the fact that SEC 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

[3]Throughout the rest of the paper, the term "funds" refers to "domestic equity funds".

ask on other derivatives.[4] We show that a non-negligible number of funds use swap contracts, which have been overlooked in the existing studies. Our analysis reveals that swaps have an important impact on fund returns, especially during the COVID-19 crisis. Moreover, Even though options are more extensively studied than other derivatives, we show options constitute a small fraction of overall derivatives in equity funds and have little effect on funds' risk exposure.

Early work finds similar performance and risk exposure of derivative users and nonusers (for exampleKoski and Pontiff (1999)). Cao et al. (2011) show that the seemingly similar performance is a result of pooling token users with other users. Natter et al. (2016) show option users have lower market risk. Our analysis reveals that the lower exposure to market risk of heavy derivative users is driven mostly by funds' derivative portfolios, but also by different equity portfolio risk exposures.

A central contribution of our paper is that we provide the first evidence on how derivative positions contribute to fund returns, including within the pandemic crisis. This is facilitated by the fact that form N-PORT is unique in providing security level information on both unrealized and realized PnL, at a monthly frequency, enabling us to derive an estimate of the returns on over-the-counter and exchange traded derivative positions that the fund utilizes. Derivatives contribute substantially to fund returns, despite their small portfolio weight. Contrary to the common belief that derivatives are used for hedging among mutual funds, we find that more funds use derivatives to amplify than to hedge their exposures to the market, as the median correlation between derivative returns and non-derivative returns is positive.

Our paper also contributes to the literature on mutual funds and the COVID-19 pandemic. The pandemic is an exogenous and unanticipated shock to financial markets that provides good identification of the impact and drivers of funds' performance and strategies.

[4]The identification of usage is derived from item 70 in the N-SAR form, either directly by the authors or from commercial data sets collecting this information. 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.

Pastor and Vorsatz (2020) study the sustainability and fund performance. Falato, Goldstein, and Hortaçsu (2020) focus on the financial fragility in corporate bond funds. We show that derivatives are used more extensively during the pandemic. The increase stems from the intensive, but not from the extensive margin. Derivative users increase their short derivative positions during the initial outbreak. This is mostly driven by funds in states with SAH in place before the end of March 2020, as the risk is likely to be more salient in states with than without SAH in place.

3 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 derivative performance 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 monthly Form N-PORT. The form provides information about their portfolio holdings and performance. Larger entities, funds that together with other investment companies in the same group of related investment companies, have net assets of $1 billion or more as of the end of the most recent fiscal year of the fund, start to report beginning June 1, 2019. Small entities begin to report beginning on March 1, 2020. Although funds report to the SEC monthly, holding reports are available to the public only at a quarterly frequency, corresponding to the fiscal quarter-ends.

We extract the following information at quarterly and monthly levels from Form N-PORT. The quarterly level data include the fund's total net assets and portfolio holdings. The holding data cover not only equity and debt positions, but also detailed descriptions of over-the-counter and exchange-traded derivative positions, which are not available in the traditional mutual fund data sources, such as the CRSP and Thompson Reuters. We extract the derivative instrument, portfolio weight, expiration date, and unrealized appreciation or depreciation for each derivative position. The derivative instrument not only includes forwards/futures and options, which are indicated by flags in Form N-SAR, but also covers swaps, swaptions, warrants, and foreign exchange contracts, which have not been documented in prior studies. Due to the small fractions of swaptions and warrants and their similarities to options, we consolidate swaptions and warrants into the options category. For swaps, we identify the securities to be paid and received, the upfront payments, and the notional amount. For futures and forwards, we identify the payoff profile (long/short) and the notional amount. For options, we identify the exercise price, whether it is a call or a put, and whether the fund writes or purchases the option. For foreign exchange contracts, we identify the currency sold/purchased and the notional amount in USD.

The monthly level data include the fund's inflows and outflows that are also available in Form N-SAR, the fund's return, and realized and unrealized PnL of each derivative instrument, which has not been recorded in other data sources.

Our sample covers 10,619 unique funds with Form N-PORT available starting from September 2019. After merging with the CRSP, we have 9950 unique funds, representing 84.83% of the CRSP and 95.04% of total net assets. Our sample contains a wide range of fund styles, including domestic and foreign equity funds, fixed-income funds, mixed funds, and other funds (mortgage-backed funds and currency funds). In this study, we focus on 2909 active domestic equity funds.

In this paper, we use the ***pre-crisis period*** to denote time before February 20, 2020. We use the ***crisis period*** or ***outbreak period*** to denote time period between February 20, 2020, and March 23, 2020, which also follows the definition in Pastor and Vorsatz (2020). We use the **recovery period** to denote time periods between March 24, 2020 and June 30, 2020.[5] For analyses with only monthly frequency available, we refer to the crisis period as February 2020 and March 2020, and the recovery period as the months between April 2020

[5]We stop on June 30, 2020 because the data only update to June 2020 as the time of writing.

and June 2020.

4 How are Derivatives Used in Mutual Funds?

Previous studies on derivative use in the mutual fund industry have almost exclusively relied on the SEC's Form N-SAR. While the Form N-SAR contains yes-no questions on whether a fund held options or futures, it fails to cover whether other important derivative categories, especially swaps, which turn out to be a major component of derivative positions, have been used by funds, to what extent these derivatives are used, or how much these derivative positions contribute to the fund return or risk. This section provides a comprehensive overview of derivative use by active domestic equity funds and addresses these unanswered questions.

In Section 4.1, we show that there is large cross-sectional variation in the extent of derivative use. Taking into account the variation in derivative use will uncover important differences in performance and risk profiles between derivative users and nonusers. Section 4.2 provides the first evidence on how much derivatives contribute to fund returns.

4.1 The Extent of Derivative Use

Descriptive Statistics of Derivative Use

Our paper uses detailed derivative holdings data and examines the extent of derivative use. We extract the portfolio weight and notional amount of each derivative position from the Form N-PORT. To proxy for the extent of derivative use, we use two measures. The first measure is the sum of *absolute derivative weights* in the portfolio. As fund managers can gain exposure by trading derivatives in both long and short sides, it is necessary to use the absolute derivative weight to capture the extent of derivative use. The second measure is the *gross leverage*, which is the sum of notional amounts of derivative positions scaled by the total net assets.

Panel A of Table 1 shows the number of funds with derivative use in our sample between

September 2019 and June 2020. A fund is classified as a derivative user if it uses derivatives at least once in the sample. The sample contains 2909 active funds, 756 of which (26%) are derivative users. Interestingly, the fraction of derivative users has not changed much in the past two decades, as the fraction of derivative users in Koski and Pontiff (1999) was 21%. Among the derivative users, 432 funds use futures or forwards, 124 funds use swaps, 317 funds use options, and 179 funds use foreign exchange contracts. As a result, by only focusing on options and futures, prior studies have misclassified a nontrivial number of swap users and foreign exchange users as nonusers.

Panel A of Table 1 further breaks down the derivative use by the types of derivatives and highlights the importance of swap contracts in mutual funds. On average, funds have a derivative weight of 2.05%, with the futures contract (0.7%) being the largest derivative type, closely followed by swaps (0.64%). Option contract only represents 0.43% of the portfolio. When measuring derivative use by gross leverage, swap positions provide the largest gross leverage of 22.9%, followed by future positions (20.3%). Option positions merely provide gross leverage of 1.8%.

Derivative Use in Cross-section

There is substantial cross-sectional variation in the extent of derivative use, with half of the funds using a negligible amount of derivatives, and some other funds use derivatives heavily. Such a pattern is also documented in Cao et al. (2011) but has not received enough attention in subsequent studies. Panel B of Table 1 shows that the mean of absolute derivative weight is 2% with a standard derivation of 4.3%. Although the derivative positions' portfolio weight seems small in absolute terms, derivatives provide funds ample exposure to the markets because of the embedded leverage. Specifically, the mean gross leverage is 51.5%, with a standard deviation of 88.1%. Figure 1 visualizes the cross-sectional variations in derivative use. On the one hand, over 50% of funds have derivative weights (gross leverage) of less than 0.2% (3%). On the other hand, 20% of funds have derivative weights (gross leverage) of more than 3% (36%).

To gain deeper insights into how funds use their derivative positions, we further group derivative users by the extent of usage into the following three categories. For each quarter, funds are sorted by the absolute derivative weight into deciles.[6] We define ***token users*** as the 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 instead of an even cut to take into account that a large number of funds only use a negligible amount of derivatives.

Table 2 shows the derivative weights and the corresponding long/short compositions by the types of derivative users. 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. In Panel A and B, we can see that futures are the most extensively used derivative class among token and medium users, whereas swaps become the dominant derivative class among heavy users. As a result, prior studies that rely on Form N-SAR to classify derivative users will omit swap users, which are likely 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%). In the subsequent analyses, we backfill the derivative use for periods prior to the availability of Form N-PORT. The persistence in derivative use alleviates the concern that derivative use in 2019 may not be representative in prior years.

Derivative Use and Fund Performance

Koski and Pontiff (1999) find that there is no direct link between fund performance and

[6] Our results are robust and quantitatively similar when we sort funds by gross leverage.

derivative use. In Table 3, we reexamine this result by taking into account the extent of derivative use and regressing equal-weighted portfolio returns of each type of derivative user on various asset pricing models in the past decade, between 2010 and 2019.[7] Since the derivative use data become available from September 2019, we backfill the derivative use data for periods before September 2019 using the fund's derivative use data in September 2019. Table 3 shows the annualized alphas in percentage points and corresponding factor loading. As shown in Panel A, there is no significant difference in performance between derivative users and nonusers after accounting for common risk factors, which is consistent with findings in Koski and Pontiff (1999). Although derivative users significantly underperform nonusers in benchmark-adjusted returns statistically, the difference of 48 bps per year is economically small.

In Panel B, we further split derivative users by their extent of derivative use into three groups. Nonusers and token users have very similar Fama-French five-factor loading and alphas, consistent with the fact that token users hold a tiny fraction of derivatives, which have a trivial impact on fund returns. However, medium and heavy users' factor loading significantly differs from nonusers and token users by having a lower market beta and size beta. Meanwhile, heavy users significantly underperform nonusers by 1.32% per year under the Fama-French five-factor model and by 1.92% per year in benchmark-adjusted returns.[8] This result is different from the findings in Koski and Pontiff (1999) that derivative users and nonusers have similar performance and beta.

An alternative explanation for the difference in factor loading between heavy users and nonusers is that they hold stocks with different risk exposure. To test this explanation, we generate hypothetical holding returns for each fund, assuming the reported equity holdings from CRSP and Thompson Reuters are held throughout the quarter.[9] We then form port-

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

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

[9]We also construct an alternative version of hypothetical holding 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

folios based on hypothetical returns and regress them on factor returns. Panel C of Table 3 reports the results. The difference in hypothetical market beta between heavy users and nonusers is -0.07, which explains 27% of the market beta difference between heavy users and nonusers, whereas the remaining difference stems from derivative positions and intra-quarter trading. The difference in size beta, to the contrary, can be almost exclusively explained by the reported equity holdings.

4.2 Derivative Contribution to Fund Returns

How derivative positions contribute to fund returns is an open question. Given the similar hypothetical equity returns but largely different realized returns between heavy users and others, it is crucially important to understand the performance of derivative positions. In this section, we extract monthly realized and unrealized PnL of derivative positions between July 2019 and June 2020, and shed light on how important derivative positions are to fund returns.[10]

We calculate derivative returns as the sum of realized PnL and the change in unrealized PnL, scaled by the fund's total net assets in the previous month. We then define the derivative contribution to fund returns as the ratio between the derivative return and the fund return. In our sample period, the average monthly derivative return is -9 bps, with a standard deviation of 127 bps, which is shown in Table 1. As a comparison, the average non-derivative return is 4 bps, and its standard deviation is 690 bps. Derivatives have very volatile returns, especially considering their relatively small portfolio weights. Specifically, the standard deviation of the monthly non-derivative returns is five times larger than that of derivative returns, but non-derivative positions weigh over 40 times larger than derivative

version.

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

positions.

$$\textit{Derivative Return}_t = \frac{PnL_t^{Realized} + PnL_t^{Unrealized} - PnL_{t-1}^{Unrealized}}{TNA_{t-1}}$$

$$\textit{Derivative Contribution}_t = \frac{\textit{Derivative Return}_t}{\textit{Fund Return}_t}$$

The blue curve in Figure 2(a) shows the CDF of derivative contribution in our sample between July 2019 and June 2020. The derivative contribution in the figure is winsorized between -0.5 and 0.5 for the ease of presentation. Derivatives contribute heavily to fund returns. Specifically, about 10% of the fund-month observations have derivative contribution over 30%, and another 10% of observations have derivative contribution less than -22%. Derivatives play a larger role in fund returns among medium and heavy users. Figure 2(b) excludes token users and focuses on medium and heavy users. In this subsample, 40% of the fund-month observations have derivative contribution above 20% or below -20%.

Taking advantage of the time-series derivative returns, we then classify funds into either the ***amplifying*** category or ***hedging*** category, depending on the correlation between derivative and non-derivative returns. Specifically, for each fund, we calculate the correlation between the derivative returns and non-derivative returns from July 2019 to February 2020.[11] Figure 3 shows the histogram and fitted kernel of the correlation. Contrary to the commonly perceived hedging purposes, the majority of funds use derivatives to amplify their market exposure. The median correlation of 0.34 is large and positive, and 63% of funds have a positive correlation. To take into account the clusters of funds in both tails of the correlation histogram, we group funds by the correlation into terciles. A fund is classified as an amplifying (hedging) fund if its correlation is in the top (bottom) tercile. The correlation of amplifying funds ranges between 0.78 and 1, whereas the correlation of hedging funds ranges between -1 and -0.08. In other words, unlike amplifying funds with highly

[11] We stop in January 2020 because we will take the pre-crisis fund types and run analysis on how amplifying/hedging funds react during the pandemic.

positive correlation, some hedging funds have relatively weak correlation between derivative and non-derivative returns.[12] Amplifying and hedging funds have similar sizes as nonusers. Specifically, hedging funds on average have a size of \$1.65 billion, amplifying funds \$1.69 billion, and nonusers \$1.73 billion. In terms of the market cap, amplifying funds in total have an asset-under-management of \$0.46 trillion, hedging funds \$0.54 trillion, and nonusers \$3.8 trillion.

The orange and the green curves in Figure 2 show the CDF of the derivative contribution for amplifying funds and hedging funds, respectively. The green curve sits higher than the orange curve, especially in the negative contribution region. The p-value of the Kolmogorov-Smirnov test, which examines the difference between two distributions, is less than 1%. The result is consistent with the classification that the derivative returns of hedging funds are negatively correlated with non-derivative returns.

Tables 4 and 5 show the derivative weight and gross leverage of amplifying and hedging funds. Take heavy users and their derivative weight as an example. Amplifying funds and hedging funds differ mainly by the composition of long and short positions. Amplifying funds tend to invest heavily in long positions, whereas hedging funds put relatively more weight in short positions. Specifically, as shown in Table 4, amplifying funds have 85% futures and 87% swaps in long positions, whereas hedging funds have 43% futures and 50% swaps in long positions. Hedging funds also invest relatively more in options, which have a portfolio weight of 1.03% on average, than amplifying funds, which have a weight of merely 0.04%. Furthermore, hedging funds tend to be more levered than amplifying funds. In Table 5, the gross leverage of hedging funds is 65.4%, almost two times larger than that of amplifying funds. The difference in gross leverage is mainly driven by swaps. For example, within heavy users, the gross leverage of swaps is 33.8% for amplifying funds, and it is 100.9% for hedging funds.

[12] We have also examined the alternative cutoff of correlations by assigning amplifying funds with a correlation above 0.5 and hedging funds with a correlation below -0.5. The results are robust to such alternative definition.

The difference in long/short derivative composition between amplifying and hedging funds also affects their factor loading, as shown in Table 6. In Panel A, hedging funds have a market beta of 0.84, and amplifying funds have a market beta of 0.93. The difference in beta between hedging funds and amplifying funds is -0.09, with a t-stat of 14. In Panel B, hedging funds and amplifying funds have the same hypothetical market beta. The result suggests that the difference in ex-post market beta between hedging and amplifying funds is due to their different strategies of derivative use.

Panel C of Table 6 compares the performance among nonusers, heavy amplifying funds, and heavy hedging funds. There is no difference in performance between heavy hedging funds and nonusers, after controlling for Fama-French five-factors. However, heavy amplifying funds significantly underperform nonusers by 2.05% per year, which explains why heavy users underperform nonusers in Table 3. Surprisingly, even though amplifying funds use derivatives to gain exposure to the market, their realized market beta is still lower than that of nonusers.

5 Derivative Use During the COVID-19 Pandemic

Unlike the financial crisis, the COVID-19 pandemic started as a healthcare crisis, which provides researchers an exogenous and unanticipated shock to financial markets. The pandemic offers good identification of the impact and drivers of funds' performance and strategies. How do fund managers trade derivatives during the COVID-19 pandemic? On the one hand, derivative users may reduce derivative positions given the extremely volatile market and pool with the majority of nonusers.[13] As derivative positions are highly leveraged, they will generate extreme returns in either direction. Due to the high employment risk faced by fund managers during the pandemic, derivative users may rather forgo the potential upside and seek job security by reducing derivative positions. Moreover, as the number of COVID-19

[13]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.

cases continued to rise in the US, many states gradually implemented Stay-at-home orders (SAH). Fund managers are restricted to work from home, which may further reduce their trading activity.

On the other hand, derivative positions allow fund managers to trade on the short side of the market, which is especially important because almost all funds' equity positions are long positions. Such flexibility provides hedging against the market downturn. Moreover, agents tend to react to salient risks (Lichtenstein et al. (1978) and Dessaint and Matray (2017)), which makes derivative trading more likely during the pandemic, especially for fund managers residing in states with SAH in place, where the risk of potential recession is likely to be more salient.

Therefore, it remains an empirical question of whether managers trade more derivatives during the pandemic, and for what purposes. In this section, we first study managers' reactions to the COVID-19 pandemic at the aggregate level. We examine the time-series changes in derivative allocation. Second, we study whether the changes in derivative allocation are greater when fund managers face more salient risk. In particular, we group fund managers by whether a fund resides in states with SAH in place before the end of March 2020, and compare the difference in change of portfolio allocation between the two groups of funds. Lastly, we study how derivative positions contribute to fund returns during the crisis and the implications of derivative performance on fund returns.

5.1 Time-series Change in Derivative Use

Table 7 shows the change in portfolio allocation from the last quarter of 2019 to the first quarter of 2020. The first column shows the unconditional change in allocation. The second to fourth columns split the sample by the derivative use into token users, medium users, and heavy users. The classification of derivative users is based on the absolute derivative weight in the last quarter of 2019 to rule out the look-ahead bias.

Derivatives are used more extensively during the COVID-19 pandemic. From column

(1) of Table 7, the absolute derivative weight increases by 1.41%. Note that the absolute derivative weight in December 2019 is 1.47%, so that the derivative use increases by 96.24% on a relative scale during the pandemic. A large part of the increase in derivative use is driven by heavy users, which is shown in column (4).

Moreover, the increase in derivative use is driven by fund managers increasing their bets on short positions. On a relative scale, derivative use in short positions increases by 134%, which almost doubles the increase of 75.7% in long positions. Interestingly, both the positive and negative derivative weights of short positions increase, suggesting that the increased bet on short positions could be a result of funds entering short derivatives at different time. Specifically, short derivative positions with positive weights increase by 193.5%, and short positions with negative weights increase by 91.4%. On the contrary, the increased derivative use in long positions is solely driven by positions with negative weights. How do short positions lose money when the market is down by 20% in the first quarter of 2020? The market is down by over 30% between Feburary 20 and March 23, then sharply rebounds to -19% by the end of March. The payoff of short positions largely depends on when managers enter positions, which we will discuss in more details in Section 5.3, where we analyze the cross-sectional derivative trading.

The increase in derivative use does not come from extensive margin, as the number of derivative users slightly changed from 742 in the last quarter of 2019 to 754 in the first quarter of 2020. Moreover, the increase in derivative use is not driven by a small number of funds heavily building up their derivative positions. Instead, it is a shift in employing more derivatives by the entire industry. As shown in Panel A of Figure 1, the CDF of the absolute derivative weight shifts to the right during the crisis. The absolute derivative weight in the pre-crisis period is first-order stochastic dominated by the crisis period with a p-value less than 0.1%, suggesting a shift towards extensively using derivatives by fund managers.

5.2 Managers' Reaction to Stay-at-home Order

The previous section shows the time-series increase in derivative use. In this section, we explore the cross-sectional variation in derivative use during the initial outbreak of the pandemic. As the number of COVID-19 cases rose in the US, many states have imposed state-level Stay-at-home Order (SAH) to reduce COVID-19 spread. The staggering of SAH introduction at the state level allows us to test, cross-sectionally, how the pandemic influence fund managers' trading strategy on derivative positions. By the end of March, 25 states have SAH in place, and 11 states do not.[14] Focusing on a sample of funds reporting in March 2020, we have 377 derivative users in states with SAH before March 31, 2020, and 72 users in states without SAH.

Figure 4 shows the 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 funds in the analysis is less than the number of all derivative users in our sample because not all funds report at the calendar quarter-end.

As shown in Panel (a) of Figure 4, derivative use, proxied by the absolute derivative weight, increases significantly from 1.3% in December 2019 to 3% in March 2020 for funds residing in states with SAH in place, whereas there are no significant reactions for funds in states without SAH. Diving into long and short positions reveals a larger jump of the absolute derivative weight from short positions on a relative scale than long positions for funds with early SAH in place. The results suggest that fund managers actively bet on short positions using swaps and futures when entering into the pandemic, and the pattern is more prevalent among managers in states with early SAH in place, as the risk of a potential recession is

[14] We only study states with at least one mutual fund. Figure 11 shows a map of states with SAH status by March 31, 2020.

likely to be more salient in them. Moreover, the change in derivative use between September 2019 and December 2019 is insignificant, which rules out the alternative explanation that there might be a common trend of increased derivative use for funds in states with early SAH.

Panel (b) of Figure 4 further decomposes the derivative weight by whether it is a long or short position and 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 in March 2020. Even though managers trade more derivatives in short positions when entering the pandemic, they enter at different time so that some funds have positive weights of short derivative positions, while others have negative weights. Note that the market rebounded sharply after March 23. The portfolio weight of short derivative positions will depend largely on when managers opened the positions. In untabulated results, we find that the average time-to-maturity of new short derivative positions significantly decreases from six months in pre-crisis period to four months during the crisis among SAH funds. In contrast, there is no change in long positions or among funds without SAH. The results suggest that, even among managers who face salient risk of recession and seek downside protections by shorting derivatives, there is large cross-sectional variation in market timing. Fund managers who opened short positions fairly late during the crisis will incur losses when the market rebounded sharply and unexpectedly after March 23, 2020.

Panel (c) of Figure 4 shows how derivative leverage changes quarter-by-quarter. The top row shows the leverage of all positions, and the bottom row shows the leverage of new positions. We can see that there is a large jump in leverage of short derivative positions for funds with SAH in place, whereas there is no response for funds without SAH by the end of March. Our results suggest, as the risk of economic downturn becomes more salient in states with SAH in place, managers actively seek exposure to hedge against market downturn.

One may concern that funds in states with early SAH are inherently different from funds in states without SAH. For example, New York, Massachusetts, and California have SAH before the end of March, and these states have large financial centers and a large number of registered mutual funds. To rule out this alternative explanation, we conduct analyses on a subsample, where states with and without SAH are geographically adjacent to each other and have a comparable number of funds. Specifically, we include funds in the following states: Colorado, Ohio, Minnesota, Wisconsin, Kansas, Texas, Pennsylvania, Missouri, Iowa, and Nebraska. The first five states have SAH before March 31, 2020, and the remaining five states do not have SAH by the end of March. A map of states with their SAH status is shown in Figure 11.

Figure 5 shows the derivative weight and leverage of funds in these ten states. Note that the number of funds in each group is now balanced, 63 funds in states with early SAH, and 69 funds in states without SAH. Funds in states with early SAH, such as Colorado, Ohio, Minnesota, Wisconsin, and Kansas, increase the derivative use, which is mainly driven by the short positions, whereas funds in the remaining five states have little change in derivative use. Our result shows that managers' response to COVID-19 crisis is more prevalent when the risk of a potential recession becomes more salient, and it is not simply driven by some unobserved characteristics among managers in large financial centers.

5.3 Derivative Performance During the Crisis

Having documented the increased derivative use during the crisis, it is interesting to see how derivative positions perform and how they contribute to fund returns, with a focus on the COVID-19 crisis period. So far, no studies systematically examine the performance of derivative positions. Using monthly level realized and unrealized PnL from N-PORT, we are the first to shed light on derivative performance and explore its impact on funds' overall returns.

Panels (a) and (b) of Figure 6 show the distribution of derivative and non-derivative returns before and during the crisis. The pre-crisis period is between July 2019 and January 2020. The crisis period includes February 2020 and March 2020. The distribution of non-derivative returns follows a bell curve centered slightly positive before the crisis, and it shifts with massive density to the left during the crisis, which is not surprising because of the market crash.

Interestingly, the distributions of derivative returns are centered around zero both pre-crisis and during the crisis. What is different in crisis period is that the distribution has fatter tails than pre-crisis period. This is consistent with the increased short derivative positions and the divided opinions on when to open these positions shown in Figure 4. Managers who built short derivative positions before or during the initial market crash will gain, whereas managers who were slower to react opened short positions around the unanticipated market rebound will lose substantially. The distributions are significantly different from each other, as the p-values of Kolmogorov-Smirnov tests are less than 1%.

Although we do not directly observe the exact date when managers trade derivatives, we show that our pre-crisis classification of amplifying and hedging funds can explain the cross-sectional variation in derivative returns during the crisis. Panels (c) and (d) of Figure 6 compare return distributions for amplifying and hedging funds. Note that the derivative returns of hedging funds are more likely to have large positive returns than amplifying funds during the crisis, whereas the distributions of non-derivative returns are similar between the two groups. Among heavy derivative users, hedging funds have derivative returns of 1.4% per month during the crisis period, whereas amplifying funds have derivative returns of -1.3% per month.

How do amplifying funds lose from derivative positions during the crisis? In untabulated results, we find that amplifying funds significantly increase short derivative composition, from the pre-crisis level of less than 10% to 27% during the crisis. The increase in short positions is not merely due to a decrease in long positions. In fact, amplifying funds actively increase their short leverage from 2.5% to 11.4%. Despite the increase in short positions, amplifying funds still have massive exposure to the market due to their outstanding long positions, which will incur large losses when the market crashes.

Amplifying funds also lose from their new short positions. The average time-to-maturity of new short positions decreases from 6 months in pre-crisis periods to 3 months during the crisis, whereas there is no change in long positions. Unlike amplifying funds, hedging funds open short positions with a time-to-maturity of 6 months, both in pre-crisis periods and during the crisis. As fund managers typically enter a fixed set of derivative contracts, the decreased time-to-maturity of amplifying funds' short positions suggests that they may enter positions later than they would otherwise in pre-crisis period.[15] When the market unexpectedly rebounds on March 23, amplifying fund managers lose on the newly entered short positions. Moreover, the negative unrealized PnL of amplifying funds' outstanding short positions in the holdings report of March 2020 also supports our conjecture that they are late to trade short derivatives. Specifically, the average unrealized PnL of amplifying (hedging) funds' short positions is about -15 bps (43 bps) in their March 2020 holdings report.

Figure 7 decomposes derivative returns by derivative instruments and show the return distribution of each instrument during the crisis. We can see that most of the cross-sectional variation in derivative returns comes from swap contracts, followed by futures. Options and foreign exchange related contracts provide limited variation in derivative returns. This finding highlights the importance of swap contracts to active equity funds, which have been overlooked in the previous studies.

Next, we show how derivative strategies impact fund returns, especially during the crisis. Table 8 shows the performance of derivative users relative to nonusers during the COVID-19 pandemic. Similar to Pastor and Vorsatz (2020), our sample spans from January 1, 2019 to June 30, 2020, and includes all derivative users and nonusers. The crisis period is defined between February 20, 2020, and March 23, 2020. The recovery period is from March 24, 2020. Derivative users are classified by the extent of derivative use and by the pre-crisis correlation between derivative and non-derivative returns into nine (3-by-3) groups, and we

[15] We find no changes in the number of unique short derivative positions from pre-crisis period to the crisis period.

only report the coefficient estimates for heavy hedging and heavy amplifying funds due to space limit.[16] All coefficient estimates are in annualized percentage points. The dependent variables from columns (1) to (4) are fund returns, benchmark adjusted returns, CAPM alphas, and Fama-French five-factor alphas. The dependent variables from columns (5) to (8) are hypothetical fund returns based on reported equity positions. All dependent variables are in annualized percentage points.

Heavy hedging funds significantly underperform nonusers in returns during normal times, while they significantly outperform nonusers by an annualized 8.9% CAPM alpha and 14% Fama-French five-factor alpha during the crash period. Such outperformance during the crash stems their derivative positions and active trading, as there is an insignificant difference in hypothetical equity returns between the two groups. Like most insurance products, although heavy hedging users outperform during the crisis, they underperform nonusers during the recovery.

Heavy amplifying funds do not differ in performance from nonusers in pre-crisis periods. They outperform nonusers by an annualized 6.7% CAPM alpha during the crisis, but the performance gap becomes insignificantly different from zero using the Fama-French five-factor model. During the recovery, heavy amplifying funds significantly outperform nonusers only by returns, but not by risk-adjusted alphas. One potential driving force of amplifying funds' mediocre performance is that they opened short derivative positions fairly late in March so that the derivative positions drag down their overall performance.

Figure 8 shows the cumulative performance of funds since 2020.[17] Consistent with Table 8, the performance gap between heavy hedging users and nonusers widens during the crisis period and gradually shrinks in the recovery period. The gap does not completely diminish by the end of June. In fact, the gap in Fama-French five-factor alpha between heavy hedging users and nonusers remains flat since May 2020. Moreover, there is no difference in hypo-

[16] Token users have very similar performance with nonusers. Medium users behave similarly as heavy users. The full table is available upon request.

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

thetical returns among all funds, suggesting that the gap in performance at least partially comes from the derivative positions.

To test how much the outperformance of heavy hedging funds is due to derivative positions and active trading of stocks, we study the monthly fund return and decompose it into derivative and non-derivative returns. Table 9 shows the return decomposition for the crisis period and recovery period. In panel A, heavy hedging funds have an average return of -5.24% during the crisis. Their derivative return is 1.4%, which plays a crucial role in helping funds minimize their losses from non-derivative positions (-6.63%). The difference between hypothetical return and non-derivative return is 2.44%, which can be viewed as the upper bound of the gain from active trading. Heavy amplifying funds, to the contrary, suffer losses both from their derivative positions (-1.3%) and from their active trading (-1.82%). Active trading by nonusers has a tiny impact on fund performance, as the difference between hypothetical return and fund return is only 0.24%. Panel B shows the decomposition for the recovery period. During the recovery period, heavy hedging funds take losses from their derivative positions (-1.68%) and active trading (-0.75%), which is consistent with their hedging strategy. Heavy amplifying funds gain from derivative returns by 0.89% per month, but the magnitude is much smaller than what they have lost during the crisis. Similar to the crisis period, they lose from active trading by 1.62%.

Figure 9 shows various risk measures of funds starting from 2020. Panel (a) and (b) show the tracking error of fund realized returns and hypothetical returns, respectively. Tracking error is calculated as the annualized 30-day rolling standard deviation of the difference between fund returns and benchmark returns.[18] Funds all started at a similar tracking error of 5% before the crisis. The tracking error of heavy hedging funds spikes up to almost 20% during the crisis period, suggesting that their performance significantly differs from their benchmark. At first glance, it seems that the derivative positions and active trading of heavy hedging funds make fund returns riskier and further deviating from the benchmark.

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

However, heavy hedging funds' hypothetical tracking error jumps up to around 30%, even more than the realized tracking error. Taking the two pieces of evidence together, we show that heavy hedging funds hold equities that perform very differently from their benchmark in the crisis, and derivative positions and active trading reduce the tracking error.

Panel (c) of Figure 9 plots the 30-day rolling volatility scaled by the 30-day rolling average of the VIX index. Heavy hedging users have lower volatility than other funds, and the gap widens during the crisis period. On the contrary, the hypothetical volatility is similar between hedging users and others, as is shown in panel (d). The result suggests that, during the crash, while equity returns have similar volatility, derivative positions of hedging funds yield positive returns. Overall, fund returns are not as volatile as other funds. Panel (e) plots the volatility of the performance gap between realized and hypothetical fund returns, scaled by the 30-day rolling average of the VIX index. A large measure suggests either active trading on equity positions, large returns from derivative positions, or both. The measure spikes for hedging users during the crisis period, but remains relatively flat for nonusers and amplifying users. This result further supports the evidence that hedging users' outperformance during the crisis is mainly from their derivatives trading, rather than equity holdings.

To formally test whether hedging users are better equipped than others when there is a market crash, we incorporate 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. We then use 5-year daily returns before 2020 to estimate the factor loading and calculate the out-of-sample daily alpha in 2020. Specifically, for each fund, we run the following regression:

$$r_t - rf_t = {}_0 + {}_1\mathbb{1}_{mktrf_t<0} + {}_2 mktrf_t + {}_3 mktrf_t^2 + {}_4 mktrf_t \mathbb{1}_{mktrf_t<0} + {}_5 mktrf_t^2 \mathbb{1}_{mktrf_t<0} + {}_t,$$

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

Figure 10 shows the cumulative alpha starting from 2020. Surprisingly, after controlling for the market downturn risk, hedging users have even positive alphas in the crisis period. Meanwhile, the gap in alphas with other funds does not diminish during the recovery period. Specifically, the performance gap is as large as 9.2% on March 23, and it remains around 6% afterward. Moreover, the gap is not driven by different equity holdings, as the hypothetical alphas are very similar across all funds. Our result has important implications for investors with strong hedging motives, who value performance the most when the market crashes.

6 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, overturning some prior conclusions.

Our data have two key advantages over the ones used in prior studies. First and foremost, our data include information not only on derivative positions, but also on realized and unrealized capital gains. This enables us to compute returns on the funds' derivative portfolios and compute derivatives' contribution to fund performance in differing market conditions. Second, capital gains of derivative positions are at a monthly frequency, allowing us to analyze behavior over fairly short time intervals, such as the crisis in financial markets during the outbreak of the Covid-19 pandemic. In addition, the data provide information not only on the extent of options and futures usage, but also on other derivative classes. Specifically, the data cover swaps, which account for a significant component of derivative portfolios of active equity mutual funds and play a significant role in generating cross-sectional differences in performance during the Covid-19 period. Swaps have been ignored by prior research on mutual funds.

Early research identified the usage but not the extent of options and futures. To a large extent, that research failed to find differences in performance and risk between derivative users and nonusers. Our analysis shows that this non-result stems from the fact that over 50% of derivative users are token users with a derivative weight of less than 0.1%. Once we focus on funds that use derivatives extensively, we find significant differences both in performance and risk. Particularly, derivative users typically underperform nonusers and have lower market risk exposure. The lower exposure to market risk stems mostly from derivative positions, but not exclusively from them. The equity portfolio of funds that extensively use derivatives has a lower market beta than that of nonusers. Furthermore, in contrast to the commonly perceived view in the literature, we show derivatives are used by the majority of funds (63%) to amplify market exposure, rather than for hedging and risk management.

We utilize the Covid-19 pandemic as an exogenous shock that significantly impacts financial markets to evaluate the impact of derivative use on fund performance during periods of uncertainty. We are able to analyze not only what is the impact of existing positions on fund performance, but also to evaluate funds' trading in response to the crisis.

We show the extent of derivative use has a substantial impact on fund performance during both the breakout and recovery phases in financial markets. Fund managers increase short derivative positions to hedge against the possible recession. However, this pattern is mostly concentrated among funds registered in states with early Stay-at-home orders, making the risk of recession highly salient. Funds that use derivatives to amplify returns prior to the pandemic also increase short positions. However, even after their shift in strategy, they remain mostly amplifiers and sustain significant losses during the outbreak phase. Furthermore, relative to hedgers, their increase of short positions is delayed. Consequently, since the recovery started unexpectedly on March 23, they enter too late into these short positions, leading to significant losses during the recovery phase as well. Hedgers, to the contrary, gain substantially from their derivative positions and outperform others during the crisis.

Although hedgers underperform nonusers during the recovery phase, the performance gap they established during the crisis does not completely diminish by the end of our sample.

There are a few natural extensions one could consider. First, consider fixed income funds, something we are starting to work on. Second, while we conducted analyses at the derivative class level, one could envision analyzing at the individual security level as well. Third, consider how derivative strategies vary throughout the calendar year and how they are related to interim past performance. These are left for future research. Specifically, since N-PORT reports become a requirement only recently, it will probably be a couple of years until one can carefully consider the third.

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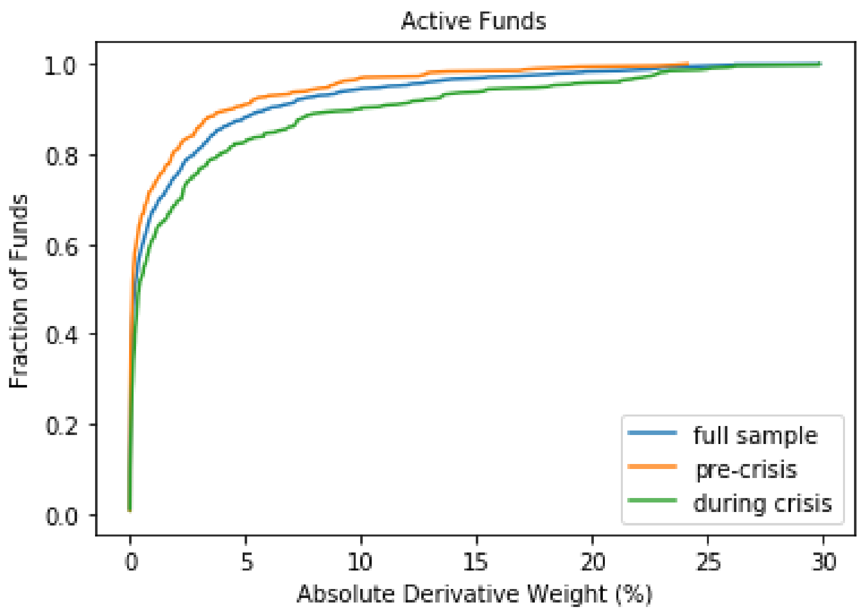
Figure 1
Cumulative Distribution Function of Derivative Use
The figure shows the cumulative distribution functions of the fund-level derivative use. The derivative use is proxied by absolute derivative weight in Panel (a), and by gross leverage in Panel (b). The numbers in x-axis are in percentage. The blue curve represents the full sample between July 2019 and June 2020. The orange curve represents the pre-crisis sample between July 2019 and January 2020. The green curve represents the COVID-19 crisis sample between February 2020 and March 2020.

(a) CDF of Absolute Derivative Weight



(b) CDF of Gross Leverage

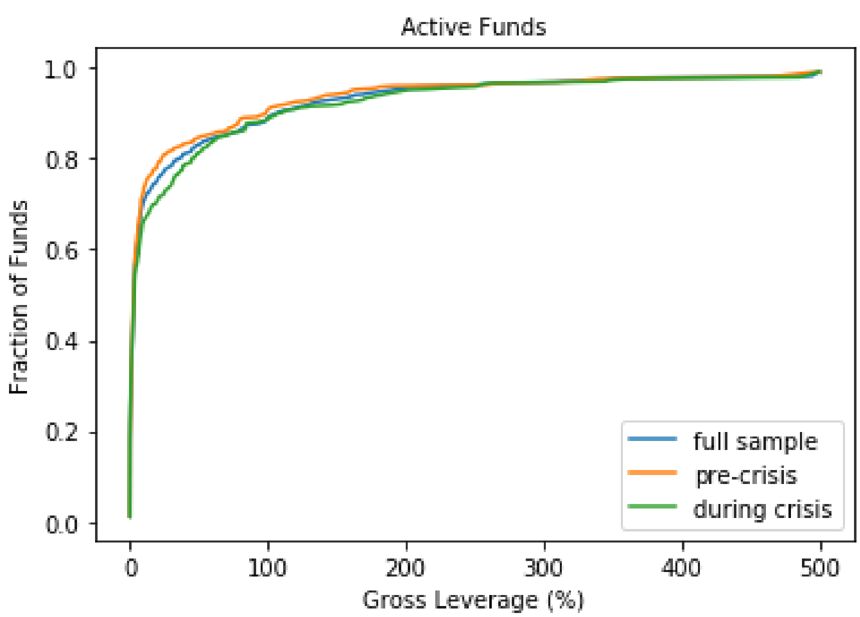
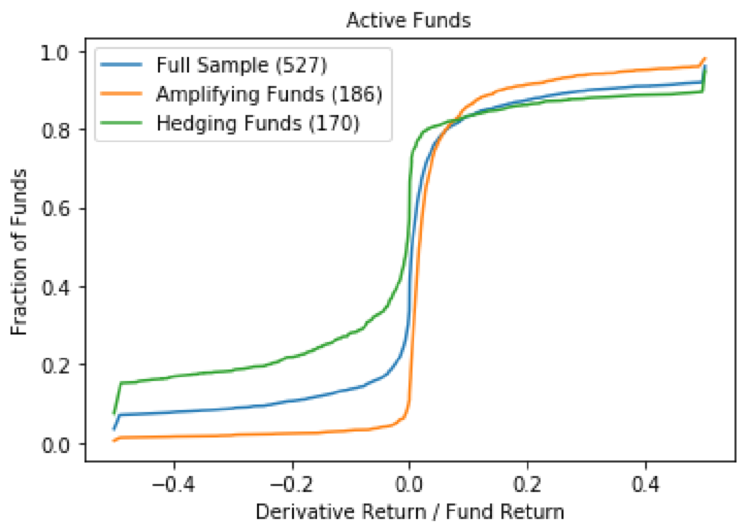


Figure 2

Derivative Contribution to Fund Return

The figure shows the cumulative distribution function of the fund-level derivative contribution to return. Derivative return 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 $t-1$. Derivative contribution to fund return is the ratio between derivative return and fund return. For each fund, we calculate the correlation between the derivative returns and non-derivative returns from July 2019 to February 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 (b) 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 Contribution for All Funds



(b) Derivative Contribution For Medium and Heavy Users

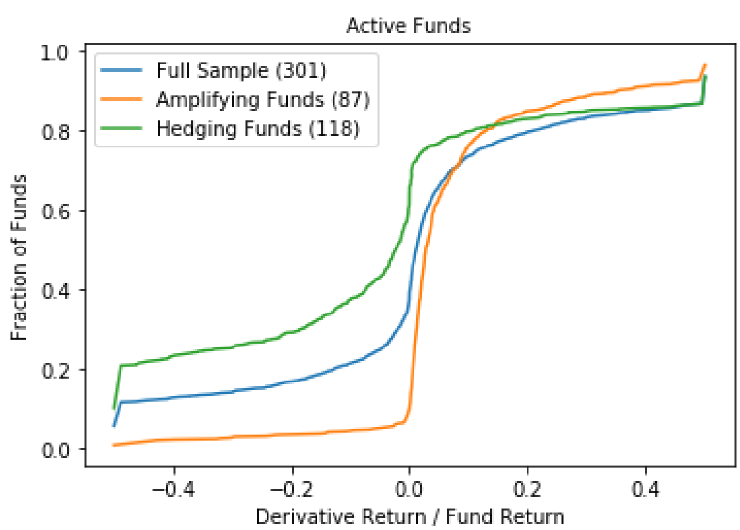


Figure 3
Distribution of the Correlation between Derivative and Non-derivative Returns
The figure shows the histogram and fitted kernel of the correlation between derivative and non-derivative monthly returns. The sample contains all active derivative users between July 2019 and January 2020.

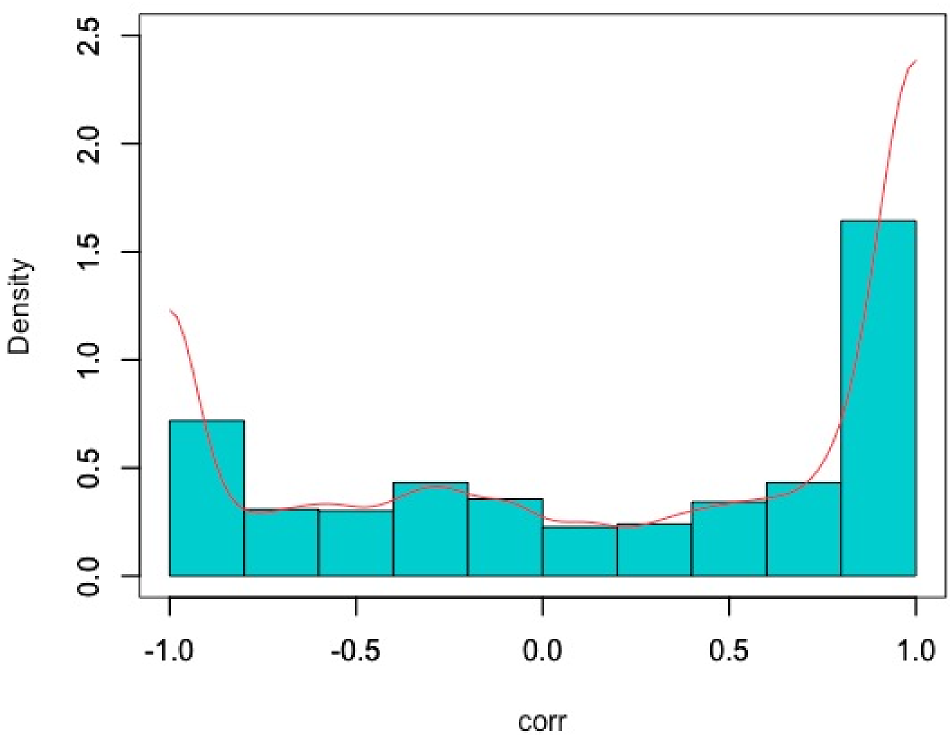
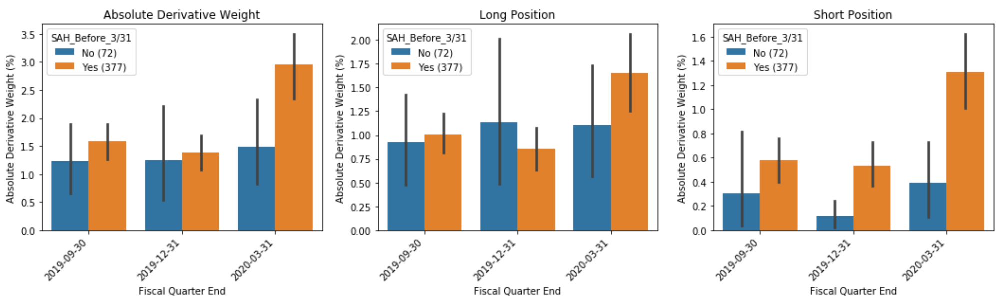


Figure 4

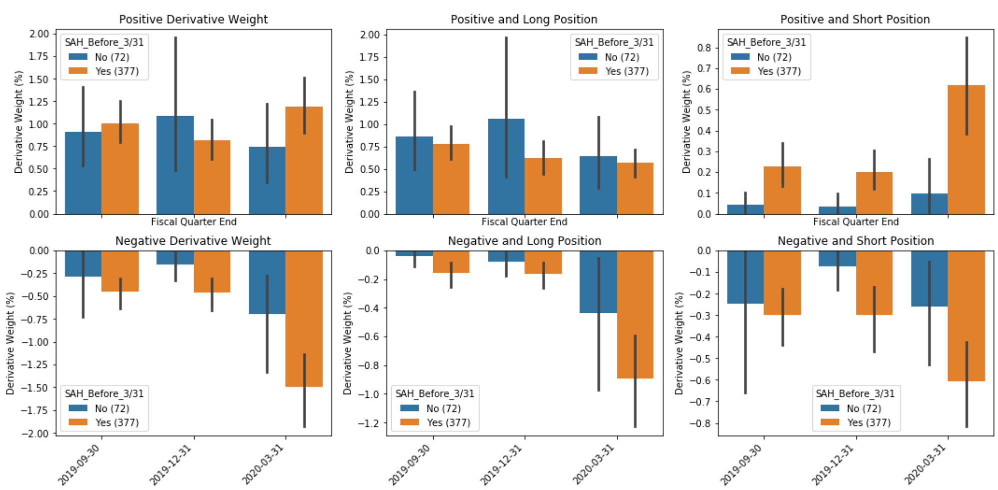
Derivative Weight and Stay-at-home Orders

The figure shows the derivative weights of active funds before and during the COVID-19 pandemic. The sample includes funds that report holdings in September 2019, December 2019, and March 2020. The orange (blue) bars show the average derivative weights 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 leverage and net leverage for both existing positions and new positions.

(a) Absolute Derivative Weight and SAH



(b) Derivative Weight Decomposition



(c) Derivative Leverage

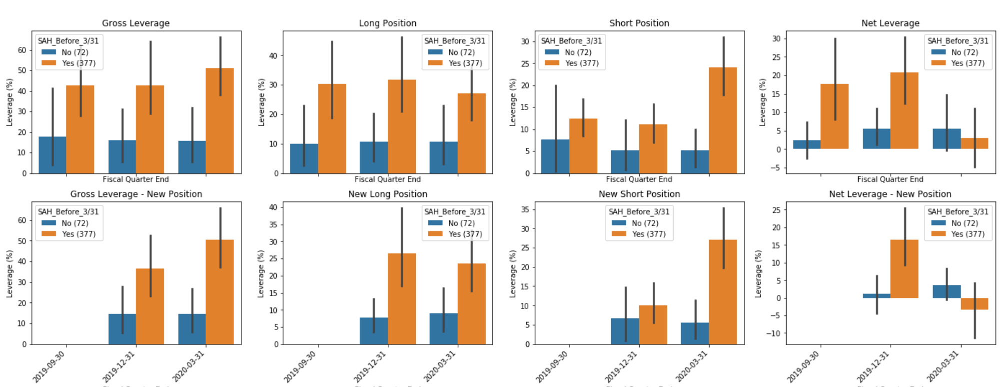
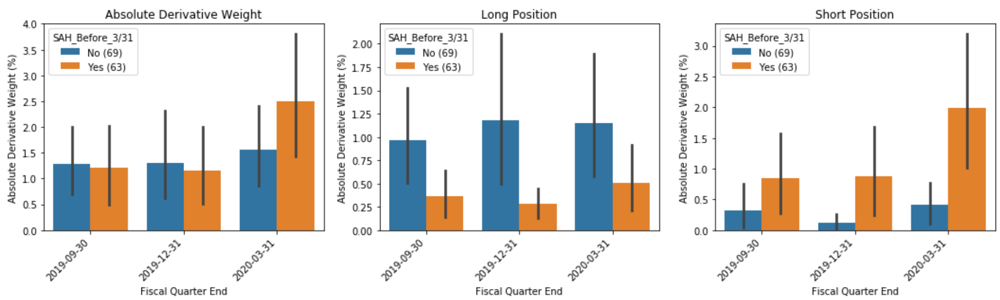


Figure 5

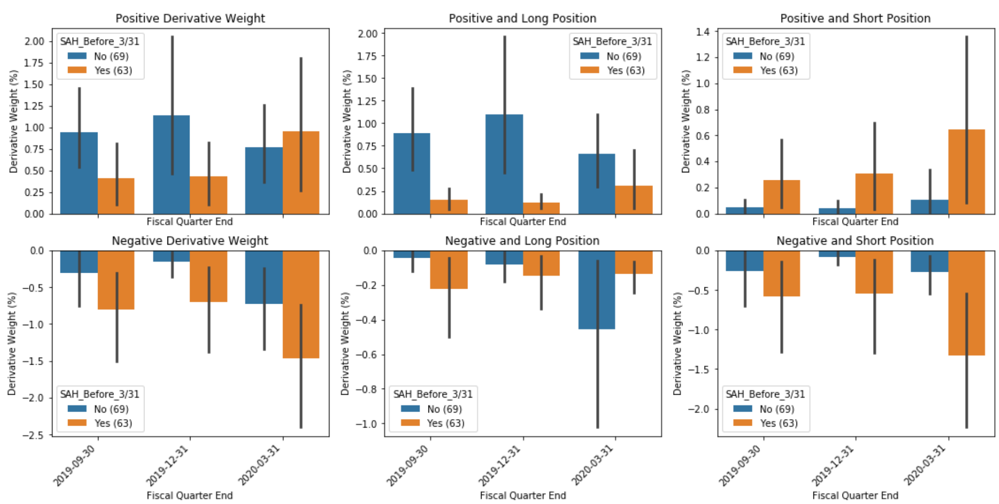
Stay-at-home Around the Border

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

(a) Absolute Derivative Weight and SAH



(b) Derivative Weight Decomposition



(c) Derivative Leverage

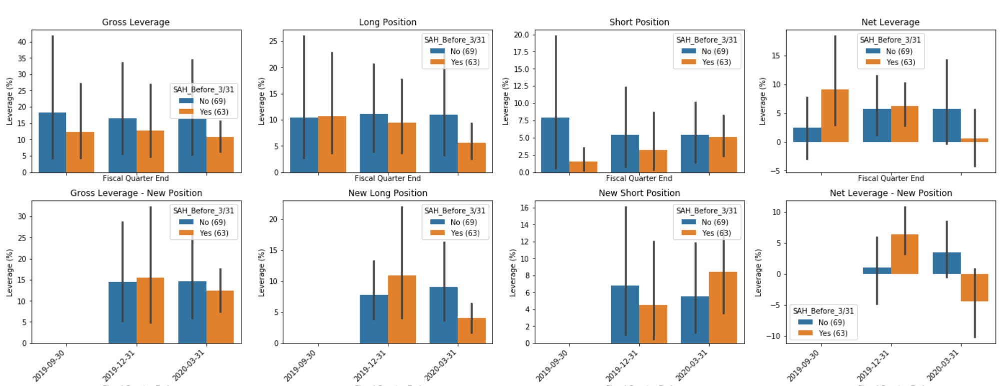
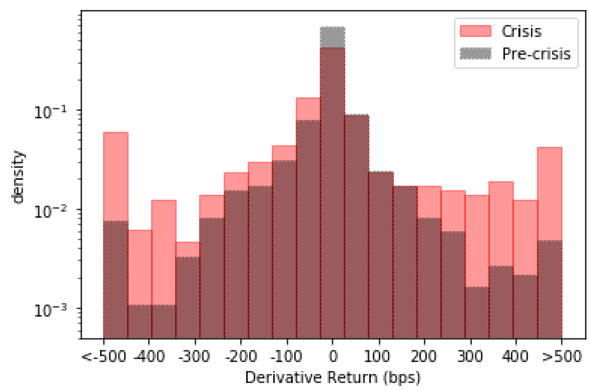


Figure 6

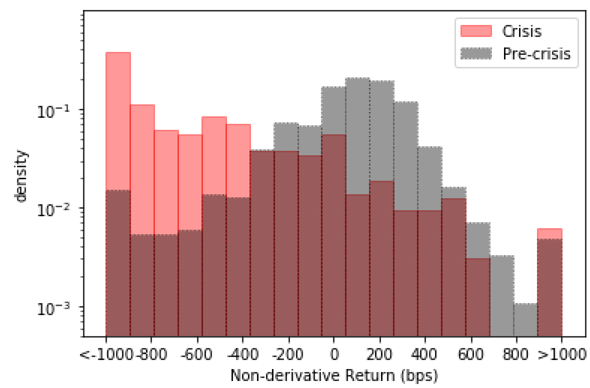
Distribution of Derivative Return in Crisis

The figure shows the distribution of derivative and non-derivative returns. Panel (a) and (b) compare the distributions in pre-crisis and during crisis periods. Panel (c) and Panel (d) compare the distributions of amplifying and hedging funds during the crisis. For panels (a) and (c), derivative returns 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 panels (b) and (d), non-derivative returns 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. Crisis period is defined as February 2020 and March 2020. Pre-crisis period is between July 2019 and January 2020. The y-axis is in log-scale.

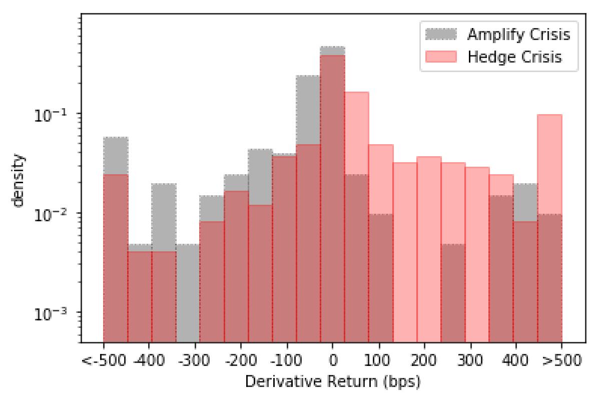
(a) Derivative Return



(b) Non-derivative Return



(c) Derivative Return - Amplify vs Hedge



(d) Non-derivative Return - Amplify vs Hedge

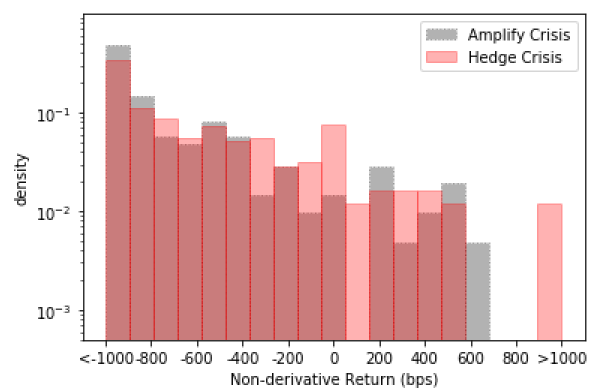
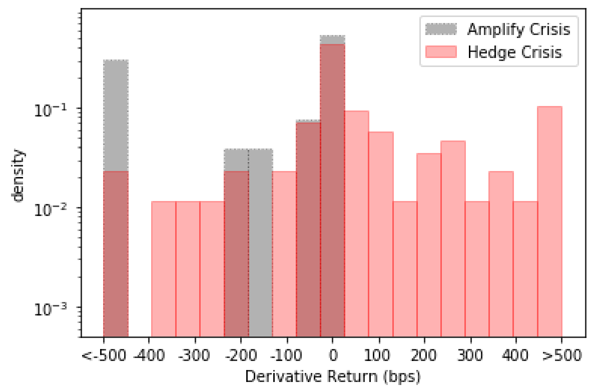


Figure 7

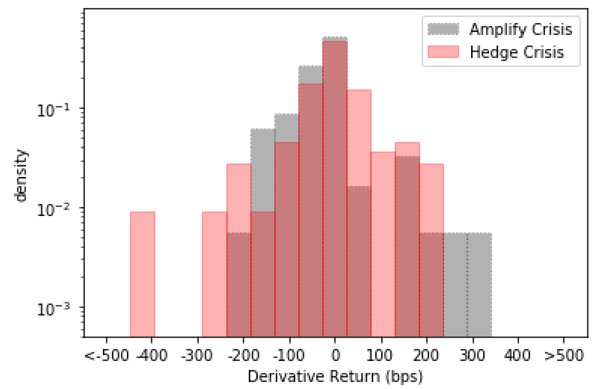
Distribution of Derivative Instrument Return in Crisis

The figure shows the return distribution of derivative instruments. For all instruments, derivative returns 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. Crisis period is defined as February 2020 and March 2020. The y-axis is in log-scale.

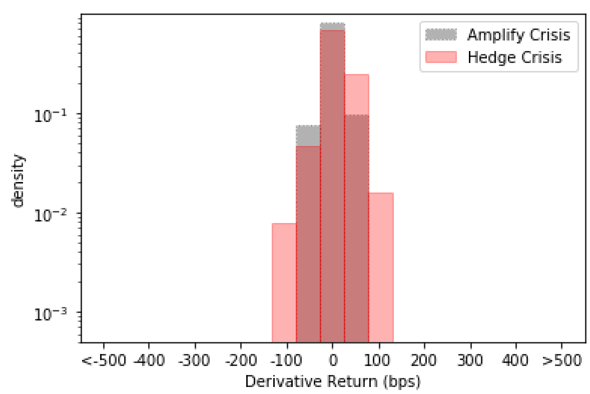
(a) Swaps



(b) Futures



(c) Options



(d) Foreign Exchange Contracts

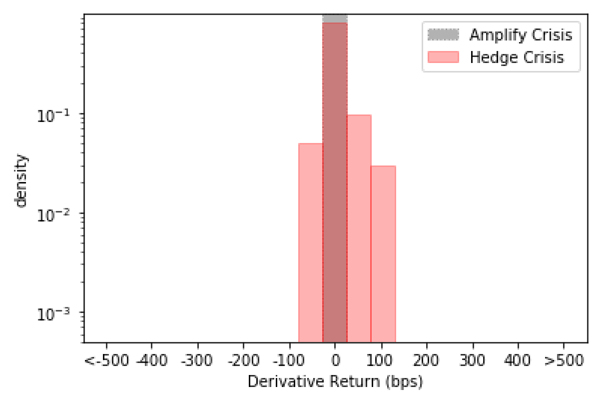
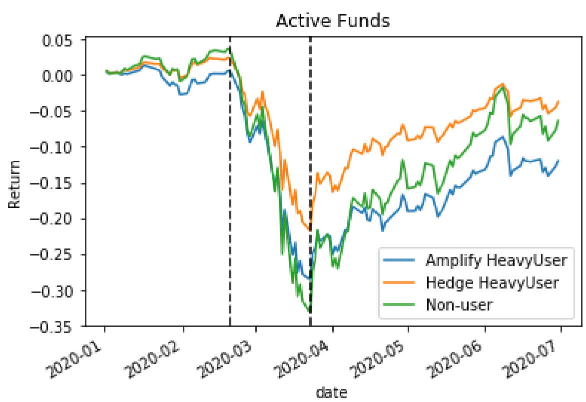


Figure 8

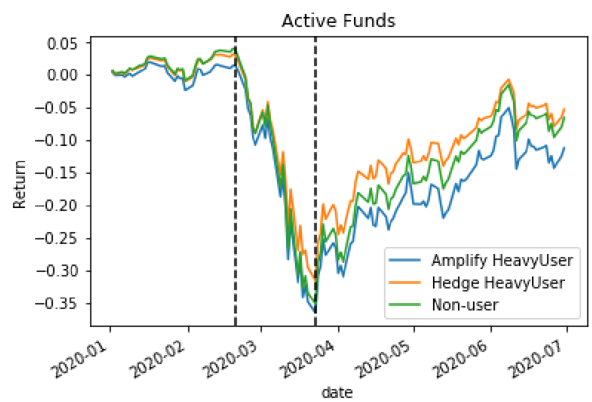
Fund Performance in COVID-19 Pandemic

The figure shows the cumulative returns and alphas for active funds starting in January 2020. Nonusers are the funds without derivative positions. For derivative users, funds are sorted by the absolute derivative weight into deciles. Token users are the funds in the bottom five deciles. Medium users are the funds between the sixth and eighth deciles. Heavy users are the funds in the top two deciles. Derivative users are further partitioned by the correlation between derivative and non-derivative returns prior to February 2020 into three terciles. Amplifying funds are in the top tercile, and hedging funds are in the bottom tercile. The figure shows the performance of nonusers, heavy amplifying users, and heavy hedging users. Token users behave similarly to nonusers. Daily alphas are estimated using a one-year rolling window. The dotted vertical lines indicate the start of crisis period (February 20, 2020) and recovery period (March 24, 2020).

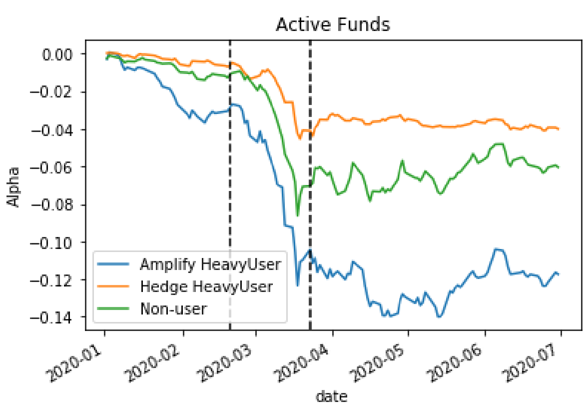
(a) Return



(b) Hypothetical Return



(c) CAPM Alpha



(d) FF5 Alpha

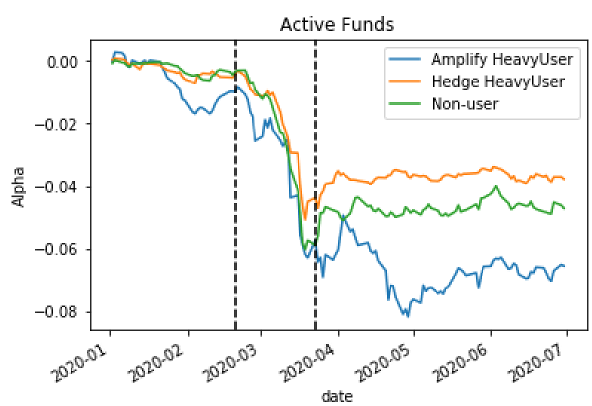
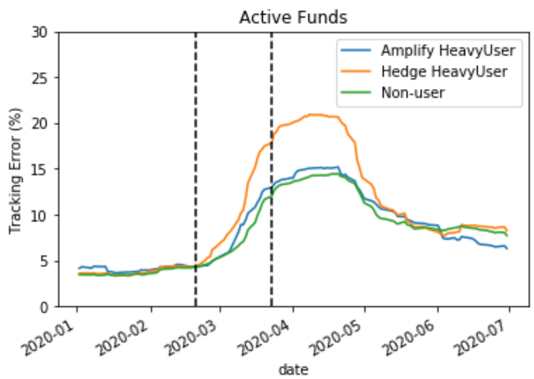


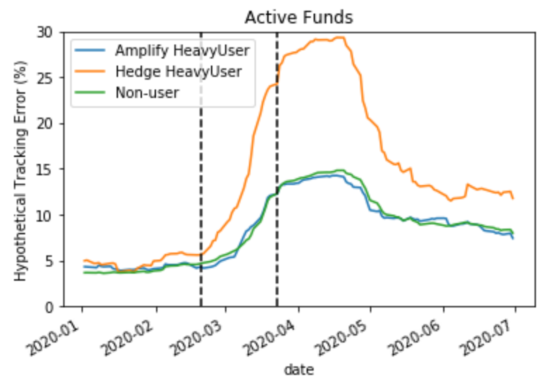
Figure 9
Fund Risk in COVID-19 Pandemic

The figure shows the tracking error and volatility of active funds starting in January 2020. Nonusers, heavy amplifying users, and heavy hedging users are defined as in Figure 8. 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. Panels (c) and (d) shows the 30-day rolling return volatility and hypothetical return volatility, scaled by the 30-day rolling average of VIX. Panel (e) shows the 30-day rolling volatility of the difference between fund return and hypothetical return, scaled by the 30-day rolling average of VIX. The dotted vertical lines indicate the start of crisis period (February 20, 2020) and recovery period (March 24, 2020).

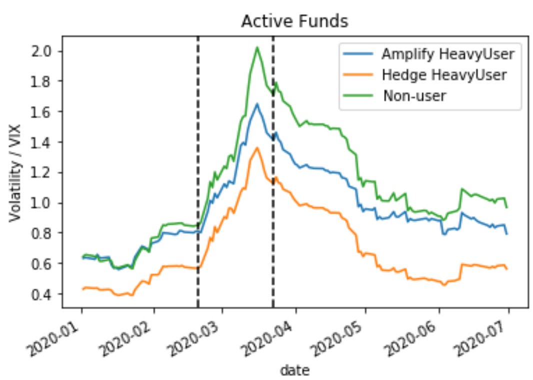
(a) Tracking Error



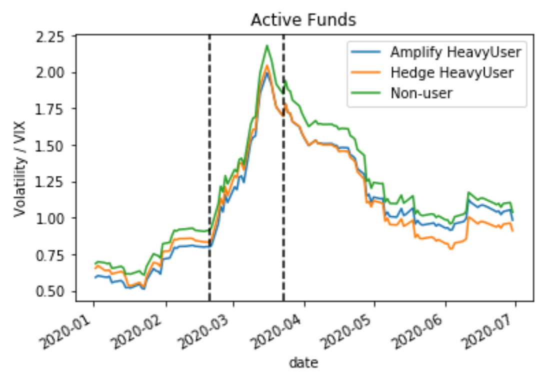
(b) Hypothetical Tracking Error



(c) Volatility / VIX



(d) Hypo Volatility / VIX



(e) Volatility of (ret - ret^{hypo}) / VIX

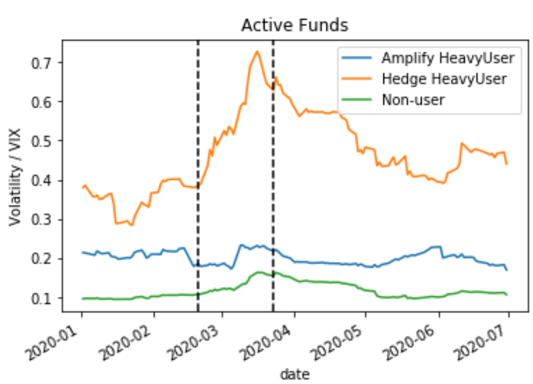
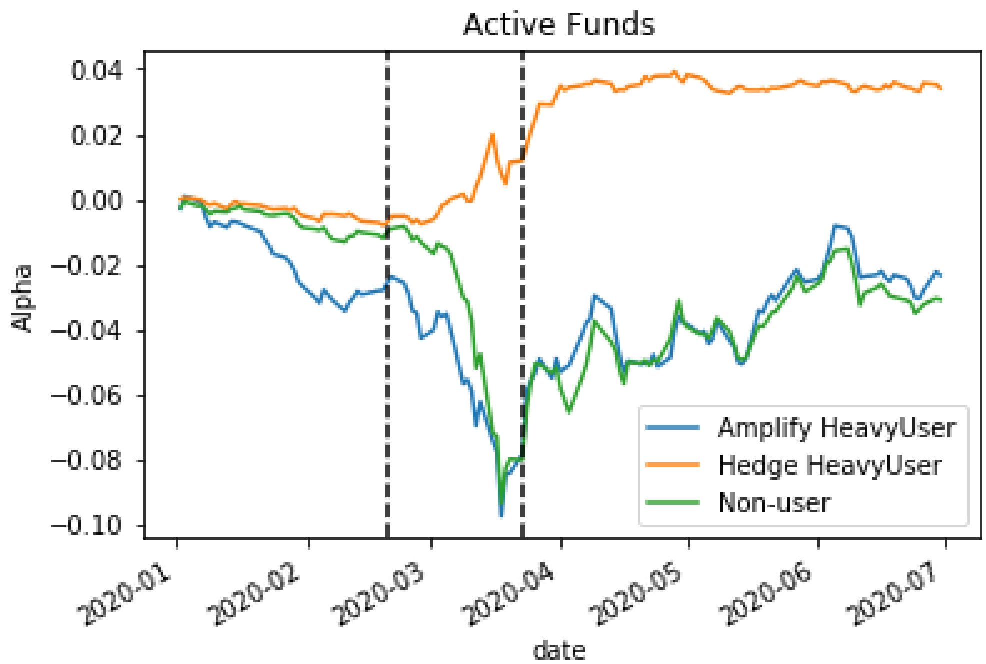


Figure 10

Derivatives and Crash Risk

The figure shows the cumulative down-market alphas starting in January 2020. Nonusers, heavy amplifying users, and heavy hedging users are defined as in Figure 8. The factor model includes a down-market dummy, the excess return of the market and its squared term, and their interaction terms with the down-market dummy. For each fund, we estimated the factor loading use 5-year daily fund returns before 2020. We then calculate the daily down-market alpha using the estimated factor loading and plot the average cumulative alpha for each fund group.

(a) Down-market Alpha



(b) Hypothetical Down-market Alpha

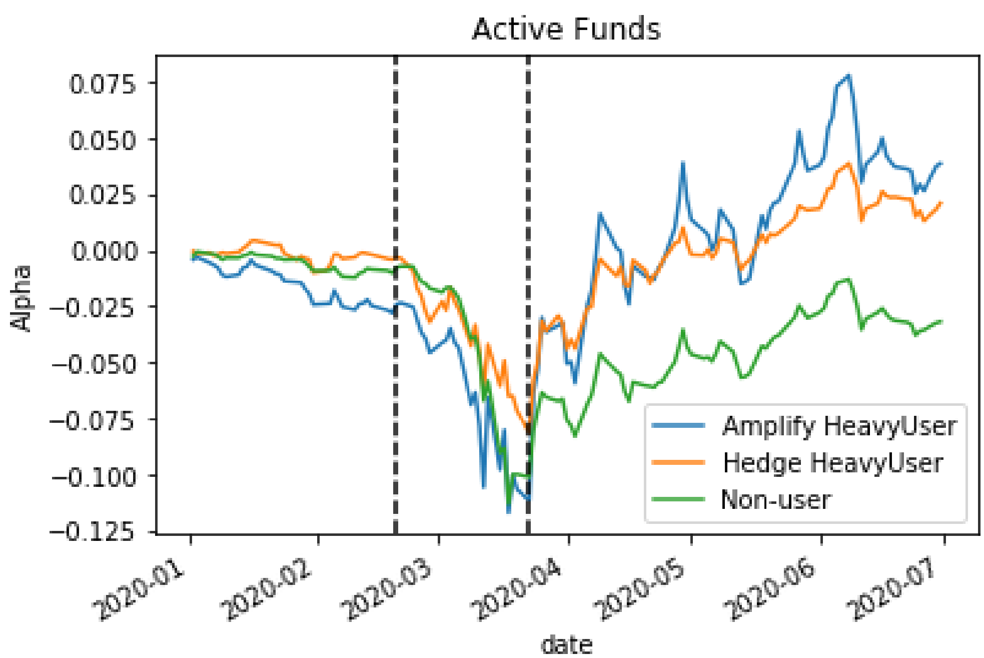


Figure 11

Map of Stay-at-home Order

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

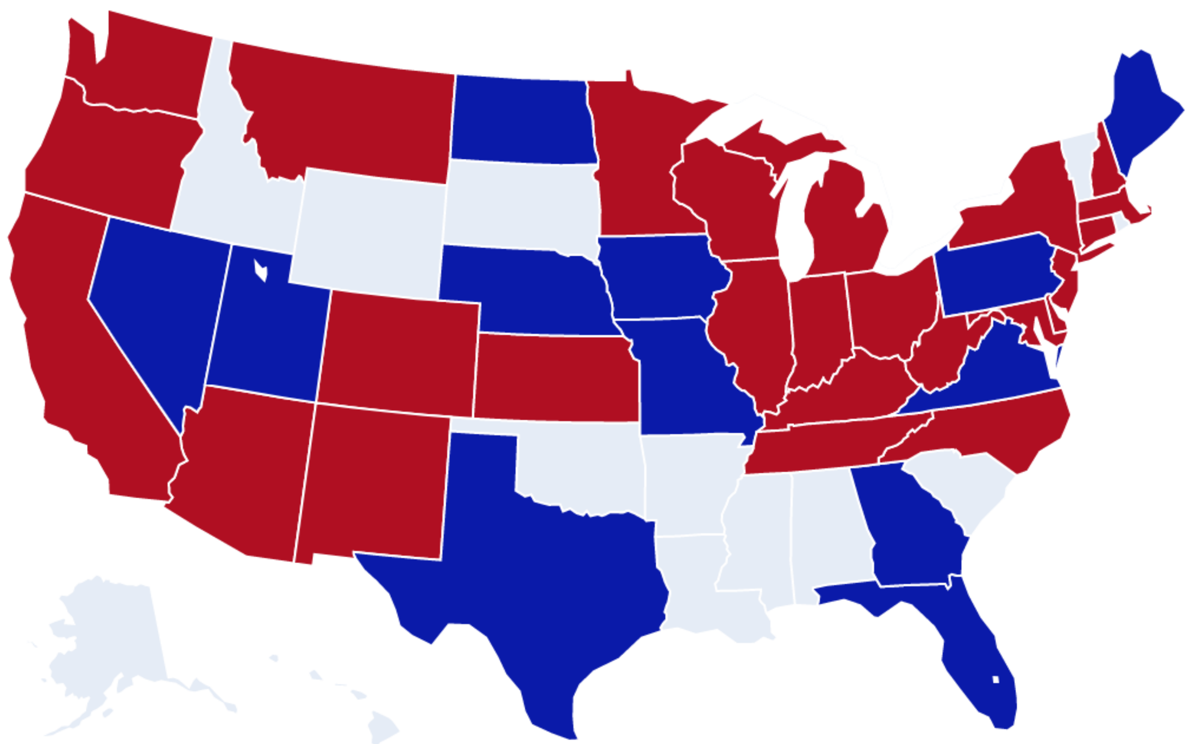


Table 1
Overview of Derivative Use

The table shows the summary of derivative use in equity domestic active funds. The sample includes all equity domestic active funds that use derivatives from September 2019 to June 2020. Panel A shows the number of funds with derivative positions, and the breakdown of derivative use by categories. Panel B shows the summary statistics of key variables. Absolute derivative weight is the sum of portfolio weights of derivative positions in absolute value, measured in percentage points. Gross leverage is the sum of notional amount of derivative positions, normalized by the fund size and shown in percentage points. TNA is the total net assets in millions. Derivative return 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 return is the difference between fund return and derivative return, shown in basis points. Derivative contribution is the ratio between derivative return and fund return, shown in percentage points. All variables are winsorized at 1% level.

Panel A: Breakdown of Derivative Usage

	No. of Funds	Absolute Weight	Gross Leverage
Swap	124	0.64	22.89
Future/Forward	432	0.70	20.33
Option	317	0.43	1.78
Foreign Exchange	179	0.28	6.46
All Derivatives	756	2.05	51.46

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 Leverage (%)	51.46	88.12	0	0	0.28	0.9	1.69	2.7	4.63	14.21	36.38	106.26	512.04
Derivative Contribution (%)	6.06	114.07	-512.49	-30.36	-2.82	-0.31	0.01	0.33	1.13	2.36	6.47	28.83	447.64
Derivative 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 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

Table 2
Derivative Weight and Leverage by the Extent of Use

The table shows fund-level derivative weight (Panel A) and gross leverage (Panel B), grouped by the extent of derivative use. The sample includes equity domestic active funds that use derivatives from September 2019 to June 2020. For each quarter, funds are sorted by the absolute derivative weight into deciles. Token users are the funds in the bottom five deciles, medium users between the sixth and eighth deciles, and Heavy users in the top two deciles. Panel C shows the transition matrix of the user type from the previous quarter to current 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	Medium Users	Heavy Users
All Derivative	2.05	0.06	1.11	8.36
Future	0.70	0.03	0.64	2.44
% in Long	68.18	88.78	69.51	67.00
Swap	0.64	0.00	0.12	3.02
% in Long	73.03	44.59	65.47	73.52
Option	0.43	0.01	0.23	1.75
% in Long	26.51	69.48	29.87	24.98
Foreign Exchange	0.28	0.02	0.12	1.15
% in Long USD	59.96	89.37	67.54	57.85

Panel B: Gross Leverage (%)

	All Users	Token Users	Medium Users	Heavy Users
All Derivative	51.46	3.04	47.39	177.15
Future	20.33	1.81	27.93	54.80
% in Long	58.11	71.32	48.38	64.39
Swap	22.89	0.28	14.42	91.32
% in Long	51.95	82.09	25.90	57.82
Option	1.78	0.04	2.15	5.56
% in Long	56.25	56.09	20.23	76.86
Foreign Exchange	6.46	0.91	2.90	25.47
% in Long USD	58.16	90.96	73.33	52.69

Panel C: Transition Matrix of User Types

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

Table 3
Performance of Derivative Users

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

Panel A: Derivative Users vs Nonusers

Users	Return	Benchmark	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Non-users	11.52***	-2.52***	-1.80***	0.988***	-0.96**	0.94***	0.179***	-0.039**	-0.054**	-0.032
	(2.84)	(-8.4)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Users	9.72***	-3.00***	-2.16***	0.884***	-1.44***	0.847***	0.117***	-0.018	-0.078**	0.045
	(2.68)	(-10.68)	(-3.51)	(68.4)	(-2.82)	(71.14)	(5.88)	(-0.79)	(-2.57)	(1.24)
Users - Non	-1.80***	-0.48***	-0.36	-0.105***	-0.48	-0.092***	-0.062***	0.021*	-0.024	0.077***
	(-3.31)	(-3.6)	(-1.04)	(-14.82)	(-1.65)	(-14.52)	(-5.83)	(1.7)	(-1.48)	(3.99)

Panel B: By Derivative Usage

Users	Return	Benchmark	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Non-users	11.52***	-2.52***	-1.80***	0.988***	-0.96**	0.94***	0.179***	-0.039**	-0.054**	-0.032
	(2.84)	(-8.4)	(-2.92)	(75.94)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Token Users	11.28***	-2.16***	-1.92***	0.979***	-0.96**	0.927***	0.17***	0.001	-0.072***	-0.019
	(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***	0.813***	-2.04***	0.791***	0.069**	-0.028	-0.071*	0.068
	(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***	0.687***	-2.28***	0.678***	0.041	-0.056	-0.056	0.155***
	(2.39)	(-12.39)	(-3.02)	(41.59)	(-2.91)	(38.03)	(1.36)	(-1.64)	(-1.25)	(2.86)
Heavy - Non	-4.56***	-1.92***	-0.48	-0.301***	-1.32**	-0.262***	-0.139***	-0.017	-0.003	0.187***
	(-3.31)	(-6.19)	(-0.8)	(-20.25)	(-2.13)	(-19.35)	(-6.12)	(-0.66)	(-0.08)	(4.56)

Panel C: Hypothetical Returns

Users	Return	CAPM Alpha	CAPM Mktrf	FF5 Alpha	FF5 Mktrf	FF5 SMB	FF5 HML	FF5 RMW	FF5 CMA
Non-users	13.44***	-0.60	1.052***	0.24	0.995***	0.212***	-0.039**	-0.051**	-0.037
	(3.12)	(-0.95)	(73.41)	(0.65)	(105.8)	(13.43)	(-2.17)	(-2.14)	(-1.3)
Token Users	13.32***	-0.96	1.06***	0.24	1.0***	0.2***	0.008	-0.079***	-0.03
	(3.06)	(-1.47)	(77.87)	(0.63)	(127.39)	(15.2)	(0.54)	(-3.97)	(-1.28)
Medium Users	12.48***	-0.48	0.971***	0.02	0.932***	0.169***	-0.029	0.004	0.024
	(3.11)	(-0.67)	(57.01)	(0.06)	(56.07)	(6.07)	(-0.91)	(0.09)	(0.48)
Heavy Users	11.88***	-0.96	0.953***	-0.48	0.924***	0.1***	-0.042	-0.065	0.011
	(3.01)	(-1.29)	(60.31)	(-0.71)	(56.01)	(3.62)	(-1.34)	(-1.54)	(0.22)
Heavy - Non	-1.56**	-0.36	-0.098***	-0.72	-0.071***	-0.112***	-0.003	-0.013	0.048
	(-2.25)	(-0.5)	(-7.16)	(-1.26)	(-4.99)	(-4.7)	(-0.12)	(-0.37)	(1.12)

t statistics in parentheses
* $p < 0{:}1$, ** $p < 0{:}05$, *** $p < 0{:}01$

Table 4
Derivative Weight by Amplifying/Hedging Funds
The table shows fund-level derivative weights, grouped by whether the fund uses derivatives for amplifying or hedging. The sample includes equity domestic active funds that use derivatives. For each fund, we calculate the correlation between the derivative returns and non-derivative returns 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: Amplifying Funds

	All Users	Token Users	Medium Users	Heavy Users
All Derivative	1.31	0.06	1.14	6.69
Future	0.79	0.06	0.99	3.22
% in Long	84.92	91.99	84.30	84.87
Swap	0.33	0.00	0.05	2.31
% in Long	87.13	100.00	87.87	87.08
Option	0.04	0.01	0.09	0.05
% in Long	46.41	77.94	41.28	51.30
Foreign Exchange	0.16	0.00	0.02	1.11
% in Long USD	47.14	84.84	61.59	46.57

Panel B: Hedging Funds

	All Users	Token Users	Medium Users	Heavy Users
All Derivative	2.75	0.08	1.03	8.04
Future	0.56	0.01	0.25	1.58
% in Long	45.68	71.26	55.85	43.65
Swap	0.67	0.01	0.15	2.10
% in Long	49.35	31.48	40.65	50.11
Option	1.03	0.02	0.41	3.00
% in Long	17.82	66.66	14.61	17.99
Foreign Exchange	0.49	0.05	0.22	1.36
% in Long USD	67.28	89.72	66.94	66.23

Table 5
Gross Leverage by Amplifying/Hedging Funds
The table shows fund-level gross leverage, grouped by whether the fund uses derivatives for amplifying or hedging returns. The sample includes equity domestic active funds that use derivatives. For each fund, we calculate the correlation between the derivative returns and non-derivative returns 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: Amplifying Funds

	All Users	Token Users	Medium Users	Heavy Users
All Derivative	23.37	2.97	23.03	105.53
Future	11.16	2.63	19.19	26.05
% in Long	64.79	85.35	52.02	78.89
Swap	5.72	0.27	3.04	33.79
% in Long	79.29	100.00	83.62	77.70
Option	0.05	0.01	0.14	0.01
% in Long	53.13	51.09	52.73	85.68
Foreign Exchange	6.45	0.05	0.67	45.68
% in Long USD	50.05	88.94	58.79	49.56

Panel B: Hedging Funds

	All Users	Token Users	Medium Users	Heavy Users
All Derivative	65.44	3.98	68.24	139.37
Future	15.86	0.93	26.55	22.40
% in Long	40.58	34.87	40.01	41.65
Swap	39.83	0.22	29.85	100.92
% in Long	24.01	52.82	7.88	29.38
Option	4.54	0.12	5.94	8.50
% in Long	51.37	55.70	15.74	79.71
Foreign Exchange	5.21	2.70	5.91	7.55
% in Long USD	71.68	91.81	72.18	62.18

Table 6
Performance of Amplifying/Hedging Funds

The table shows the performance of amplifying and hedging funds between 2010 and 2019. We backfill the derivative use data for periods before September 2019 using the funds' information in September 2019. Panel A shows the factor loading of real returns. Panel B shows the factor loading of hypothetical returns, assuming the equity positions are held throughout the quarter. In Panel C, funds are double sorted by the extent of derivative use and by whether the fund is an amplifying or a hedging fund into groups. The panel compares the performance among nonusers, heavy amplifying funds, and heavy hedging funds. The monthly five-factor alphas are reported for each portfolio. All returns and alphas are annualized and in percentage points.

Panel A: Amplifying vs Hedging Funds

	ret	alpha	mktrf	smb	hml	rmw	cma
Amplifying	10.80***	-1.44***	0.928***	0.18***	0.006	-0.026	-0.005
	(2.71)	(-3.94)	(111.97)	(12.94)	(0.35)	(-1.22)	(-0.19)
Hedging	10.08***	-0.96**	0.837***	0.056***	-0.024	-0.111***	0.053
	(2.87)	(-2.06)	(78.45)	(3.11)	(-1.19)	(-4.12)	(1.65)
Hedging - Amplifying	-0.72	0.48	-0.091***	-0.124***	-0.03**	-0.086***	0.058***
	(-1.17)	(1.64)	(-13.99)	(-11.35)	(-2.39)	(-5.17)	(2.93)

Panel B: Hypothetical Returns

	ret	alpha	mktrf	smb	hml	rmw	cma
Amplifying	13.08***	-0.04	0.99***	0.213***	-0.007	-0.018	-0.016
	(3.05)	(-0.08)	(121.73)	(15.63)	(-0.43)	(-0.89)	(-0.64)
Hedging	13.44***	0.24	0.999***	0.109***	0.004	-0.088***	0.001
	(3.16)	(0.72)	(127.92)	(8.35)	(0.26)	(-4.46)	(0.03)
H-L	0.36	0.20	0.01	-0.104***	0.011	-0.07***	0.016
	(0.91)	(0.84)	(1.31)	(-8.31)	(0.74)	(-3.71)	(0.73)

Panel C: Decompose Heavy Users

	ret	alpha	mktrf	smb	hml	rmw	cma
Nonusers	11.52***	-0.96**	0.94***	0.179***	-0.039**	-0.054**	-0.032
	(2.84)	(-2.48)	(100.74)	(11.48)	(-2.17)	(-2.27)	(-1.13)
Heavy Amplifying	6.72*	-3.01***	0.775***	0.224***	0.047	-0.038	0.056
	(1.9)	(-3.53)	(36.41)	(6.28)	(1.14)	(-0.7)	(0.87)
Heavy Hedging	8.76***	-1.32*	0.741***	-0.033	-0.102***	-0.112**	0.186***
	(2.87)	(-1.66)	(41.04)	(-1.11)	(-2.94)	(-2.45)	(3.39)
Hedging - Amplifying	2.04*	1.69**	-0.034*	-0.257***	-0.148***	-0.074	0.13**
	(1.82)	(2.02)	(-1.69)	(-7.56)	(-3.81)	(-1.44)	(2.1)
Amplifying - Nonusers	-4.68***	-2.05***	-0.163***	0.043	0.081**	0.013	0.086
	(-4.86)	(-2.99)	(-9.48)	(1.48)	(2.48)	(0.31)	(1.66)
Hedging - Nonusers	-2.64**	-0.36	-0.197***	-0.215***	-0.067**	-0.061	0.216***
	(-2.04)	(-0.42)	(-13.64)	(-8.87)	(-2.41)	(-1.66)	(4.92)

Table 7

Change in Portfolio Allocation During COVID-19

The table shows the change in portfolio allocation of active funds during the COVID-19 pandemic. The sample includes derivative users that report holdings in February 2020 and March 2020. Funds are sorted by the absolute derivative weight at the last quarter of 2019 into token users, medium users, and heavy users, following a 50/30/20 cut. The percentage numbers in parenthesis show the relative change in weight from the previous quarter.

	Full Sample	Token Users	Medium Users	Heavy Users
Absolute Derivative Weight	1.41*** (96.24%)	0.32*** (974.99%)	1.1*** (172.39%)	4.72*** (73.31%)
- Long	0.72*** (75.7%)	0.1*** (320.33%)	0.45*** (111.88%)	2.73*** (65.5%)
- Long Positive	-0.03 (-3.6%)	0.04*** (200.54%)	0.24*** (71.02%)	-0.62 (-18.42%)
- Long Negative	0.75*** (415.05%)	0.05*** (597.92%)	0.21*** (311.46%)	3.36*** (422.56%)
- Short	0.69*** (134.31%)	0.23*** (7286.57%)	0.64*** (278.84%)	1.99*** (87.69%)
- Short Positive	0.42*** (193.52%)	0.03*** (3336.36%)	0.36*** (326.52%)	1.51*** (161.97%)
- Short Negative	0.27*** (91.44%)	0.2*** (8909.38%)	0.28*** (234.1%)	0.48 (35.94%)
Equity	-2.2*** (-2.66%)	-1.22*** (-1.31%)	-3.91*** (-5.08%)	-2.29*** (-3.59%)
Debt	0.24 (4.34%)	0.13 (8.01%)	0.03 (0.42%)	0.98 (6.33%)
STIV/Repo	1.4*** (20.15%)	0.7*** (16.36%)	2.44*** (31.93%)	1.71 (12.74%)
Cash	0.83*** (47.36%)	0.79*** (111.84%)	1.12*** (29.71%)	0.56 (36.36%)

Table 8

Performance During the COVID-19 Pandemic: Amplify vs Hedging

The table shows the performance of derivative users From January 1, 2019, to June 30, 2020. Daily alphas are estimated using fund daily returns with a one-year rolling window. All dependent variables are in annualized percentage points. The dummy variable *crash* is equal to one between February 20, 2020, and March 23, 2020. The dummy variable *recovery* is equal to one between March 24, 2020, and June 30, 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 returns 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 only report heavy amplifying funds and heavy hedging funds due to page space. All regression specifications include fund controls, time fixed effect, and style fixed effect. All standard errors are clustered at fund level.

	(1) Ret	(2) $Ret^{BenchAdj}$	(3) $CAPM$	(4) $FF5$	(5) Ret_{hypo}	(6) $Ret^{BenchAdj}_{hypo}$	(7) $CAPM$ $hypo$	(8) $FF5$ $hypo$
AmplifyHeavy	0.0361	1.884	1.995	1.284	-5.393	-3.692	-3.676	-3.183
	(0.01)	(1.57)	(0.97)	(0.81)	(-1.96)	(-2.01)	(-1.44)	(-1.63)
HedgeHeavy	-3.462	1.004	0.210	-0.426	-0.365	2.860	-0.290	-0.502
	(-2.19)	(1.32)	(0.16)	(-0.43)	(-0.22)	(2.59)	(-0.19)	(-0.43)
AmplifyHeavy × crash	33.54	-7.393	6.673	-0.474	4.317	-2.20	-4.804	-11.30
	(8.78)	(-4.02)	(2.12)	(-0.20)	(1.15)	(-0.82)	(-1.38)	(-4.24)
HedgeHeavy × crash	36.45	-9.573	8.889	14.01	6.984	-2.93	1.640	6.223
	(6.81)	(-3.72)	(2.02)	(4.13)	(1.34)	(-1.56)	(0.34)	(1.68)
AmplifyHeavy × recovery	-26.07	2.659	-2.859	-1.382	-7.095	0.990	-0.489	-0.935
	(-4.93)	(1.05)	(-0.66)	(-0.41)	(-1.16)	(0.24)	(-0.09)	(-0.22)
HedgeHeavy × recovery	-49.02	-9.110	-9.539	-6.024	-12.83	16.81	-5.009	-2.549
	(-14.12)	(-5.45)	(-3.34)	(-2.74)	(-3.50)	(6.87)	(-1.48)	(-0.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StyleFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0833	0.0615	0.123	0.0760	0.0874	0.0465	0.134	0.0770
F	118.7	30.92	9.979	18.02	8.473	96.42	3.448	12.04
N	1024206	1024206	1024206	1024206	944067	944067	943817	943817

t statistics in parentheses

* $p < 0{:}1$, ** $p < 0{:}05$, *** $p < 0{:}01$

Table 9
Fund Return Decomposition

The table shows the monthly fund return decomposition for the crisis period and recovery period. Similar to Table 8, the table presents heavy amplifying funds, heavy hedging funds, and nonusers. For each fund-month observation, fund return is decomposed into two parts: derivative return and non-derivative return. We also calculate the monthly hypothetical equity return based on the most recent equity holdings. Columns 1-4 show monthly averages of derivative return, non-derivative return, fund return, and hypothetical return, respectively. All numbers are at monthly frequency and are in percentage points. The crisis period is between February 2020 and March 2020. The recovery period is between April 2020 and June 2020.

Panel A: Crisis Period

	Derivative Return	Non-derivative Return	Fund Return	Hypothetical Return
Nonusers			-11.78	-11.54
Heavy Amplify	-1.31	-10.02	-11.33	-8.20
Heavy Hedging	1.40	-6.63	-5.24	-9.07

Panel B: Recovery Period

	Derivative Return	Non-derivative Return	Fund Return	Hypothetical Return
Nonusers			6.88	6.82
Heavy Amplify	0.89	4.87	5.76	6.49
Heavy Hedging	-1.68	5.17	3.49	5.92