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Abstract

In the decade following the financial crisis of 2008, investment funds in corporate bond markets became prominent market players and generated concerns of financial fragility. The COVID-19 crisis provides an opportunity to inspect their resilience in a major stress event. Using daily microdata, we document major outflows in these funds during this period, far greater than anything they experienced in past events. Large outflows were sustained over several weeks and were widespread across funds. Inspecting the role of sources of fragility, we show that both the illiquidity of fund assets and the vulnerability to fire sales were important factors in explaining outflows in this episode. The exposure to sectors most hurt by the COVID-19 crisis was also important. Two policy announcements by the Federal Reserve about extraordinary direct interventions in corporate-bond markets seem to have played an important role in calming down the panic and reversing the outflows.

1 Introduction

Financial fragility can take different forms, which evolve over time, as financial regulation and institutions change in response to past crises, emerging technologies, and changing demands. One of the most prominent concerns emerging after the financial crisis of 2008-2009 and its aftermath was the fragility imposed by investment funds – including mutual funds and exchange-traded funds (ETFs) – investing in illiquid assets, such as corporate bonds. For example, the Financial Stability Board flagged this combination of investment funds investing in illiquid assets as one of the key vulnerabilities in its 2017 report.[1] Just last year, Mark Carney, the governor of the Bank of England, warned that investment funds that include illiquid assets but allow investors to take out their money whenever they like were "built on a lie" and could pose a big risk to the financial sector.[2]

Figure 1 demonstrates the dramatic growth of assets under management of US investment funds investing in corporate bonds in proportion to the size of the corporate-bond market over the last decade since the 2008-2009 crisis. Part of this growth is attributable to the increased regulation of banks, which led market forces to push some of the activities from banks to other market-based intermediaries. The prominence of investment funds in the market coupled with the channels for fragility fueled the concerns about them. However, while these concerns were constantly discussed among academics, policymakers, and practitioners, and led to new rules and regulations, the last decade did not feature major stress events in the corporate-bond market (and the financial sector as a whole). Hence, while fragility of corporate-bond investment funds could be detected, there was no evidence to test their resilience in large stress events.

Recent events around the COVID-19 crisis provide an opportunity to conduct such an analysis. The COVID-19 crisis unfolded quickly in the US and around the world in early 2020, bringing

[1] See: https://www.fsb.org/wp-content/uploads/FSB-Policy-Recommendations-on-Asset-Management-Structural-Vulnerabilities.pdf

[2] See: https://www.reuters.com/article/us-woodford-inv-suspension-carney/illiquid-investment-funds-built-on-a-lie-boes-carney-says-idUSKCN1TR1LK

the economy to a halt, and having a major impact om financial markets. Initial declaration of a public health emergency was made in January 31, continuing with various reports of confirmed infections in February. These reports intensified in March, such that in the second week of March governors throughout the US declared states of emergency. At the end of the week, on March 13, a national emergency at the federal level in the US was declared. Financial markets were quick to react and tumbled as these events took place.

Various pieces of evidence already speak to the stress in bond markets, and corporate bond markets in particular, during this episode. Current papers by Haddad, Moreira, and Muir (2020) and Kargar, Lester, Lindsay, Liu, Weill and Zúñiga (2020) provide interesting evidence on major liquidity problems in the corporate-bond market during the COVID-19 episode. Such market stress is expected to aggravate the sources of fragility associated with investment funds in these markets. These issues have been commented on in the press in real time as the crisis unfolded.[3] Our goal in this paper is to provide systematic empirical analysis of the fragility experienced by these funds during this time in light of these market stresses. Although mutual funds and ETFs differ along several important institutional dimensions and have been generally studied separately in the literature, we include them both in the analysis to provide a more comprehensive overall view of the stress episode.[4] We use daily data on flows into and out of mutual funds and ETFs in corporate bond markets during this crisis. In comparing these flows to those observed in recent history, we assess the impact that this extreme market stress event had on these market players. Our data enables us to shed light on the determinants of flows across different funds, and so to understand better the sources of fragility, and also what helped mitigate it. This analysis carries important lessons for the continued effort of designing and regulating these activities in an attempt to improve resilience going forward.

We start by documenting the scale of the stress imposed on investment funds in corporate

[3] See: https://www.barrons.com/articles/coronavirus-crash-bond-fund-pricing-problem-51585848504

[4] As we detail below (see Section 3.1), we include controls for fund fixed effects in all tests to ensure that our estimates do not pick up spurious cross-sectional variation across different types of funds.

bond markets during the COVID-19 crisis. Simple charts and statistical analysis show that funds experienced outflows that were unprecedented relative to what they have seen over the decade since becoming such prominent players in corporate bond markets. Between the months of February and March the average fund experienced cumulative outflows of about 9% of net asset value, far larger than the average cumulative outflows of about 2.2% at the peak of the Taper Tantrum in June-July of 2013, which was the other most stressful episode over the last decade. Other dimensions we look at also point to a bigger and deeper stress experienced during the current crisis. The fraction of funds experiencing extreme outflows and the fraction of those experiencing such outflows over a couple of days or more went up to levels far higher than ever recorded, including during the taper-tantrum episode.[5] Hence, by all measures the COVID-19 crisis brought investment funds in corporate-bond markets to an uncharted territory in having to deal with massive outflows.

Inspecting the development of flows over the period of the COVID-19 crisis, we split the period into different sub-periods. First, we consider the month of February as a "build-up" phase, the first half of March (till March 13) as the "outbreak" phase, and the second half of March into April as the "peak" phase. We note that when looking at the universe of investment funds in corporate-bond markets, this analysis reveals that funds suffered the outflows mostly in the peak phase. This suggests that investors in these funds did not panic till fairly late in the crisis, when the indications for impact on the US economy were very clear. However, as we will discuss below, looking in the cross section of funds reveals a more subtle message.

Second, we incorporate information about the Fed policy responses. In March 23, the Fed announced the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF), which are designed to purchase $300bn of investment-grade corporate bonds. Then, in April 9, the Fed announced expansion of these programs to a total of

[5]Feroli, Kashyap, Schoenholtz, and Shin (2014) provide interesting analysis of the taper-tantrum episode and its effect on investment funds.

$850bn and an extension of coverage to purchase high-yield bonds if they were investment-grade as of March 22. These announcements were unprecedented in the history of the Fed, as this was the first time the US got into the purchase of corporate bonds. As such, they had a major impact on financial markets, and corporate-bond markets in particular. Spreads for both investment-grade and high-yield rated corporate bonds, which almost tripled relative to their pre-pandemic level by March 23, reversed after the two policy announcements. We thus split the overall crisis period into three phases: before the first announcement, between the two announcements, and after the second announcement. Interestingly, we show that it is only the second announcement that had significant impact of stopping and reversing the outflows from corporate-bond funds.

Going into the sources of fragility, we start by analyzing the effect of the illiquidity of the fund's assets. The source of fragility highlighted in previous research by Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) is the liquidity mismatch that funds exhibit. When they hold illiquid assets but promise their investors high levels of liquidity, funds create a "run" dynamic across investors encouraging them to withdraw before others. This has been shown in the past to amplify withdrawals from mutual funds. This force is particularly strong for mutual funds investing in corporate bonds, given the general illiquidity of corporate bonds. We split funds based on the levels of liquidity of their holdings, employing common measures of bond liquidity. Confirming the hypothesis that illiquidity amplifies fragility, we show that illiquid funds suffered much more severe outflows during the COVID-19 crisis than liquid funds. Interestingly, while for the overall fund population withdrawals did not start until the peak of the crisis, for illiquid funds they started well before. This indicates that investors started to panic early in illiquid funds, understanding that run dynamics in play make it important to act before redemptions accelerate.

We also explore other sources of fragility. Building on recent work by Falato, Hortacsu, Li, and Shin (2019), we split the universe of funds according to a measure of vulnerability, capturing the extent to which they are exposed to fire-sale risk. A fund is more exposed to such risk when it has greater commonality in holdings with other funds and when the assets it holds are more likely to exhibit higher price impact. We show that more vulnerable funds were exposed to greater outflows pressure during this COVID-19 episode. Similarly, younger funds – who are less experienced and more prone to be hurt by market turmoil – and funds with longer maturity assets – which are more affected by market fluctuations – also saw greater outflow pressure.

In previous research, fragility in corporate-bond funds was manifested through greater sensitivity of outflows to bad performance. Goldstein, Jiang, and Ng (2017) show that the well known convexity in flow-performance relation in equity funds disappears in corporate-bond funds, as they feature a concave relation. This greater sensitivity of outflows to bad performance is shown to be a result of the illiquidity of funds' assets. We inspect what the COVID-19 episode did to the sensitivity of outflows to bad performance to get another perspective on the resulting fragility. Indeed, we show that investors in corporate-bond funds started responding much more strongly to negative performance of their funds over the previous days when making outflows decisions. As investors saw that their funds are not coping well with the market stress, and realizing that a first-mover-advantage is in place, they rushed to take their money out, aggravating the stress.

Zooming in on the unique forces at play in the COVID-19 episode, we classify funds based on their exposure to the crisis. Fahlenbrach, Rageth and Stulz (2020) look at stock-price reactions for firms in different industries and compare those in highly affected industries to those in less affected industries. We build on their classifications, and using the particular bonds held by different funds, we compare outflows from more affected funds to those from less affected funds. We show that funds holding bonds in affected industries suffered greater outflows. They are also the ones who experienced the greater reversal of outflows following the Fed's second announcement. These results further support the idea that the particular forces that were in play during the COVID-19 crisis affected the funds investing in corporate bonds.

Overall, our results show that the investment funds operating in the illiquid corporate-bond sector experienced major stress during the COVID-19 crisis. Concerns about the potential for fragility coming from these funds have been expressed in recent years, and the current episode, which was the most significant stress event they experienced, confirms the importance of some of the underlying forces – such as the illiquidity of their assets and the vulnerability to fire sales. Attempting to quantify the size of the effects of these factors on outflows during the crisis, we show that each one of them can explain close to a half of experienced outflows. Regarding the mitigation of the outflows and fragility, while the counterfactual is not observed, our analysis of the evolution of flows throughout this episode points to the critical role that the Fed's announcement of its purchases of corporate bonds had in calming down investors and stopping the outflows. Interestingly, it was an announcement effect only, as the actual purchases were scheduled to begin much later.

When thinking about the implications from this event for the future of investment funds in illiquid markets, we caution that such announcement of massive Fed intervention in the market should not be expected to become the norm. Hence, some of the structural fragilities in the way investment funds operate in illiquid markets, which we confirm here to have played a role in the recent episode, have to be addressed. One prominent tool – swing pricing – which is meant to mitigate the run dynamics by penalizing investors for withdrawing when many other investors withdraw, has been introduced in the US in November 2018, but is still not implemented. Recent research by Jin, Kacperczyk, Kahraman, and Suntheim (2020) demonstrates the stabilizing effect this pricing rule has had over the years in the UK where it was implemented much earlier. The effectiveness of this tool in a major stress event like that studied here remains an open question. Similarly, there are implications for the way funds manage their liquidity, which is a topic that has been studied before the COVID-19 crisis by Chernenko and Sunderam (2016), Morris, Shim, and Shin (2017), and Zeng (2017).

The remainder of this paper is organized as follows. Section 2 describes the data and motivates the analysis with a long-term perspective of the COVID-19 episode relative to aggregate fund flows in the corporate bond sector over the last decade. Section 3 presents the main findings about fund fragility in the COVID-19 crisis. Section 4 introduces cross-sectional evidence in an attempt to better understand the sources of fund fragility and uses an Oaxaca-Blinder style decomposition to quantify the relative importance of different economic mechanisms. Section 5 concludes.

2 Data and Motivating Evidence

This section details our sample construction procedure and provides motivating evidence on the COVID-19 episode relative to the long-term historical experience of the corporate bond sector over the last decade. Details of all variables' definitions are in Appendix A.

2.1 Measurement of Daily Flows, Returns, and Other Fund Characteristics

The primary data for our analysis is high-frequency real-time information on daily fund flows and returns, as well as fund characteristics such as size (net assets) and age, from Morningstar. From Morningstar, we retrieve via their Morningstar Direct platform information on the universe of open-end corporate-bond US funds and ETFs between January 2010 and April 2020, which leads to a sample of 4,952,183 fund share class-day observations for 4,142 (1,511) unique share-classes (funds).[6] Although we recognize that funds and ETFs differ along several important institutional dimensions and have been generally studied separately in the literature, we opted for including them both in the analysis to provide a more comprehensive overall view of the stress episode. As we detail below (see Section 3.1), we include controls for fund fixed effects in all tests to ensure that our estimates do not pick up spurious cross-sectional variation across different types of funds.

When necessary, we supplement the core daily dataset with additional quarterly data on fund

[6] To ensure that the dataset is survivorship-bias-free, we include funds that are inactive by the time of our data pull. Additional details on Morningstar Direct are at: https://www.morningstar.com/products/direct.

characteristics from the CRSP Survivorship-Bias-Free Mutual Fund database and security-level holdings from the Thomson Reuter/Lipper eMAXX fixed income database. We complement these additional data with information on security-level corporate bond trading volume and liquidity from TRACE and bond maturity and ratings from FISD to construct holding-based measures of fund liquidity, vulnerability to fire-sales, and sector exposure to COVID-19.

Our main dependent variable of interest is fund flows. Mutual fund flows are estimated following the prior literature (e.g., Chevalier and Ellison (1997)), which is to define net flows of funds to mutual fund (share class) i in day t as the percentage growth of new assets:

$$Flows_{i,t} = (TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1})/TNA_{i,t-1}$$

where $\text{TNA}_{i,t}$ is the total net assets under management of fund i in day t and $\text{r}_{i,t}$ is the fund's return over the period.[7] Mutual fund performance is measured using daily fund returns. For both flows and return, we show results using business-week (5-business-days) moving averages and weekly rates to mitigate the effect of high-frequency noise.

Table 1 provides basic descriptive statistics of the time-distribution of our sample (number of share classes and funds in Panel A) and main dependent variables (means, standard deviations, and p95-p5 ranges in Panel B). Sample coverage is comprehensive and comparable to other recent studies that use different data sources. Average fund flows and performance are also in line with previous studies. For example, Goldstein, Jiang, and Ng (2017)'s sample includes 4,679 unique fund share classes and 1,660 unique corporate bond funds, with average monthly flows of 0.82% and 0.42%, which are comparable to our implied average monthly counterparts of 0.64% and 0.28%, respectively. Finally, there is substantial heterogeneity in fund flows and performance, as well as in fund characteristics such as size. About 60% of the sample is comprised of investment-

[7] As it is also standard practice in the literature, fund flows are winsorized at the 1% and 99% percentiles to mitigate the influence of outliers.

grade funds and ETFs comprise 13% of the sample.

2.2 Motivating Evidence

Corporate-bond markets in the U.S. experienced severe stress in March 2020. As shown in Figure 2, spreads for both investment-grade and high-yield rated corporate bonds increased dramatically starting from early March and peaked on March 23, when the Federal Reserve announced unprecedented direct interventions in the market via direct purchases of investment-grade corporate bonds by its Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF). The market further stabilized and reversed the spike in spreads after a second announcement by the Federal Reserve on April 9 about expanding the facilities to allow for purchases of ETFs and certain recently downgraded high-yield bonds.

While spreads almost tripled at their peak, they did not reach their financial crisis records. That said, the size of the bond market is much larger today, with corporate bonds outstanding standing at about \$5.8T in 2019Q4 relative to \$2.9T back in 2007Q4 (based on Financial Accounts, Table L.213). And market commentary and policy reports noted that market functioning and liquidity were severely strained. For example, the latest Federal Reserve's Financial Stability Report (May, 2020) noted that "for a time, markets were severely dislocated, with volatilities historically high and liquidity conditions severely strained."[8] Haddad, Moreira, and Muir (2020) document large discounts for corporate bonds and bond ETFs relative to their CDS spreads and NAVs, respectively. Kargar, Lester, Lindsay, Liu, Weill and Zúñiga (2020) confirm the deterioration of liquidity and detail its timing for several measures of liquidity, including the bid-ask spread, which roughly tracked the movement in spreads.[9]

As market conditions deteriorated, bond mutual funds and ETFs experienced record selloffs.

[8] https://www.federalreserve.gov/publications/2020-may-financial-stability-report-asset-valuation.htm

[9] Jiang, Li, Sun, and Wang (2020) also document evidence of bond price disruptions, with corporate bonds held by illiquid funds experiencing larger discounts in March 2020. Among the market and policy commentary on the episode, former Federal Reserve chairs Bernanke and Yellen described the corporate bond market as "under significant stress" (Bernanke and Yellen,2020) and argued for direct policy interventions. Vissing-Jorgensen (2020) also argues for aggressive purchase programs that include riskier high-yield debt.

Figure 3 shows that corporate bond funds and ETFs experienced aggregate net outflows in March of over 4% relative to net assets, far greater than in previous stress episodes over the last decade. For example, the other large stress episode on record is the Taper Tantrum in the summer of 2013, which has been studied extensively in the literature (see, for example, Feroli et al (2014)). The Taper Tantrum led to aggregate monthly outflows of about 3% and, as we discuss in more detail below (see Table 10), to cumulative outflows for the average fund of about 2.2% in June-July of 2013, far smaller than the about 9% outflows in February-March 2020. For reference, Morningstar estimated that redemptions from mutual funds and ETFs totalled $326 billion overall in March — more than three times the $104 billion in outflows in October 2008, in the midst of the financial crisis.

Figure 4 provides additional evidence that the stress on bond funds and ETFs during the COVID crisis was truly unprecedented. Panel A shows that, on net, in mid-March more than a third of the bond funds and ETFs experienced very large daily outflows, defined as outflows that correspond to the bottom 10% of the unconditional distribution of net fund flows, as it is standard in the literature (see, for example, Coval and Stafford (2007)). Over the last decade, on most days funds experienced large inflows, on net. And again the only previous stress episode was the Taper Tantrum, when less than a fifth of the funds experience large outflows. Panel B shows that outflows were not only large in the March 2020 episode, but also persistent, as more than a fifth of the bond funds and ETFs experienced two consecutive days of large outflows in mid-March, a record for the last decade.

Finally, anecdotal reports in funds' quarterly earnings calls for 2020Q1 confirm that funds experienced severe stress in March and that the policy response helped to alleviate fund stress. For example, in the earnings call of Allianz, an analyst asked: "What would happen if we had a repeat of mid-March when bond markets were close, even the treasury market was struggling, and if at the same time, you had a sudden acceleration of redemptions. Because people like me thought, oh my gosh, I need to go and buy some more – some food and I need to redeem my mutual fund. How does that impact Allianz?" The CFO of Allianz, Giulio Terzariol, answered: "So I would say, when you have a situation like that, usually, you can count on the central banks to have a liquidity. I would say, no, we just went through the situation, if you want, in Q1." In Europe, there were also reports of funds suspending redemptions in March.[10]

3 Sizing Up Fragility: Baseline Estimates

This section assesses fund fragility in the COVID-19 crisis using high-frequency real-time daily microdata on bond funds and ETFs. Large outflows were sustained for weeks, widespread among both investment-grade and high-yield funds, persistent, and correlated across asset-classes within-funds. Two policy announcements by the Federal Reserve about extraordinary direct interventions in corporate-bond markets were effective at alleviating fund stress.

3.1 Graphical Analysis and Research Design

Before proceeding to the formal regression analysis, we start with graphical analysis of fund flows in the COVID-19 crisis. Figure 5 shows daily aggregate net flows of bond funds and ETFs as a percentage of aggregate net assets. Two features stand out: first, daily outflows started in the last week of February and accelerated as the crisis precipitated in the second and third weeks of March, peaking at almost 1% of net assets. After the initial declaration of a public health emergency on January 31, sparse reports of confirmed infections, including several cruise ships, started to appear in February and official reports of severe disruptions to everyday life and the first official death were reported in the last week of February. In the first week of March, official reports of first confirmed infection cases outside of California and Washington started to trickle in with New York announcing its first case on March 2, followed by most other states by the end of the week.

[10] https://www.fitchratings.com/research/fund-asset-managers/european-mutual-fund-gatings-rise-as-coronavirus-spooks-markets-20-04-2020

In the second week of March, governors throughout the US declared states of emergency starting with Ohio on March 9 and the official tally of infections started ramping up. At the end of the week, on March 13, a national emergency at the federal level in the US was declared.

Second, outflows started to mitigate in the last week of March, after the first policy announcement by the Federal Reserve about direct interventions in corporate-bond markets on March 23. The first announcement was about the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF), which were designed to make outright purchases of corporate bonds issued by investment grade US companies, along with US-listed exchange-traded funds (ETFs) that invested in US investment grade corporate bonds.[11] However, outflow did not fully reverse until after the second announcement of a strengthening of the direct interventions on April 9. This second announcement involved a significant expansion of both facilities to $850bn (from less than $300bn) and an extension of coverage of SMCCF to purchase high-yield bonds if they were investment-grade as of March 22.[12]

Figure 6 repeats the graphical analysis of daily aggregate net flows by sub-group for the different types of bond funds, investment-grade funds (Panel A), high-yield funds (Panel B), and ETFs (Panel C). Stress in March was widespread across the board of the different fund types. While investment-grade funds and ETFs experienced large and sustained outflows, outflows were outsized and started a bit earlier for high-yield funds.

Next, we provide a more formal assessment of fund fragility in the COVID-19 crisis using

[11] For PMCCF, see https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm. For SMCCF, see https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm. On March 23, the SEC also announced regulatory relief measures for funds, including temporary flexibility for registered investment companies affected by the pandemic to borrow funds from certain affiliates and to enter into certain other lending arrangements (https://www.sec.gov/news/press-release/2020-70).

[12] For the public release, see https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm.

Before these announcments, other emergency policy measures by the Federal Reserve were announced between March 15 and March 18, including a rate cut to zero and three other facilites, the commercial paper funding facility (CPFF), the primary dealer credit facility (PDCF), and the money market funding facility (MMFF), which were not specifically targeted to the corporate bond market.

regression analysis. To that end, we examine the following main relation:

$$Flows_{i,t} = \alpha + \beta \times Crisis_t + \gamma \times X_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t} \tag{1}$$

where the outcome variable, $Flows_{i,t}$, is primarily the daily fund's net flows for fund i in day t, and the main variable of interest, $Crisis_t$, is an indicator that equals one in the crisis period. We include data from January 1, 2019 to April 17, 2020 for all the domestic corporate bond funds and ETFs, and set Crisis to one starting from February 1, 2020. To better understand the evolution of flows during the crisis, we also consider a richer specification with a finer set of indicators for sub-periods within the crisis: a *Buildup* indicator for days in February 2020, an *Outbreak* indicator for the March 1, 2020 to March 13, 2020 period, and a *Peak* indicator for days after March 13, 2020. Finally, to better distinguish the initial impact of infections from the subsequent policy response, we also examine a specification with a *Crisis* indicator for the day before the policy response (February 2020 till March 23), a *First Response* indicator for the March 23, 2020 to April 9, 2020 period, and a *Second Response* indicator for days after April 9, 2020. $X_{i,t-1}$ is a vector of controls for standard fund characteristics, which include fund size.

In estimating equation (1), we address unobserved heterogeneity by including for all tests a specification that controls for the full set of fund-specific dummies, η_i. The inclusion of fund fixed effects ensures that the parameter of interest, β, which represents the impact of the COVID-19 shock on fund flows, is estimated only from within-fund time-series variation. To address other contemporaneous common shocks, which are unrelated to the COVID-19 crisis and could be a potential confound for our estimates, in all the tests we include a full set of month-specific dummies, λ_t.[13] The inclusion of month effects ensure that β is estimated from within-month variation – i.e., it reflects the impact of the COVID-19 crisis period for each month in 2020 relative to the same month in 2019. The idiosyncratic error term, $\nu_{i,t}$, is assumed to be correlated within fund and po-

[13]We have experimented with including alternative time dummies, either quarter-specific or week-specific, both of which lead to only minor changes in our estimates.

tentially heteroskedastic (Petersen (2006)) and clustered standard errors are reported throughout (in parentheses).

3.2 Baseline Estimates

The next three tables present our baseline estimates of the COVID-19 impact on fund fragility. Table 2 presents the estimates from equation (1) using fund flows as the outcome variable (Columns 1 and 2). To clarify the impact on large outflows, we also report estimates of quantile regressions with fund flows as the outcome variables conditional on the bottom decile of the distribution (Column 3) and for a linear-probability model that uses an indicator for extreme outflows (a dummy for fund flows in the bottom decile of the distribution) as the outcome variable (Column 4). Panel A shows results for the overall Crisis dummy, while Panels B and C are for the more granular dummies for the crisis and policy response sub-periods, respectively.

In line with the graphical evidence, the coefficient on Crisis is negative (positive) and highly statistically significant for fund flows (large outflows) (Panel A), indicating that the COVID-19 shock was a significant stress event for funds. The result is robust to controlling for unobserved heterogeneity by including fund fixed-effects (Column 2, Panel A). And it is much stronger for funds in the bottom decile of flows (Column 3, Panel A). Finally, as for the timing of the effect, also in line with the graphical analysis, the bulk of the effect is concentrated in the second half of March and April (Panel B) and does not fully reverse until after the second policy announcement on April 9 (Panel C). The dynamics of the effect on large outflows is a bit less delayed and more persistent, with large outflows starting to pick up in the first half of March (Panel B) and not fully reversing even after April 9 (Panel C).

The impact of COVID-19 on fund flows is strongly economically significant. For example, the estimates in Column 2 of Panel A imply that the crisis led to about 30 bps decrease in weekly flows, which is roughly twice as large as the sample mean of flows, and those in Column 2 of

Panel B imply that at the peak the crisis led to over 60 bps decrease in weekly flows, which is four times as large as the sample mean of flows. The effect of the crisis was truly outsized for large outflows, with a 10 percentage points increase in the likelihood of large outflows overall (Panel B) and 20 percentage points increase at the peak (Panel B), respectively as large and twice as large as the unconditional likelihood of large outflows. And the estimates in Column 3 imply that, at the peak, funds in the bottom decile of flows experienced outflows of over 2 and a half percentage points (Panel B).

To further put these estimates into context, we conduct three exercises. First, we examine how the crisis moves a fund in the distribution of flows. The estimated 30 (68) bps decrease in weekly flows overall (at the peak) corresponds to about half (a full) of an interquartile range movement in the distribution of fund flows (the interquartile range is 59 bps) – i.e., at the peak the impact of the crisis was large enough to move a fund from the top to the bottom quartile of the distribution of flows. Second, we compare the marginal effect of the crisis to that of standard fund-level covariates, such as fund size. We calculate the marginal effect by multiplying the respective estimates by the standard deviation of fund size. The marginal impact of the crisis is of the same order of magnitude as that of fund size (1-standard deviation change in size is associated with a 30 bps change in flows), which further corroborates the notion that the COVID-19 crisis was an economically significant stress event for funds. Finally, the impact of the crisis is much larger than that of the largest previous stress episode in the last decade, the Taper Tantrum. When we re-estimate equation (1) in the full sample, the estimated coefficient on a dummy for the peak month of the Taper Tantrum, June 2013, implies an effect on flows of about 19 bps, which is roughly a third of the estimated peak effect in Panel B.

Tables 3 and 4 examine the impact of the crisis on two additional aspects of fund fragility, persistence and co-movement of fund flows. We estimate equation (1) using as the dependent variable a dummy for multiple (2 or 3) consecutive days of large outflows (Table 3) and a dummy for multiple (2 or 3) share-classes experiencing large outflows within any given fund (Table 4), in turn. For each table, we again show results for the overall Crisis dummy in Panel A, and for the more granular dummies for the crisis and policy response sub-periods in Panels B and C, respectively. For both metrics, there is a strong positive and highly statistically significant association with the crisis indicator (Panel A), which further corroborates the notion that the crisis led to severe stress for funds. The timing of the impact on both the persistence and co-movement of large fund outflows is in line with the baseline estimates for flows, with the bulk of the effect in the second half of March and April (Panel B). As for the impact of the policy interventions, there is evidence of partial reversal after the second policy announcement on April 9 (Panel C), but there are indications of continued strains based on these measures.

The impact of the crisis on the additional measures of stress is also strongly economically significant. For example, the estimates in Column 2 of Table 3 (Panel A) imply that the crisis led to about 9 percentage points increase in the likelihood of large outflows in two consecutive days, which is about as large as the unconditional likelihood of 2-day large outflows, and those in Column 2 of Table 4 (Panel A) imply that the crisis led to about 13 percentage points increase in the likelihood of large outflows for at least two share-classes within-fund, which is also about as large as its unconditional likelihood. At the peak, the stress was severe, with Panel B of Table 3 implying an 18 percentage points increase in the likelihood of 2-day large outflows and Panel B of Table 4 implying a 25 percentage points increase in the likelihood of large outflows for at least two share-classes within-fund, both more than twice as large as their respective unconditional likelihood. Again, for historical comparison, when we re-estimate equation (1) in the full sample, the estimated coefficients on a dummy for the peak month of the Taper Tantrum, June 2013, imply an effect of about 9 percentage points for 2-day large outflows and 15 percentage points large outflows for at least two share-classes within-fund, respectively, which are roughly half as large as the estimated peak effects in Panel B.

4 Sources of Fragility

Having established that the COVID-19 crisis was a unique stress event for corporate bond funds and ETFs, next we use sample-split analysis to explore which economic mechanisms were at play. We provide comprehensive evidence that fund illiquidity and vulnerability to fire-sale spillovers were important sources of fragility, which each account for up to about half of the cumulative outflows throughout the stress episode.

4.1 Fund Illiquidity and Fire-Sale Vulnerability

One potential economic mechanism at play is fund illiquidity. As emphasized in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017), this mechanism is based on the idea that strategic complementarities exist among investors in corporate bond mutual funds driven by the illiquidity of their assets. When investors redeem their shares, they get the net asset value as of the day of redemption. The fund then has to conduct costly liquidation that hurts the value of the shares for investors who keep their money in the fund. Hence, the expected redemption by some investors increases the incentives of others to redeem. Greater illiquidity at the level of the fund is expected to generate stronger strategic complementarities among investors when deciding to redeem their shares. Funds with more liquid assets will not have to bear high costs liquidating their positions on short notice to meet redemption requests, mitigating the negative externalities following redemptions. Thus, fund liquidity should alleviate the tendency of investors to run.

Table 5 examines the illiquidity mechanism using sample-split analysis. We report the estimates from equation (1) using fund flows as the outcome variable for different sub-sample splits based on empirical proxies for the extent to which funds have more illiquid bond holdings. The gist of these tests is to examine whether the impact of the COVID-19 crisis on fund flows is more pronounced for those funds that the theory predicts should be more prone to runs in the cross-section. To measure asset liquidity at the fund level, we use three different measures, which are all standard in the literature: the Roll (1984) measure, the bid-ask spread, and bond ratings. The Roll measure captures the serial covariance of intraday bond returns. Intuitively, bond prices bounce back and forth between the bid and ask prices, and hence higher bid-ask spreads would lead to higher negative covariance between consecutive returns.[14] We split the sample into two sub-samples based on the top vs. bottom quartiles of each of these measures at the beginning of the sample period (as of 2018Q4), in turn. Panel A shows results for the overall Crisis dummy, while Panels B and C are for the more granular dummies for the crisis and policy response sub-periods, respectively.

In line with theory, the coefficient on Crisis is reliably negative and highly statistically significant but only for illiquid funds (Panel A), indicating that illiquidity was an important economic mechanism through which the COVID-19 shock led to fund stress. The result is robust across each of the three holding-based liquidity measures, and the difference between the estimated coefficients in the two sub-samples of liquid vs. illiquid funds is large and statistically significant for all the measures (t-stat=-4.46, -3.70, and -7.18 for the Roll (1984) measure, the bid-ask spread, and bond ratings, respectively). For example, the estimates for the Roll measure in Panel A imply that illiquid funds were much more fragile in the crisis, as they experienced outflows that were about four times as large, on average, relative to those of liquid funds.

The timing of the effect provides further corroborating evidence that illiquidity led to fund fragility in the crisis. The coefficient estimates on the Outbreak (Mar 1-13, 2020) dummy in Panel B are reliably positive only for relatively more liquid funds, while the estimates on the Peak (Mar 13-April, 2020) dummy are negative in both sub-samples. These results indicate that there were differences in the timing of the impact, as outflows started earlier in March for relatively more illiquid funds (Panel B). Finally, the coefficient estimates on the Second Response (Apr 9-, 2020)

[14]The quarterly Roll measure for each bond is the median of the daily Roll measure within the quarter. In each quarter, we aggregate the bond-level Roll measure into a fund-level Roll measure by taking value-weighted averages using the fund's bond holdings. The bid-ask and ratings measures are calculated similarly as the value-weighted average of bid-ask and ratings for each corporate bond held by a given fund, respectively. See Appendix A for more details.

dummy in Panel C indicate that, while the effect reverses for both liquid and illiquid funds, low-rated funds benefitted the most from the April 9 policy announcement that was specifically targeted to support them (Panel C).

Another potential economic mechanism is costly fire-sales. As emphasized by a classical literature starting from Shleifer and Vishny (1992, 1997), in the presence of a downward-sloping demand for corporate bonds, fire-sales of a fund's portfolio securities – i.e., sales that are forced by redemptions – have a price-impact.[15] By depressing security prices, flow-related sales lead to spillovers because the valuation losses hurt the performance of peer funds that hold the same securities. In turn, spillovers may lead to redemptions at peer funds through the performance-flow relationship. Falato, Hortacsu, Li, and Shin (2019) provide direct evidence that there are sizable fire-sale spillovers in debt markets and that spillovers aggravate a specific type of market instability – volatility – by amplifying the effect of an initial shock to fund flows that is otherwise unrelated to fundamental asset values. The mechanism is that outflows at peer funds lead to a second round of outflows that further depresses bond prices over and above the initial effect of a given adverse shock. As a result, spillovers lead to higher volatility by increasing the exposure of funds and bonds to non-fundamental risk.

Table 6 expands on the sample-splits analysis to examine the fire-sale mechanism. We report the estimates from equation (1) using fund flows as the outcome variable for a sub-sample split based on an empirical proxy for the extent to which funds are vulnerable to fire-sale spillovers. The proxy is constructed as Falato, Hortacsu, Li, and Shin (2019), to which we refer to details. The vulnerability measure captures the degree of overlap between the bond holdings of a given fund and those of other funds, as well as the strength of the price-impact of flow-driven fire sales. Intuitively, the measure ranks as more vulnerable funds for which peer outflows are more likely

[15]Several factors have been identified in the literature as potentially leading to downward-sloping demand, including illiquidity due to transaction costs as well as, more broadly, slow-moving capital factors that make high-valuation bidders relatively scarce and lead to arbitrage persistence. A number of recent papers have put forward potential explanations for the existence of persistent mispricing in financial markets. Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010) discuss the role that slow-moving capital may play in allowing arbitrage opportunities to exist for extended periods of time.

to lead to own outflows and it is higher whenever 1) there is a higher degree of overlap in bond holdings with other funds; and 2) debt market conditions are such that forced sales have a larger price impact. In Columns 1-2, we split the sample into two sub-samples based on the top vs. bottom quartiles of the fire-sale vulnerability measure at the beginning of the sample period (as of 2018Q4). Panel A shows results for the overall Crisis dummy, while Panels B and C are for the more granular dummies for the crisis and policy response sub-periods, respectively.

The results are stronger in the sub-sample of more vulnerable funds (Panel A, Columns 1-2) and the difference between the estimated coefficients on Crisis in the two sub-samples of more vs. less vulnerable funds is large and statistically significant (t-stat=-1.84), indicating that fire-sale spillovers were another mechanism through which the COVID-19 shock led to fund stress. The estimates imply that vulnerable funds were much more fragile in the crisis, as they experienced outflows that were almost twice as large, on average, relative to those of less vulnerable funds. As for the timing of the effect, similar to the liquidity results, outflows started earlier for more vulnerable funds (Panels B-C).

In Columns 3-6, we split the sample based on two additional measures: fund age (Columns 3-4) and maturity (Columns 5-6). Younger funds may face higher illiquidity and fire-sale costs either because they are run by less experienced managers or because there is more uncertainty about their performance. Longer maturities may also exacerbate runs because bonds with longer maturity have higher interest rate risk relative to bonds with shorter maturities. Consistent with this reasoning, the results for these additional measures indicate that the impact of the COVID-19 shock was much stronger for younger funds and those with longer maturities of their bond holdings. Specifically the estimates in Panel A imply that younger funds experienced outflows in the crisis that were about three times as large as those of older funds, while funds with longer maturities had outflows that were five times as large as those of funds with shorter maturities.

4.2 Flow-Performance Relation and Fund Sector Exposure

Next, we inspect the flow-performance relation and fund sector exposure to gain further insight into the sources of fragility. The two main economic mechanisms we have highlighted, liquidity and fire-sales, both operate via the flow-performance relation, which has a long tradition in the literature at least since Chevalier and Ellison (1997). Goldstein, Jiang, and Ng (2017) show that the well-known convexity in flow-performance relation in equity funds disappears in corporate-bond funds, as they feature a concave relation. This greater sensitivity of outflows to bad performance is shown to be a result of the illiquidity of funds' assets. Falato, Hortacsu, Li, and Shin (2019) show that fire-sale spillovers also lead to fragility via the flow-performance relation, because they depress bond valuations and lead, in turn, to bad fund performance.

To inspect what the COVID-19 episode did to the sensitivity of outflows to bad performance, we modify our baseline specification as follows:

$$Flows_{i,t} = \alpha + \beta_1 \times Crisis_t + \beta_2 \times Crisis_t \times \mathrm{Re}\,turn_{it-1} + \gamma \times X_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t} \qquad (2)$$

where the outcome variable, $Flows_{i,t}$, is the daily fund's net flows for fund i in day t, and the main variable of interest is the interaction of the $Crisis$ indicator with lagged fund performance, $\mathrm{Re}\,turn$. As in the main analysis, we also consider a richer specification with a finer set of interacted indicators for sub-periods within the crisis: a $Buildup$ indicator for days in February 2020, an $Outbreak$ indicator for the March 1, 2020 to March 13, 2020 period, and a $Peak$ indicator for days after March 13, 2020, and an interacted specification with a $Crisis$ indicator for the day before the policy response (February 2020 till March 23), a $First\ Response$ indicator for the March 23, 2020 to April 9, 2020 period, and a $Second\ Response$ indicator for days after April 9, 2020. For each of these specifications, we show estimates of the flow-performance relation for good vs. bad performance using piece-wise linear functions of positive ($\mathrm{Re}\,turn^+$) vs. negative ($\mathrm{Re}\,turn^-$) fund returns, to allow for asymmetries as in Goldstein, Jiang, and Ng (2017). $X_{i,t-1}$ is a vector of controls for standard fund characteristics, which include fund size as well as non-interacted lagged fund performance.

The results on the flow-performance relation are summarized in Table 7. In line with the main evidence, the coefficient on the interaction of Crisis with fund performance is positive and highly statistically significant (Panel A, Column 1), indicating that there was an increased sensitivity of flows to performance in the COVID-19 crisis. The result is robust to controlling for persistence in flows by including the lagged dependent variable (Column 2, Panel A). And it is driven by greater sensitivity of flows to bad performance (Columns 3-4, Panel A), suggesting that investors responded much more strongly to negative performance of their funds when making outflows decisions in the crisis. The timing of the effects is also in line with the sample splits, with the bulk of the spike in the sensitivity of flows to bad performance concentrated especially in the second half of March and April (Panel B) and evidence of reversal only after the April 9 policy announcement (Panel C). In all, this evidence indicates that heightened sensitivity of flows to bad performance was an important way in which fragility manifested itself in the COVID-19 crisis.

Finally, to zoom in on the unique forces at play in the COVID-19 episode we classify funds based on their exposure to the crisis. Fahlenbrach, Rageth and Stulz (2020) look at stock-price reactions for firms in different industries and compare those in highly affected industries to those in less affected industries. We build on their classifications, and using the particular bonds held by different funds, we compare outflows from more affected funds to those from less affected funds. To that end, we enrich the baseline specification with an interaction term between the crisis indicator and a cross-sectional indicator for high fund exposure to COVID-19, which is calculated for each fund at the beginning of the sample period (as of 2018Q4) by taking the sum of the value of bond holdings in the following Fama-French 49 industries, which were most severely impacted (see Fahlenbrach, Rageth and Stulz (2020) for supporting evidence): Entertainment, Construction, Automobiles and trucks, Aircraft, Ships, Personal services, Business services, Transportation, Wholesale, Retail, and Restaurants, hotels and motels. Specifically, we use the following regression specification:

$$Flows_{i,t} = \alpha + \beta_1 \times Crisis_t + \beta_2 \times Crisis_t \times High\ Exposure\ Fund_i + \gamma \times X_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t} \quad (3)$$

where the outcome variable, $Flows_{i,t}$, is as in the baseline the daily fund's net flows for fund i in day t, and the main variable of interest, $Crisis_t$, is an indicator that equals one in the crisis period. To better understand the evolution of flows during the crisis, we again consider also a specification with a finer set of indicators for sub-periods within the crisis: a *Buildup* indicator for days in February 2020, an *Outbreak* indicator for the March 1, 2020 to March 13, 2020 period, and a *Peak* indicator for days after March 13, 2020. Finally, to better distinguish the initial impact of infections from the subsequent policy response, we also examine a specification with a *Crisis* indicator for the day before the policy response (February 2020 till March 23), a *First Response* indicator for the March 23, 2020 to April 9, 2020 period, and a *Second Response* indicator for days after April 9, 2020. The *High Exposure Fund* indicator equals one for funds in the top quartile of COVID-19 sector exposure and zero for those in the bottom quartile. $X_{i,t-1}$ is a vector of controls for standard fund characteristics, which include fund size as well as the non-interacted exposure variable for the specification that does not include fund effects.

Table 8 summarizes the results of the analysis by fund sector exposure. In line with the main estimates, the coefficient estimate on the interaction term of Crisis with High Exposure Fund is negative and highly statistically significant (Columns 1-2), indicating that funds holding bonds in affected industries suffered more severe stress in the COVID-19 crisis. The result is robust to controlling for unobserved heterogeneity by including fund fixed-effects (Column 2).[16] The estimates for the timing of the effect indicate that funds holding bonds in the most affected industries started to suffer outflows already in the first half of March (Columns 3-4) and experienced a stronger reversal of outflows following the Fed's second announcement on April 9 (Columns 5-6). These

[16]The coefficient estimate on the non-interacted exposure variable is small and not statistically significant (Column 1), indicating that there are no differential pre-crisis trends in flows between high vs. low exposure funds.

results further support the idea that the particular forces that were in play during the COVID-19 crisis affected the funds investing in corporate bonds.

4.3 Quantifying the Sources of Fragility

How far can one go toward explaining the impact of the COVID-19 crisis on fund fragility with the main mechanisms we highlighted, illiquidity and vulnerability to fire-sales? In our final analysis, we use an Oaxaca-Blinder style decomposition to better quantify the relative importance of different explanations for the spike in outflows during the crisis.

As shown in Table 9, corporate bond funds and ETFs experienced cumulative outflows of about 9% relative to their net assets, on average, in the period from February to March 2020 and of about 6% in the period from March to April 2020. Confirming out findings from the sample-split analysis, average cumulative outflows were even more severe for illiquid funds and for funds that were vulnerable to fire-sales. Illiquid funds experienced cumulative outflows of about 19% relative to their net assets, on average, in the period from February to March 2020 and of about 15% in the period from March to April 2020. Funds that were vulnerable to fire-sales experienced cumulative outflows of about 17% and 11% relative to their net assets, on average, over the two crisis sub-periods.

To gauge the contribution of these two different sources of fragility to cumulative outflows in the crisis, we use an Oaxaca-Blinder style regression-based approach. For example, take illiquidity. We split the sample into two sub-samples based on top vs. bottom quartiles of the illiquidity proxy (Roll). We estimate equation (1) using two-month cumulative fund flows as the outcome variable in the sub-sample of liquid funds. We store the estimated coefficients and use them to predict cumulative flows for illiquid funds, which provides the counterfactual of flows for illiquid funds "as if" they were liquid. Finally, we take the difference between cumulative flows and predicted cumulative flows for illiquid funds, which is our measure of the impact of COVID-19 on cumulative flows that can be attributed to illiquidity. We tabulate the % share explained by illiquidity, which is the ratio of the mean difference between cumulative flows and predicted cumulative flows divided by mean cumulative flows for illiquid funds.

The results of this decomposition are shown in Table 9. Both mechanisms can explain a sizable fraction of the spike in outflows during the COVID-19 crisis. Specifically, the illiquidity mechanism can explain about 45% of the mean cumulative outflows from February to March 2020 and about 32% of the mean cumulative outflows from March to April 2020. Fire-sale vulnerability can account for about 62% of the mean cumulative outflows from February to March 2020 and about 44% of the mean cumulative outflows from March to April 2020. For reference, we also report results of the same approach for COVID-sector exposure as well as for the estimated flow-performance relation. The explanatory power of illiquidity and fire-sale vulnerability is roughly comparable to these benchmarks for the size of the shock. For example, COVID-19 sector exposure can account for about 72% of the mean cumulative outflows from February to March 2020 and about 65% of the mean cumulative outflows from March to April 2020.

The main takeaway from this section is that fund illiquidity and vulnerability to fire-sale spillovers were important sources of fragility in the COVID-19 crisis. In fact, our Oaxaca-Blinder decomposition indicates that each of these mechanisms can account for up to about half of the cumulative outflows throughout the stress episode.

5 Conclusion

Non-bank intermediaries such as mutual funds and ETFs have become important players in debt markets over the last decade, but whether and why they are vulnerable and prone to fragility in times of stress remains an openly debated academic and policy question. In order to understand the fragility of the asset management sector, we have used rich high-frequency microdata on individual fund flows, returns, and holdings of corporate debt funds and ETFs, and the COVID-19 crisis as a laboratory to evaluate different forces that lead to fragility. We have shown evidence that funds were under severe stress in the COVID-19 crisis and particularly so those that were illiquid and vulnerable to fire-sales.

The COVID-19 crisis offers a unique opportunity to evaluate fund fragility first-hand now that the fund sector has grown enough in size to have a potentially large impact on the broader debt markets. There are several venues along which our analysis can be further extended. First, we took a step in the direction of evaluating the effectiveness of policy announcements to mitigate stress, but clearly as the Fed facilities become operational there will be more opportunities to further evaluate their effectiveness as financial stability tools.

Second, it would be interesting to study fragility in a more explicit structural setting. A structural extension would allow for quantitative evaluation of the welfare consequences of policy counterfactuals, including stress testing of funds that has been under consideration by the Financial Stability Oversight Council (FSOC), conventional monetary policy (Stein (2012)), as well as more targeted policies such as exit fees or fund gating. Finally, extending the analysis to an international setting could also help to understand the role of features such as swing pricing and gating, which are more commonly used outside of the US and have reportedly helped to mitigate stress for UK and EU funds.

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Appendix A: Details of Variable Definitions

The variables used in this paper are extracted from four major data sources for the 2010M1–2020M4 period: daily mutual fund flows, net assets, and returns from the Morningstar Database; quarterly mutual fund characteristics from the CRSP Mutual Fund Database; quarterly security-level holdings of fixed income securities by U.S.-domiciled mutual funds from Thompson Reuters/Lipper eMAXX database; security-level data from TRACE, FISD and the three major credit rating agencies (Fitch, Moody's, and S&P).

The variables are defined as follows:

Main Fund-Level Outcomes:

Flows (%) is defined as $\text{FLOW}_{j,t}$= $(\text{TNA}_{j,t}-(1+\text{r}_{j,t})\text{TNA}_{j,t-1})/\text{TNA}_{j,t-1}$, where $\text{TNA}_{j,t-1}$ is the total net assets under management at the end of the previous period, and $\text{r}_{j,t}$ is the return (net of fees and expenses) over the period.

Large Outflows is defined as a dummy that takes value of one for fund-day observations in the bottom decile of the distribution of fund flows.

2-day (3-day) Large Outflows is defined as a dummy that takes value of one for fund-day observations corresponding to 2 (3) consecutive days in the bottom decile of the distribution of fund flows.

2+SC (3+SC) Large Outflows is defined as a dummy that takes value of one for fund-day observations corresponding to funds with at least 2 (3) share classes in the bottom decile of the distribution of fund flows.

Fund Characteristics:

Return (%) is the daily net fund return.

Illiquidity (Roll). We use TRACE transaction data to calculate various daily liquidity measure for each bonds. We then take the within-quarter average of daily measures to get quarterly liquidity measure. Roll's bid-ask spread based on Roll's (1984):

$$Liq_{i,d}^{Roll} = \sqrt[2]{-cov(\Delta P_{i,d}^{j}, \Delta P_{i,d}^{j-1})}$$

where $\Delta P_{i,d}^{j}$ is the price of jth trade (ordered by time) of bond i at day d.

Illiquidity (Bid-Ask). We use TRACE transaction data to calculate various daily liquidity measure for each bonds. We then take the within-quarter average of daily measures to get quarterly liquidity measure. Bid-ask is the difference between weighted average dealer ask prices and weighted average dealer bid prices. The weights are par volume of trades.

Illiquidity (Ratings). Average rating of the bond holdings of the mutual fund, expressed in quarters.

Vulnerability to Fire-Sale Spillovers. We use data on portfolio holdings to construct estimates of the effect of 100 basis points increase in fund family j's fund flow-driven fire-sale pressure on i's current flows, b_{ij}. Given these estimates and an assumption for the attenuation factor a (set as 0.9), we calculate a fund i's vulnerability following Falato, Hortacsu, Li, and Shin (2019), as:

$$Vu\ln erability_i = \frac{1}{n}\sum_{s=1}^{\infty}\sum_{j=1}^{n} a^s b_{ij}^s$$

Maturity. Average maturity of the bond holdings of the mutual fund, expressed in quarters.

Age. Fund age, defined as the number of years since fund inception.

COVID-19 Sector Exposure. Calculated for each fund at the beginning of the sample period (as of 2018Q4) by taking the sum of the value of bond holdings in the following Fama-French 49 industries, which were most severely impacted (see Fahlenbrach, Rageth and Stulz (2020) for supporting evidence): Entertainment, Construction, Automobiles and trucks, Aircraft, Ships, Personal services, Business services, Transportation, Wholesale, Retail, and Restaurants, hotels and motels.

Expense ratio (%) is the fund's expense ratio in the most recent fiscal year, defined as the total investment that the shareholders pay for the fund's operating expenses (including 12b1 fees).

Fund Size (log$Million) is the natural log of total net assets.

Fund Age is the number of years since fund inception.

Table 1: Summary Statistics

This table presents time distribution (Panel A) and summary statistics (Panel B) for our sample, which comprises domestic US corporate bond funds and ETFs. The data span the period January 2010-April 2020 and consists of 4,952,183 share class-day observations for 4,142 (1,511) unique share classes (funds). Variable definitions are in Appendix A.

Panel A: Sample Distribution, Full Sample			
	Obs fund-day	Share Classes	Funds
2010	396,750	2,160	781
2011	410,361	2,274	835
2012	406,275	2,300	854
2013	436,277	2,383	899
2014	467,723	2,600	962
2015	512,731	2,760	1,000
2016	528,468	2,835	1,032
2017	535,465	2,940	1,054
2018	540,693	3,007	1,118
2019	554,235	2,972	1,137
2020	163,205	2,901	1,110
Tot.	4,952,183	4,142	1,511

Panel B: Summary Statistics, Crisis Sample (2019-2020)			
	Mean	Std Dev	p95-p5
Main Outcomes:			
Flows (%)	0.16	1.69	5.17
Large Outflows	0.10	0.31	1.00
2-day Large Outflows	0.06	0.25	1.00
3-day Large Outflows	0.04	0.19	0.00
2+SC Large Outflows	0.12	0.32	1.00
3+SC Large Outflows	0.04	0.20	0.00
Fund Characteristics:			
Return (%)	0.07	0.76	2.22
Fund Size ($Mil)	574.62	1,527.34	3,325.14
Investment-Grade Fund	0.60	0.49	1.00
ETF	0.13	0.34	1.00

Table 2: Sizing Up Fragility in the COVID-19 Crisis: Analysis of Fund Flows

This table reports share class-level regressions of daily flows on an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Crisis				
	Flows (%) OLS	Flows (%) FE	Flows (%) Bottom Decile	Large Outflows
	(1)	(2)	(3)	(4)
Crisis (Feb-April 2020)	-0.25***	-0.30***	-1.47***	0.10***
	(0.02)	(0.02)	(0.01)	(0.00)
FE	Month	Month, Fund	Month	Month
N obs	717,440	717,440	717,440	717,440
R^2(%)	0.6	12.6	3.0	2.6
Panel B: Evolution of the Crisis				
	Flows (%) OLS	Flows (%) FE	Flows (%) Bottom Decile	Large Outflows
	(1)	(2)	(3)	(4)
Buildup (Feb 2020)	0.08***	0.02	0.09***	-0.01***
	(0.02)	(0.02)	(0.01)	(0.00)
Outbreak (Mar 1-13, 2020)	0.11***	0.05	-1.26***	0.05***
	(0.03)	(0.03)	(0.04)	(0.00)
Peak (Mar 13-April, 2020)	-0.63***	-0.68***	-2.61***	0.20***
	(0.03)	(0.17)	(0.02)	(0.00)
FE	Month	Month, Fund	Month	Month
N obs	717,440	717,440	717,440	717,440
R^2(%)	1.1	13.1	5.1	3.7
Panel C: Evolution of the Crisis and Policy Response				
	Flows (%) OLS	Flows (%) FE	Flows (%) Bottom Decile	Large Outflows
	(1)	(2)	(3)	(4)
Crisis (Feb-Mar 23, 2020)	-0.10***	-0.16***	-1.11***	0.06***
	(0.02)	(0.02)	(0.03)	(0.00)
First Response (Mar 23-Apr 9, 2020)	-0.63***	-0.68***	-2.40***	0.19***
	(0.03)	(0.03)	(0.03)	(0.00)
Second Response (Apr 9-, 2020)	-0.03	-0.08*	-0.58***	0.08***
	(0.04)	(0.05)	(0.05)	(0.01)
FE	Month	Month, Fund	Month	Month
N obs	717,440	717,440	717,440	717,440
R^2(%)	0.9	12.8	3.5	3.0

Table 3: Sizing Up Fragility in the COVID-19 Crisis: Analysis of the Dynamics of Large Outflows

This table reports share class-level regressions of daily persistent large outflows on an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Crisis

	2-day Large OutFlows OLS (1)	2-day Large OutFlows FE (2)	3-day Large OutFlows OLS (3)	3-day Large OutFlows FE (4)
Crisis (Feb-April 2020)	0.08***	0.09***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	2.5	9.4	2.0	6.3

Panel B: Evolution of the Crisis

	2-day Large OutFlows OLS (1)	2-day Large OutFlows FE (2)	3-day Large OutFlows OLS (3)	3-day Large OutFlows FE (4)
Buildup (Feb 2020)	-0.01***	-0.01**	-0.01***	-0.0**
	(0.00)	(0.00)	(0.00)	(0.00)
Outbreak (Mar 1-13, 2020)	0.03***	0.04***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Peak (Mar 13-April, 2020)	0.17***	0.18***	0.11***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	3.7	10.5	2.9	7.1

Panel C: Evolution of the Crisis and Policy Response

	2-day Large OutFlows OLS (1)	2-day Large OutFlows FE (2)	3-day Large OutFlows OLS (3)	3-day Large OutFlows FE (4)
Crisis (Feb-Mar 23, 2020)	0.05***	0.05***	0.03***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
First Response (Mar 23-Apr 9, 2020)	0.17***	0.17***	0.10***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
Second Response (Apr 9-, 2020)	0.05***	0.06***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	3.1	10.0	2.4	6.7

Table 4: Sizing Up Fragility in the COVID-19 Crisis: Analysis of the Within-Fund Comovement of Large Outflows

This table reports share class-level regressions of daily correlated large outflows on an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Crisis

	2+SC Large OutFlows OLS (1)	2+SC Large OutFlows FE (2)	3+SC Large OutFlows OLS (3)	3+SC Large OutFlows FE (4)
Crisis (Feb-April 2020)	0.13***	0.13***	0.09***	0.09***
	(0.00)	(0.00)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	3.4	22.2	4.4	16.3

Panel B: Evolution of the Crisis

	2+SC Large OutFlows OLS (1)	2+SC Large OutFlows FE (2)	3+SC Large OutFlows OLS (3)	3+SC Large OutFlows FE (4)
Buildup (Feb 2020)	-0.02***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Outbreak (Mar 1-13, 2020)	0.08***	0.08***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Peak (Mar 13-April, 2020)	0.25***	0.25***	0.18***	0.19***
	(0.00)	(0.00)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	4.9	23.7	6.7	18.6

Panel C: Evolution of the Crisis and Policy Response

	2+SC Large OutFlows OLS (1)	2+SC Large OutFlows FE (2)	3+SC Large OutFlows OLS (3)	3+SC Large OutFlows FE (4)
Crisis (Feb-Mar 23, 2020)	0.08***	0.08***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
First Response (Mar 23-Apr 9, 2020)	0.24***	0.24***	0.18***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)
Second Response (Apr 9-, 2020)	0.12***	0.12***	0.07***	0.08***
	(0.01)	(0.01)	(0.00)	(0.00)
FE	Month	Month, Fund	Month	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	4.1	22.9	5.5	17.4

Table 5: Sources of Fragility in the COVID-19 Crisis: Heterogeneity by Fund Liquidity

This table reports results of sample split analysis of daily flows regressed on an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). Sample splits are by fund liquidity based on Roll (Columns 1-2), bid-ask spreads (Columns 3-4), and bond ratings (Columns 5-6). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Crisis

	Roll		Bid-Ask		Ratings	
	Illiq	Liq	Illiq	Liq	Illiq	Liq
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis (Feb-April 2020)	-0.36***	-0.10	-0.40***	-0.06	-0.44***	0.08
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	86,954	87,134	88,600	86,599	100,923	86,795
R^2(%)	12.9	7.4	12.0	6.3	12.6	7.3

Panel B: Evolution of the Crisis

	Roll		Bid-Ask		Ratings	
	Illiq	Liq	Illiq	Liq	Illiq	Liq
	(1)	(2)	(3)	(4)	(5)	(6)
Buildup (Feb 2020)	-0.03	0.26***	-0.09	0.28***	-0.13**	0.20***
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Outbreak (Mar 1-13, 2020)	0.16**	0.39***	-0.30***	0.40***	-0.49***	0.55***
	(0.07)	(0.10)	(0.08)	(0.10)	(0.07)	(0.11)
Peak (Mar 13-April, 2020)	-0.71***	-0.55***	-0.69***	-0.50***	-0.67***	-0.20**
	(0.07)	(0.10)	(0.07)	(0.09)	(0.07)	(0.10)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	86,954	87,134	88,600	86,599	100,923	86,795
R^2(%)	13.4	8.0	11.5	7.2	12.8	7.7

Panel C: Evolution of the Crisis and Policy Response

	Roll		Bid-Ask		Ratings	
	Illiq	Liq	Illiq	Liq	Illiq	Liq
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis (Feb-Mar 23, 2020)	-0.30***	0.14**	-0.41***	0.16**	-0.54***	0.28***
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)
First Response (Mar 23-Apr 9, 2020)	-0.63***	-0.67***	-0.53***	-0.55***	-0.48***	-0.37***
	(0.07)	(0.10)	(0.07)	(0.09)	(0.08)	(0.10)
Second Response (Apr 9-, 2020)	-0.01	0.08	0.05	-0.03	0.45***	0.06
	(0.10)	(0.13)	(0.11)	(0.13)	(0.13)	(0.15)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	86,954	87,134	88,600	86,599	100,923	86,795
R^2(%)	13.1	8.1	11.3	7.1	13.0	7.7

Table 6: Sources of Fragility in the COVID-19 Crisis: Heterogeneity by Fund Fire-Sale Spillovers, Age, & Maturity

This table reports results of sample split analysis of daily flows regressed on an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). Sample splits are by fund vulnerability to fire-sale spillovers (Columns 1-2), age (Columns 3-4), and maturity (Columns 5-6). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Crisis						
	Vulnerability		Age		Maturity	
	Low	High	Young	Old	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis (Feb-April 2020)	-0.19***	-0.32***	-0.32***	-0.11***	-0.04	-0.20**
	(0.04)	(0.04)	(0.05)	(0.03)	(0.11)	(0.09)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	165,403	177,561	169,086	182,969	32,973	33,710
R^2(%)	9.8	13.6	15.4	9.6	5.51	9.83
Panel B: Evolution of the Crisis						
	Vulnerability		Age		Maturity	
	Low	High	Young	Old	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Buildup (Feb 2020)	0.13***	-0.02	0.07	0.07**	0.24**	0.12
	(0.04)	(0.04)	(0.06)	(0.03)	(0.10)	(0.16)
Outbreak (Mar 1-13, 2020)	0.09	0.01	-0.10	0.22***	0.57***	0.23
	(0.05)	(0.06)	(0.07)	(0.06)	(0.18)	(0.14)
Peak (Mar 13-April, 2020)	-0.54***	-0.67***	-0.59***	-0.37***	-0.48***	-0.60***
	(0.05)	(0.05)	(0.07)	(0.04)	(0.16)	(0.10)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	165,403	177,561	169,086	182,969	32,973	33,710
R^2(%)	10.5	14.0	13.6	9.7	6.57	10.82
Panel C: Evolution of the Crisis and Policy Response						
	Vulnerability		Age		Maturity	
	Low	High	Young	Old	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis (Feb-Mar 23, 2020)	-0.06*	-0.24***	-0.22***	-0.03	0.21*	-0.01
	(0.04)	(0.04)	(0.06)	(0.04)	(0.11)	(0.11)
First Response (Mar 23-Apr 9, 2020)	-0.51***	-0.58***	-0.56***	-0.33***	-0.61***	-0.63***
	(0.05)	(0.05)	(0.08)	(0.05)	(0.14)	(0.11)
Second Response (Apr 9-, 2020)	-0.06	-0.09	-0.22**	0.08	0.11	-0.13
	(0.09)	(0.08)	(0.10)	(0.08)	(0.18)	(0.20)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	165,403	177,561	169,086	182,969	32,973	33,710
R^2(%)	10.1	13.8	15.5	9.4	6.26	10.38

Table 7: Sources of Fragility in the COVID-19 Crisis: Analysis of the Flow-Performance Relation

This table reports share class-level regressions of daily flows on daily performance and its interaction with an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

	Panel A: Crisis			
	Flows (%) FE	Flows (%) FE, lag dep	Flows (%) FE	Flows (%) FE, lag dep
	(1)	(2)	(3)	(4)
Crisis (Feb-April 2020)	-0.30***	-0.20***	-0.07***	-0.05**
	(0.02)	(0.02)	(0.03)	(0.02)
Return	2.62***	3.50***		
	(0.88)	(0.84)		
Crisis*Return	17.07***	14.74***		
	(1.08)	(0.97)		
Return^{-}			0.10	-0.18
			(1.24)	(5.45)
Return^{+}			4.49***	6.32***
			(1.28)	(1.21)
Crisis*Return^{-}			35.45***	28.94***
			(1.86)	(1.59)
Crisis*Return^{+}			-6.24***	-2.28
			(1.95)	(1.68)
FE	Month, Fund	Month, Fund	Month, Fund	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	14.3	22.4	14.5	22.5

Table 7: Sources of Fragility in the COVID-19 Crisis: Analysis of the Flow-Performance Relation (Continued)

This table reports share class-level regressions of daily flows on daily performance and its interaction with an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel B: Evolution of the Crisis				
	Flows (%) FE	Flows (%) FE, lag dep	Flows (%) FE	Flows (%) FE, lag dep
	(1)	(2)	(3)	(4)
Buildup (Feb 2020)	0.03	0.02	0.08***	0.08***
	(0.02)	(0.02)	(0.03)	(0.02)
Outbreak (Mar 1-13, 2020)	0.04	-0.00	0.16***	0.10**
	(0.03)	(0.03)	(0.05)	(0.04)
Peak (Mar 13-April, 2020)	-0.66***	-0.44***	-0.49***	-0.33***
	(0.03)	(0.02)	(0.04)	(0.03)
Return	3.21***	3.86***		
	(0.87)	(0.84)		
Buildup*Return	11.44***	9.63***		
	(1.72)	(1.60)		
Outbreak*Return	17.58***	14.32***		
	(1.41)	(1.33)		
Peak*Return	18.62***	16.21***		
	(1.29)	(1.16)		
Return^{-}			0.05	-0.13
			(1.25)	(1.15)
Return^{+}			5.48***	6.87***
			(1.26)	(1.20)
$\text{Buildup*Return}^{-}$			21.93***	21.15***
			(3.01)	(2.75)
$\text{Outbreak*Return}^{-}$			27.05***	23.53***
			(2.48)	(2.19)
Peak*Return^{-}			31.06***	25.74***
			(2.42)	(2.04)
$\text{Buildup*Return}^{+}$			-1.85	-4.79
			(3.84)	(3.40)
$\text{Outbreak*Return}^{+}$			0.16	-1.26
			(4.12)	(3.60)
Peak*Return^{+}			5.79**	6.92***
			(2.42)	(2.03)
FE	Month, Fund	Month, Fund	Month, Fund	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	14.8	22.6	14.9	22.6

Table 7: Sources of Fragility in the COVID-19 Crisis: Analysis of the Flow-Performance Relation (Continued)

This table reports share class-level regressions of daily flows on daily performance and its interaction with an indicator variable for the COVID-19 crisis (Panel A), indicator variables for different stages of the crisis (Panel B), and indicator variables for different stages of the crisis and policy response (Panel C). The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel C: Evolution of the Crisis and Policy Response				
	Flows (%) FE	Flows (%) FE, lag dep	Flows (%) FE	Flows (%) FE, lag dep
	(1)	(2)	(3)	(4)
Crisis (Feb-Mar 23, 2020)	-0.03	-0.04**	0.10***	0.07***
	(0.02)	(0.02)	(0.03)	(0.02)
First Response (Mar 23-Apr 9, 2020)	-0.74***	-0.46***	-0.50***	-0.31***
	(0.03)	(0.02)	(0.04)	(0.03)
Second Response (Apr 9-, 2020)	-0.30***	-0.23***	-0.38**	-0.31***
	(0.08)	(0.07)	(0.08)	(0.07)
Return	3.19***	3.84***		
	(0.87)	(0.84)		
Crisis*Return	26.33***	20.42***		
	(1.25)	(1.10)		
First Response*Return	19.04***	16.67***		
	(1.58)	(1.44)		
Second Response*Return	10.70**	8.93**		
	(4.40)	(3.75)		
Return^-			0.10	-0.15
			(1.24)	(1.14)
Return^+			5.32***	6.80***
			(1.28)	(1.21)
Crisis*Return^-			36.99***	30.36***
			(1.96)	(1.69)
First Response*Return^-			43.87***	33.80***
			(3.01)	(2.60)
Second Response*Return^-			-61.93**	-54.23**
			(31.47)	(26.07)
Crisis*Return^+			0.88	-0.95
			(3.04)	(2.56)
First Response*Return^+			0.50	3.85*
			(2.30)	(2.04)
Second Response*Return^+			13.94***	10.85***
			(4.32)	(3.71)
FE	Month, Fund	Month, Fund	Month, Fund	Month, Fund
N obs	717,440	717,440	717,440	717,440
R^2(%)	14.7	22.5	14.8	22.6

Table 8: Sources of Fragility in the COVID-19 Crisis: Analysis by Fund Sector Exposure

This table reports share class-level regressions of daily flows on an indicator for fund COVID-19 sector exposure and its interaction with an indicator variable for the COVID-19 crisis (Columns 1-2), indicator variables for different stages of the crisis (Columns 3-4), and indicator variables for different stages of the crisis and policy response (Columns 5-6). The COVID-19 sector exposure is based on holdings of the following Fama-French 49 industries: Entertainment, Construction, Automobiles and trucks, Aircraft, Ships, Personal services, Business services, Transportation, Wholesale, Retail, and Restaurants, hotels and motels. The time period is 2019-2020. All specifications include controls for fund size and month. Standard errors (in parentheses) are clustered by share class, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Variable definitions are in Appendix A.

Panel A: Analysis by Fund Sector Exposure						
	Crisis		Evolution		Response	
	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis (Feb-April 2020)	-0.15***	-0.19***				
	(0.05)	(0.05)				
Buildup (Feb 2020)			0.18***	0.14***		
			(0.05)	(0.05)		
Outbreak (Mar 1-13, 2020)			0.23***	0.18**		
			(0.08)	(0.08)		
Peak (Mar 13-April, 2020)			-0.57***	-0.60***		
			(0.07)	(0.07)		
Crisis (Feb-Mar 23, 2020)					-0.01	-0.05
					(0.05)	(0.05)
First Response (Mar 23-Apr 9, 2020)					-0.50***	-0.52***
					(0.07)	(0.07)
Second Response (Apr 9-, 2020)					-0.14	-0.16
					(0.13)	(0.13)
High Exposure Fund	-0.01		-0.02		-0.02	
	(0.03)		(0.03)		(0.03)	
High Exposure Fund*Crisis	-0.27***	-0.22***				
	(0.06)	(0.06)				
High Exposure Fund*Buildup			-0.20***	-0.18***		
			(0.06)	(0.06)		
High Exposure Fund*Outbreak			-0.69***	-0.64***		
			(0.12)	(0.12)		
High Exposure Fund*Peak			-0.12	-0.07		
			(0.10)	(0.10)		
High Exposure Fund*Crisis					-0.42***	-0.39***
					(0.06)	(0.06)
High Exposure Fund*First Response					0.03	0.03
					(0.10)	(0.10)
High Exposure Fund*Second Response					0.32*	0.37**
					(0.17)	(0.18)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes	No	Yes
N obs	183,331	183,331	183,331	183,331	183,331	183,331
R^2(%)	1.2	11.5	1.8	12.1	1.5	11.8

Table 9: Sources of Fragility in the COVID-19 Crisis: Implications for Cumulative Flows

This table reports an Oaxaca-Blinder style regression-based quantification of the contribution of different sources of fragility to cumulative outflows in the COVID-19 crisis. For each source of fragility (illiquidity, fire-sale vulnerability and sector exposure), we use the following approach. For example, take illiquidity. We split the sample into two sub-samples based on top vs. bottom quartiles of the illiquidity proxy (Roll). We regress cumulative fund flows (relative to net assets) on the crisis dummy as well as fund controls (size) for liquid funds. We store the estimated coefficients and use them to predict cumulative flows for illiquid funds, which provides the counterfactual of flows for illiquid funds if they were liquid. Finally, we take the difference between cumulative flows and predicted cumulative flows for illiquid funds, which is our measure of the impact of COVID-19 on cumulative flows that can be attributed to illiquidity. We report the % share explained, which is the ratio of the difference between cumulative flows and predicted cumulative flows divided by cumulative flows for illiquid funds. The flow-performance sensitivity estimates are from Table 8, Panel A. For reference, we also report in the bottom panel cumulative flows in the Taper Tantrum. Variable definitions are in Appendix A.

Panel A: Cumulative Flows in the Crisis		
	Feb-Mar, 2020	Mar-Apr, 2020
	(1)	(2)
Cumulative Flows	-9.1%	-5.7%
Cumulative Flows, Illiquid Funds (Roll)	-18.7%	-14.8%
Cumulative Flows, Fire-Sale Vulnerable Funds	-16.5%	-11.4%
Cumulative Flows, High Sector Exposure Funds	-21.4%	-16.6%
Flow-Performance Sensitivity	(0.29, 0.35)	(0.29, 0.35)
Cumulative Returns	-9.8%	-6.0%
Share Explained (Fund Liquidity (Roll))	44.9%	32.4%
Share Explained (Fund Fire-Sale Vulnerability)	62.4%	43.9%
Share Explained (Fund Sector Exposure)	71.5%	65.1%
Share Explained (Flow-Performance Sensitivity)	(31.2%, 37.7%)	(30.5%, 36.8%)
Historical Comparison: Taper Tantrum	May-Jun, 2013	Jun-Jul, 2013
Cumulative Flows	-1.9%	-2.2%

Figure 1: The Growing Importance of Funds in the Corporate Bond Market

This figure plots the quarterly time-series of an estimate of the importance of corporate bond funds and ETFs. The numerator is the aggregate dollar value of net assets of bond funds and ETFs, which is calculated by aggregating over individual funds' net assets. The denominator is the aggregate dollar value of nonfinancial corporate bonds outstanding. Time period is 2010Q1 to 2019Q4. Data source: Morningstar for net assets and Flow of Funds (Federal Reserve Board Financial Accounts, Z.1) for bonds outstanding.

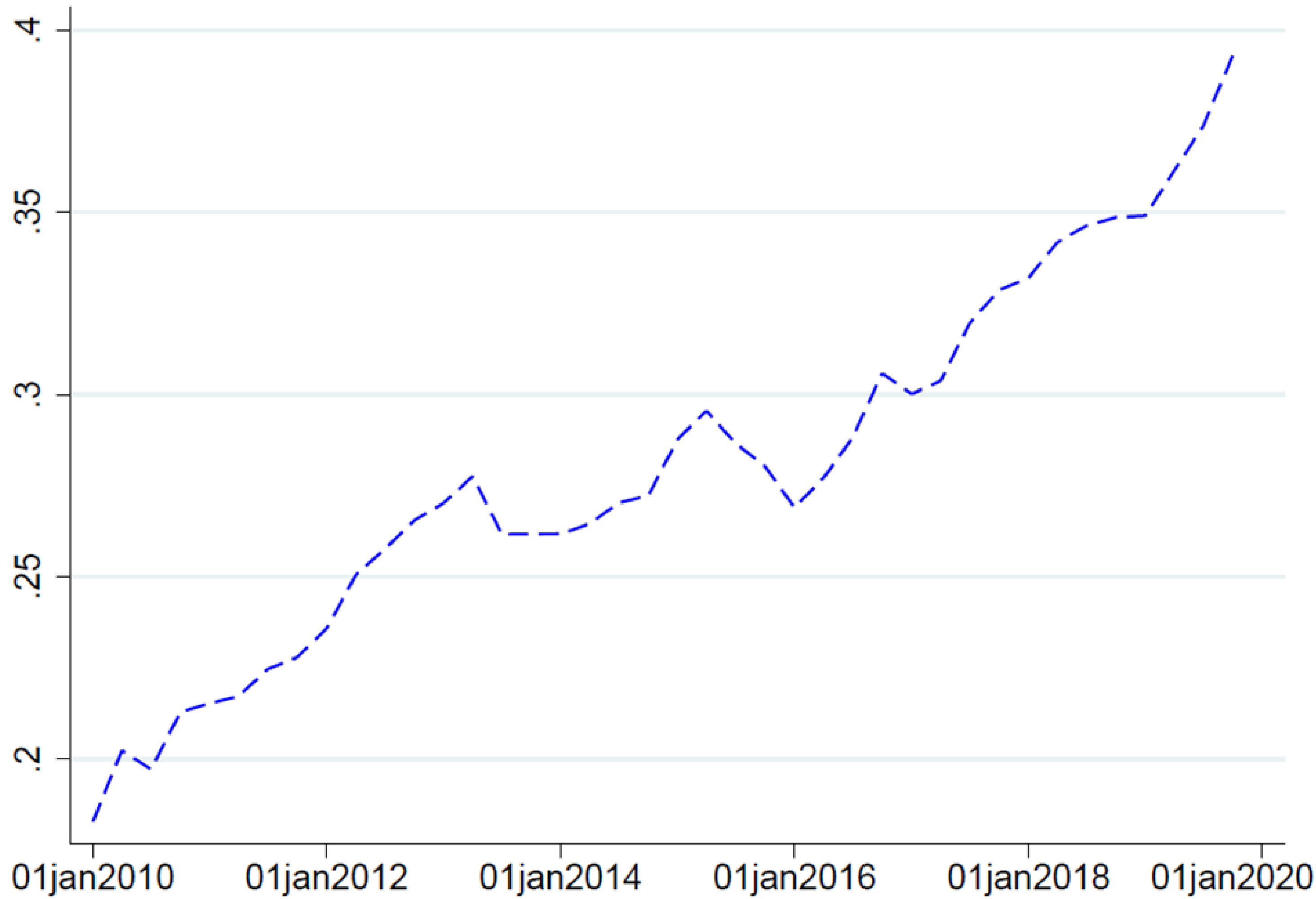
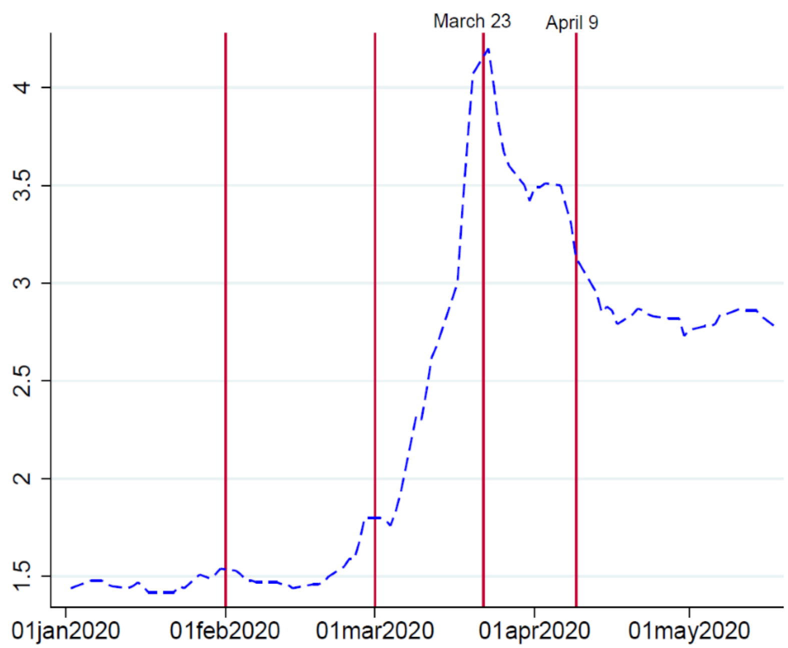


Figure 2: Stress in the Corporate Bond Market

This figure plots the daily time-series of spreads for investment-grade (Panel A) and high-yield (Panel B) rated nonfinancial corporate bonds. Spreads are defined as the difference between the respective corporate bond yields and those of comparable-maturity treasuries. Time period is January 1, 2020 to May 18, 2020. Data Source: ICE indices.

Panel A: Investment-Grade Bond Spreads



Panel B: High-Yield Bond Spreads

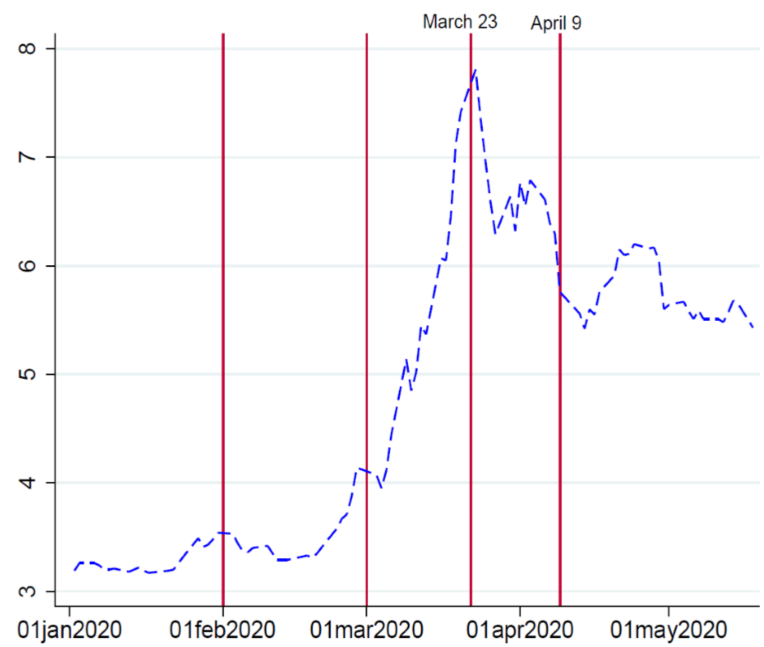


Figure 3: Long Term Perspective on Fund Fragility, Monthly Aggregate Net Fund Flows

This figure plots the monthly time-series of aggregate net flows of corporate bond funds and ETFs as a percentage of their aggregate net assets. The numerator is the aggregate dollar growth of new assets of bond funds and ETFs, which is calculated by aggregating over individual funds' growth of new assets. The denominator is the aggregate dollar value of their net assets at the beginning of each month, which is calculated by aggregating over individual funds' net assets. Time period is January 2020 to April 2020. Data Source: Morningstar.

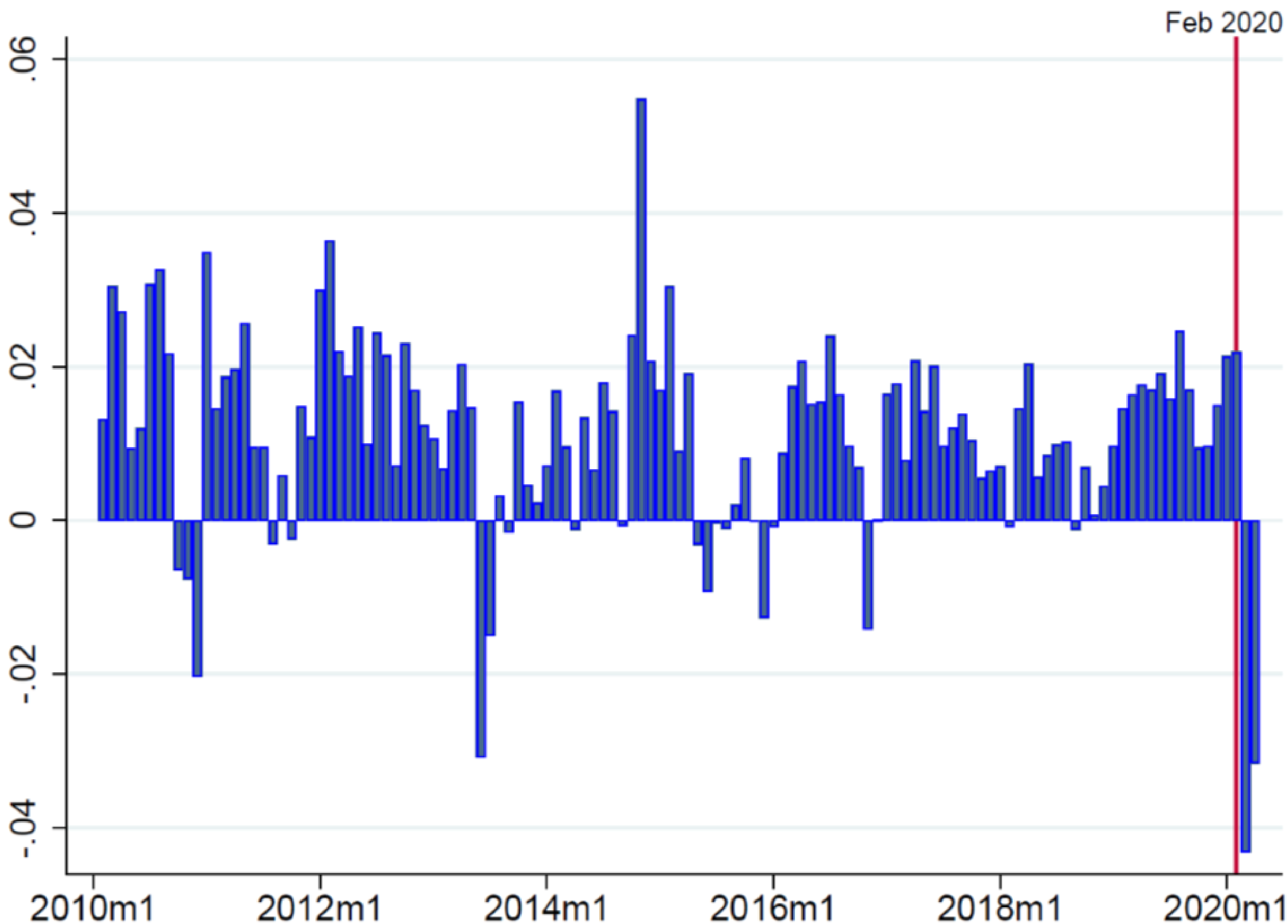
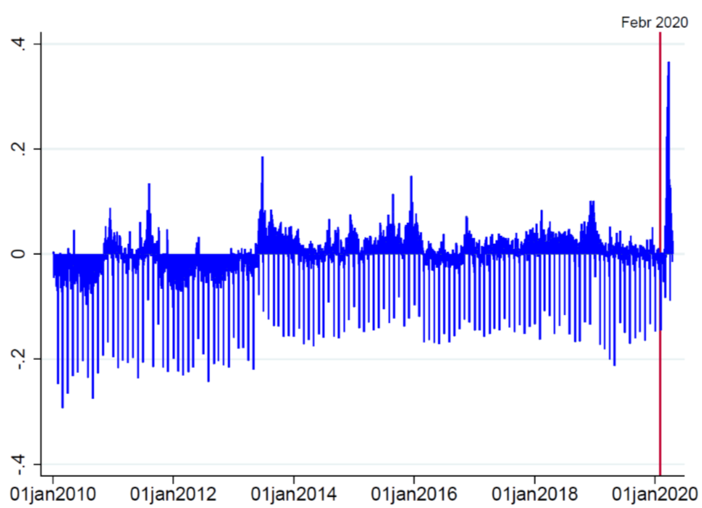


Figure 4: Long Term Perspective on Fund Fragility, Additional Outcomes

This figure plots the daily time-series of the fraction of corporate bond funds and ETFs that experience large outflows (Panel A) and large persistent outflows (Panel B). Large outflows are defined as those in the bottom 10% of the unconditional distribution of individual funds' net fund flows relative to net assets, as it is standard in the literature (see, for example, Coval and Stafford (2007)). Large persistent outflows are defined as large outflows in two consecutive days. Time period is January 2020 to April 2020. Data Source: Morningstar.

Panel A: Daily Net Fraction of Funds with Large Outflows



Panel B: Daily Net Fraction of Funds with Large Persistent Outflows

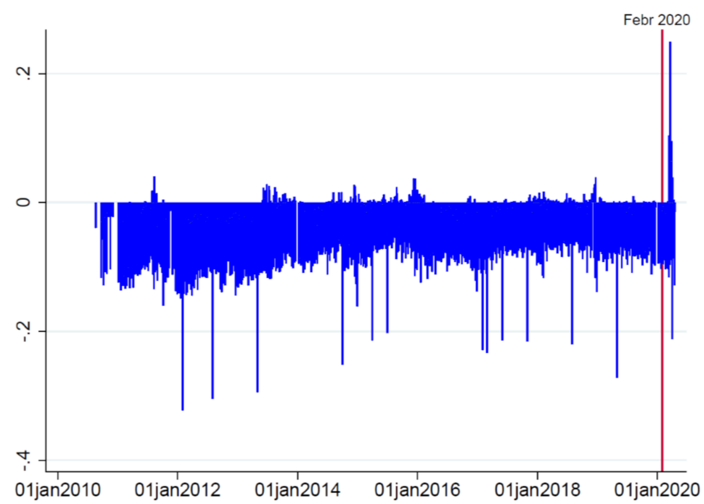


Figure 5: Evolution of Flows over the Crisis, Daily Aggregate Net Fund Flows

This figure plots the daily time-series of aggregate net flows of corporate bond funds and ETFs as a percentage of their aggregate net assets. The numerator is the aggregate dollar growth of new assets of bond funds and ETFs, which is calculated by aggregating over individual funds' growth of new assets. The denominator is the aggregate dollar value of their net assets at the beginning of each day, which is calculated by aggregating over individual funds' net assets. Time period is January 2020 to April 2020. Data Source: Morningstar.

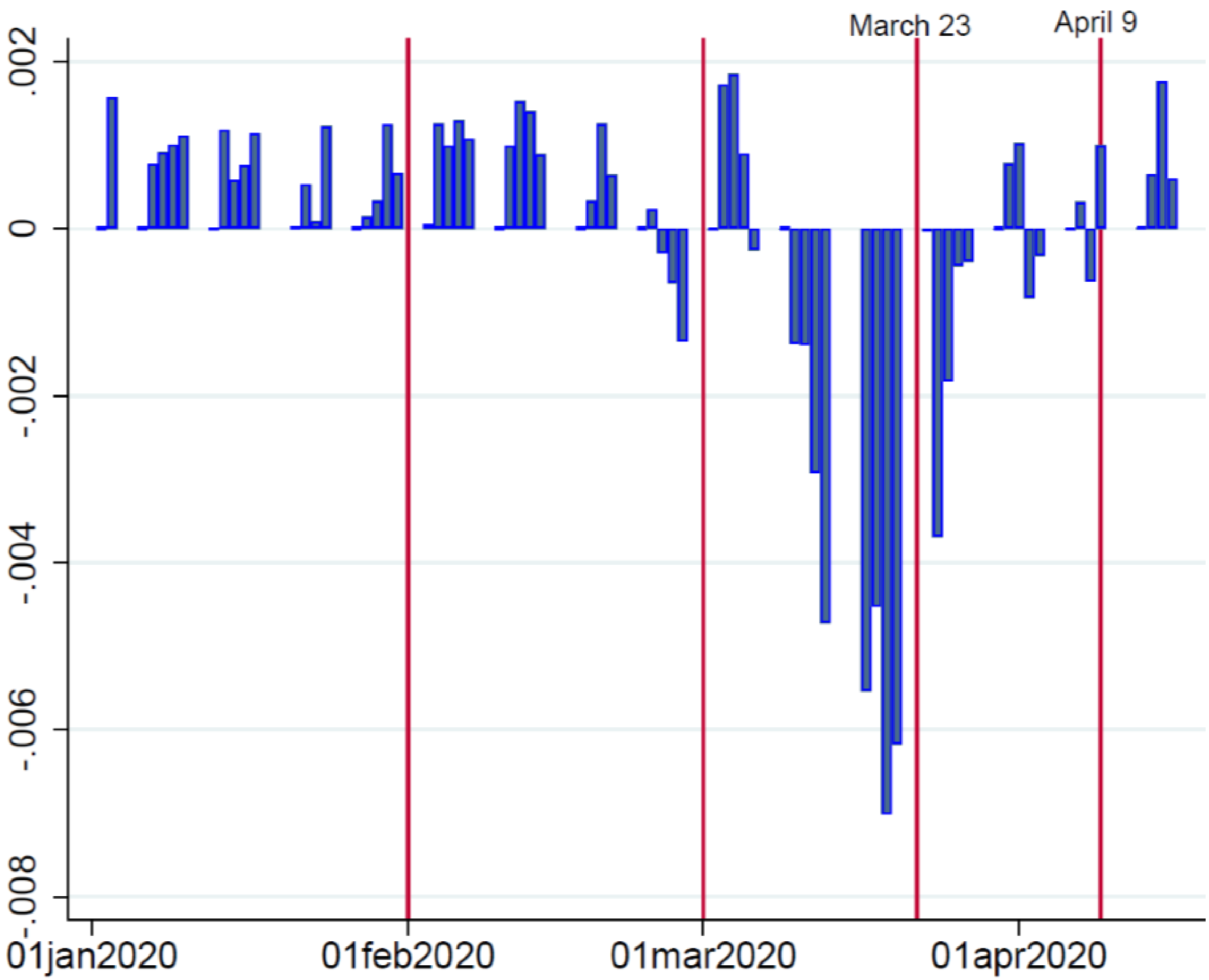
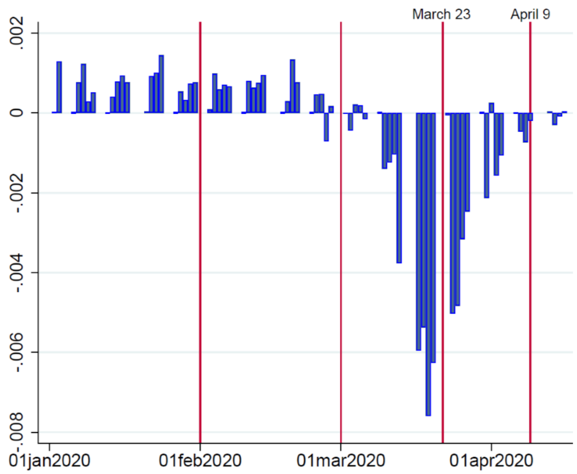


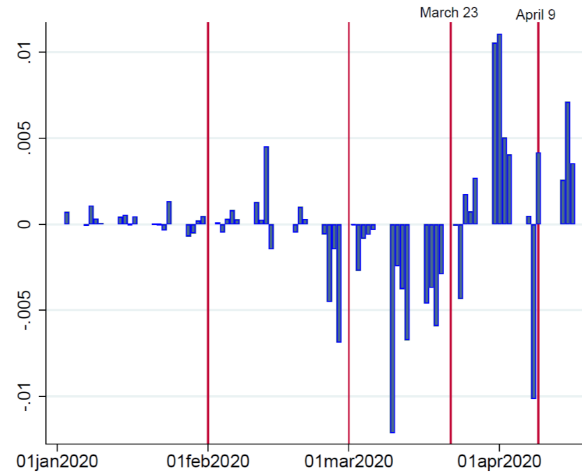
Figure 6: Evolution of Flows over the Crisis, Daily Aggregate Net Fund Flows by Fund Type

This figure plots the daily time-series of aggregate net flows of corporate bond funds and ETFs as a percentage of their aggregate net assets separately for investment-grade funds (Panel A), high-yield funds (Panel B), and ETFs (Panel C). The numerator is the aggregate dollar growth of new assets of bond funds and ETFs, which is calculated by aggregating over individual funds' growth of new assets. The denominator is the aggregate dollar value of their net assets at the beginning of each day, which is calculated by aggregating over individual funds' net assets. Time period is January 2020 to April 2020. Data Source: Morningstar.

Panel A: Investment-Grade Funds



Panel B: High-Yield Funds



Panel C: ETFs