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Risks and Vulnerabilities in the U.S. Bond Mutual Fund Industry

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Risks and Vulnerabilities in the U.S. Bond Mutual Fund Industry*

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Abstract

This paper assesses liquidity risk for the United States (U.S.) bond mutual funds industry and performs a range of analyses to identify which fund categories are more vulnerable to distress than others, and how sales from funds can impact financial stability. We develop a new measure to identify vulnerable categories based on expected outflows labelled 'Flows in Distress'. Overall, most U.S. mutual funds are resilient yet high yield (HY) and loan funds would face a liquidity shortfall when faced with severe redemption shocks. Combined sales from funds can have a sizeable price impact. Finally, our contagion analysis using data on fund flows and returns shows that Investment Grade (IG) corporate bonds funds, municipal bond funds and government bond funds are more likely to spread distress to other fund categories than HY, EM and loan funds. When the first type of funds experiences stress, other funds categories are likely to experience stress as well.

JEL Classification Numbers: C32, C15, E44, G12, G23

Keywords: Stress test; liquidity; investment funds; dependence; spillovers; systemic risk

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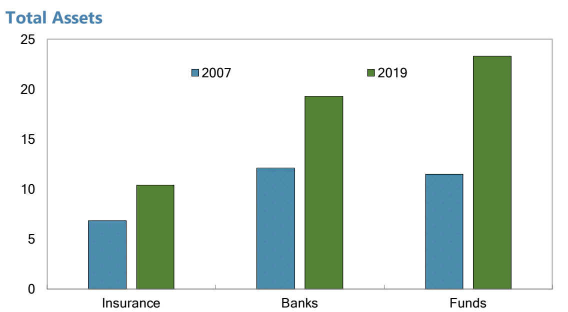
I. Introduction

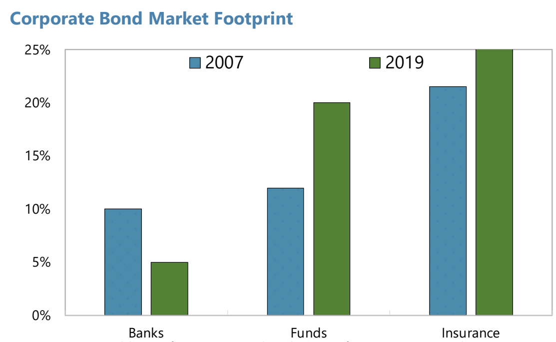
The U.S. asset management industry has grown significantly since the Global Financial Crisis (GFC), with total assets amounting to U.S. dollar (USD) 23 trillion end-2019 against USD 11 trillion in 2007 (Figure 1). In that context, mutual funds play an important role in credit intermediation, as evidenced by the increase in their market footprint: mutual fund holdings of U.S. corporate bonds account for 20 percent of amounts outstanding, against 12 percent in 2007 (Figure 2). Within the mutual fund industry, funds can have very different investment policies based on the asset classes they primarily invest in, which range from HY corporate bonds, leveraged loans and HY bonds to Treasuries and municipal bonds.

Figure 1. Total Assets of Selected U.S. Financial Institutions



Note: Total assets in trillion of US dollars. Funds include mutual funds, money market funds, exchange-traded funds and closed-end funds.
Sources: Flow of Funds, Refinitiv/Thomson Reuters Datastream.

Figure 2. Holdings of U.S. Corporate Bonds



Note: Holdings of US corporate bonds, in % of amounts outstanding.
Sources: Flows of Funds, Refinitiv Datastream.

Against that backdrop, policymakers have raised concerns about risks to financial stability stemming from the asset management industry. In 2013, the Office of Financial Research released a report on asset management and financial stability (OFR, 2013) followed by further work across international institutions (IMF, 2015a; FSB, 2017).

One of the main risks identified is related to liquidity mismatch: mutual funds offer daily liquidity to investors, while they can invest in a range of asset classes, with different degrees of liquidity. If large redemptions from investors were to occur, funds would need to sell a large amount of securities which could have a large price impact, given the limited absorption capacity of underlying markets. While the action of one fund is unlikely to impact markets, the simultaneous action of multiple funds could have a large impact (ESMA, 2019).

In that context, this paper looks at three different and complementary issues:

- To what extent can bond funds withstand severe but plausible redemptions shocks?
- Could sales from bond funds have a sizeable impact on bond markets?
- Which type of funds are more vulnerable to distress from other funds?

To address these issues, we assess liquidity risk for the U.S. mutual funds industry and perform a range of analyses to identify which fund categories are more vulnerable to distress, and which fund categories are more systemic, in the sense that when in distress, other funds are more likely to be in distress as well.

This paper is mainly based on the work done in the context of the 2020 U.S. Financial Sector Assessment Program (FSAP) and presented in IMF (2020a) and IMF (2020b) and includes additional analysis to account for the stress that occurred during the COVID-19 crisis in March 2020.

Compared to previous analyses, our work provides four main contributions:

First, we extend the liquidity stress testing framework developed by the IMF (2015b, 2017, 2018) by estimating the price impact of fund sales.

Second, we apply the connectedness framework of Diebold and Yilmaz (2014) to a set of financial institutions (mutual funds) that has not been analyzed in that context before.

Third, we develop a new measure of vulnerability (Flows in Distress, FiD) based on a copula-dependence framework. This measure estimates how much redemptions a fund should expect when another fund is in distress. Such interconnectedness effects can come from a range of factors. In the case of positive dependence, some funds might face outflows when other funds are in distress due to common exposures on the asset side which can create complementarities. In addition, some funds might have a similar investor base, resulting in simultaneous outflows when investors sentiment change. Finally, the dependence can be negative (funds facing inflows when other funds are in distress) due to substitution effects, for example between HY bond funds and sovereign bond funds. The dependence approach can therefore be used to assess vulnerable funds, i.e. funds with high expected redemptions when other funds are in distress. Systemic funds could also be identified using this approach, i.e. funds that when in distress are associated with high redemptions from other funds.

Finally, we apply the liquidity stress framework to the period of intense stress that occurred in March 2020. We design a macrofinancial scenario based on the observed decline in valuation in asset classes bond funds invest in and estimate fund outflows and sales of assets by funds.

Overall, we obtain three main results. First, most U.S. mutual funds would have enough highly liquid assets to meet investors' redemptions. However, most funds exposed to HY and leveraged loans would not have enough highly liquid assets and would need to sell liquid securities in their portfolio.

Second, asset sales by mutual funds to meet redemptions could have a sizeable impact on markets. When several funds sell the same type of assets simultaneously, the price of the assets decline, given the limited absorption capacity of the market. When markets are already under stress, this price impact is even higher, as sellers have to accept high discounts on their assets so as to dispose of them. The price impact of sales from mutual funds ranges between 50 to 200 basis points (bps) in normal times, and between 150 to 700 bps during stress periods. For IG and HY corporate bonds, the price impact can amount to around 300bps during stress period, in line with the findings of IMF (2020c) regarding the impact of assets sales by funds during the COVID-19 crisis.

Third, some fund categories are particularly vulnerable to distress from other fund categories, with consistent results based on flow and returns. Such fund categories include IG corporate bond funds, municipal bonds funds and government bond funds. It implies that several funds can be simultaneously forced to sell assets to meet redemptions, thereby amplifying downward price pressure on asset classes they are exposed to. Given the large size of those fund categories, such effects can be large. In addition, such analyses show that some fund categories may require more monitoring than others given their levels of interconnectedness.

The remainder of the paper is as follows: Section II provides an overview of the literature, section III details the models used, Section IV provides the results, Section V puts the results in the context of COVID-19 crisis, Section VI discusses policy options to mitigate identified risks, and Section VII concludes.

II. LITERATURE REVIEW

A growing literature has emerged looking at liquidity risk and fire sales dynamics from mutual funds, as well as contagion effects in the fund industry.

Regarding liquidity risks and the impact of sales from mutual funds, Zeng (2017) shows with a dynamic theoretical model that mutual funds are subject to bank-run-like risks. Following outflows from investors, mutual funds use first their cash buffers to meet redemptions. Then funds rebuild their cash buffers in the next period, through the sales of illiquid assets. Those forced sales have a negative impact on the net asset value of the fund, which in turn creates a first-mover advantage for investors leading to further outflows. The combination of a floating Net Asset Value (NAV) and the fund's desire to rebuild cash buffers create a time-consistency problem and strategic complementarities among shareholders, in line with Chen et al. (2010). The model is consistent with empirical work from Coval and Stafford (2007), Chen et al. (2010) and Goldstein et al. (2015) who show that outflows can predict future decline in fund NAV and that flow-induces sales of illiquid asset can create temporary price overshooting. In addition, Goldstein et al. (2015) find that corporate bond funds exhibit a concave flow-return relationship, with higher levels of outflows following negative performance than following positive performance. Brunnermeier and Pedersen (2009) also present a model showing that, under certain conditions, margins are destabilizing, and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals.

Regarding liquidity management and the impact of sales of assets following outflows, Chernenko and Sunderam (2016) report that even careful liquidity management by funds cannot fully alleviate fire sale costs. Equity and bond mutual funds manage liquidity by holding cash to actively manage their liquidity provision and reduce the price impact of asset sales. Funds build cash buffers when they receive inflows and draw down their cash buffers when facing outflows, in line with the theoretical prediction from Chordia (1996). In particular, funds exposed to less liquid assets tend to use cash more aggressively than other funds. Cash holdings are found to be positively correlated to asset illiquidity and flow volatility. Morris et al. (2017) presents a global game model of investor runs and identifies conditions under which asset managers hoard cash and finds that cash hoarding is the rule rather than the exception and that less liquid bond funds display a greater tendency toward cash hoarding. Jiang et al. (2016) shows that, during tranquil market conditions, mutual funds tend to reduce liquid asset holdings to meet investor redemptions and temporarily increase their relative exposures to illiquid asset classes. During periods with heightened aggregate uncertainty, mutual funds tend to scale down their liquid and illiquid asset proportionally, thereby preserving the liquidity of their portfolios but facing trading costs related to the sale of illiquid securities. Zhang (2019) empirically shows that loose monetary policy exacerbates the fragility of corporate bond funds, measured by the sensitivity of outflows to negative performance.

Using data on U.S. mutual funds, Girardi et al. (2017) show that funds with relatively low levels of cash tend to have worse performance than their peers, due to the price impact of their trades. Dotz and Weth (2019) report that liquidation strategies are different for institutional and retail German bond funds. In times of high uncertainty, managers of institutional-oriented funds sell their most liquid bonds first, thereby preserving short-term performance at the cost of increasing liquidity risk. At the same time, retail-based funds do not let portfolio liquidity deteriorate—presumably to attenuate incentives for runs. More recently, Coudert and Salakhova (2020) analyze a sample of French corporate bond funds and find that outflows from mutual funds generate significant effects on corporate bond yields. When net flows are split between inflows and outflows, outflows generate significant upward pressure on yields, while inflows have no significant effect.

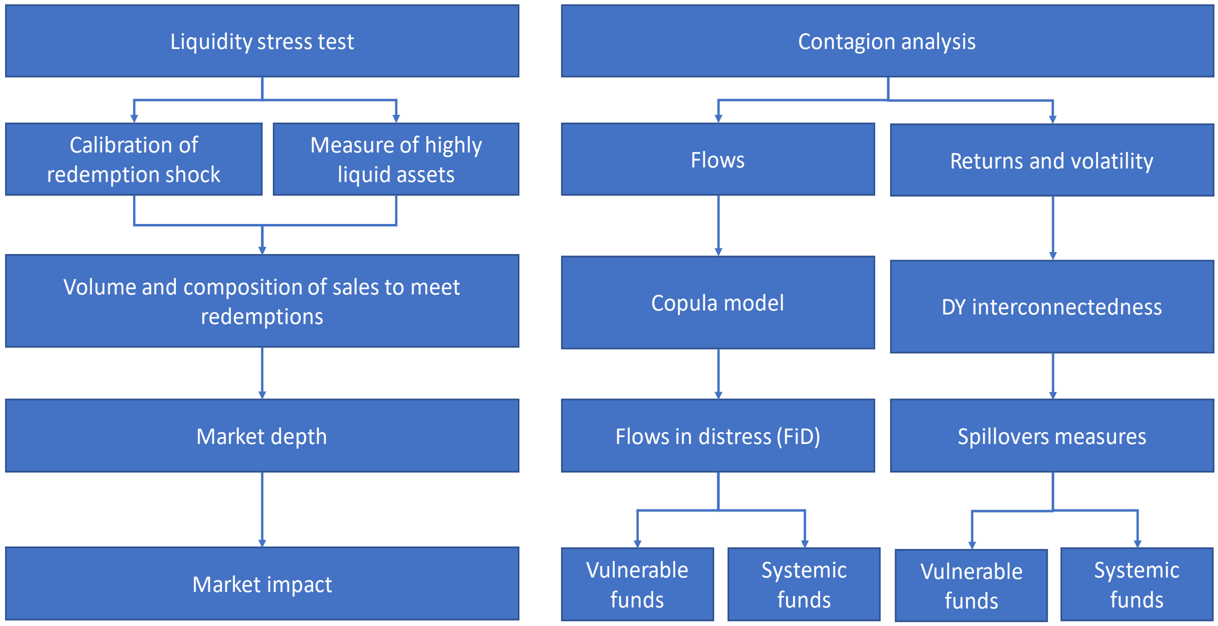
The issues of the transmission of shocks through the fund industry and risks of contagion have also gained prominence in the academic literature. Beyond the effects of forced sales, Boyson et al. (2010) show that hedge fund returns correlate more strongly than suggested by fundamentals, because of common shocks to funding markets. Hau and Lai (2017) document that shocks to bank stocks during the GFC spilled over to non-bank stocks because of outflows from funds invested in both assets. Beyond mutual funds, several papers have studied the network between financial institutions, especially between banks. Brunetti et al. (2019) study two network structures, correlation networks based on publicly traded bank returns and physical networks based on interbank lending transactions. They find during the crisis the correlation networks shows an increase in interconnectedness, while the physical network highlights a marked decrease in interconnectedness and physical networks forecast liquidity problems, while correlation networks forecast financial crisis. Roukny et al. (2013) investigates the stability of several benchmark topologies in a simple default cascading dynamic in bank networks and finds scale-free networks can be both more robust and more fragile than homogeneous architectures. Huang and Wang (2020) investigates the impact of financial system on China's economic output from a financial institution tail-event driven networks (TENETs) perspective and finds that estimated network topological measurements present a highly accurate forecast for China's economic output.

III. Overview of the Methodology

A. Main Features

To identify and assess potential risks and vulnerabilities within the U.S. mutual fund industry, we run a series of analyzes based on two pillars: a liquidity stress test and a contagion analysis. In particular, we perform liquidity stress testing and contagion analyses based on flow and return data at different degrees of granularity (fund level and by fund categories), as shown in Figure 3.

Figure 3. Overview of the Methodology



Regarding the liquidity stress test, we extend the framework developed initially for the 2015 U.S. FSAP (IMF, 2015b) and refined since then (IMF, 2017; ESMA, 2019), by modelling explicitly the price impact of sales from funds on the underlying asset classes. Mutual funds are subject to a redemption shock, and their ability to withstand this shock is estimated by comparing the outflows to the level of highly liquid assets held by each fund.

To assess the market-wide impact of fund sales, funds are assumed to dispose of cash and assets to meet redemption, resulting in selling pressure. The volume of sales is then compared to market depth to calculate the price impact of the trades on the underlying markets, at asset class level.

Finally, a contagion analysis is performed based on two sub-pillars. A flow-based pillar estimates for each fund category, the expected net flows conditional on each other fund category being in distress (Flows in Distress measure or FiD). This analysis corresponds to a what if scenario: what would be the expected net flows for High Yield bond funds or municipal bond funds if Investment Grade corporate bond funds are in distress?

In addition, a return-based pillar is computed, by applying Diebold and Yilmaz (2014) connected analysis on a sample of the largest mutual funds for each category. This approach measures how shocks to funds spillover to other funds.

B. Liquidity Stress Test

Calibration of Redemption Shocks

To assess liquidity risk for mutual funds, we calibrate a redemption shock which is then compared to a measure of highly liquid assets. The objective of this approach is to assess funds' ability to withstand redemptions shocks. Following recent work done by the IMF in the context of FSAPs (IMF, 2015b; 2017, and 2018), the redemption shock is calibrated based on the distribution of historical net flows by fund categories.

FSAPs usually follow a Value-at-Risk (VaR) approach, where the 1st percentile of net flows is used to calibrate the shock. Formally, the VaR at the α level is given by:

$$VaR(\alpha) = F^{-1}(\alpha) \tag{1}$$

where F^{-1} is the inverse of the distribution function of net flows.

However, as discussed in a report from the European Securities and Markets Authority (ESMA, 2019), this approach has some drawbacks. First, extreme shocks below the VaR are not taken into account, and second, when using a parametric approach, the VaR is subject to model risk (Emmer et al., 2015). To address those two issues, the redemption shock is based on the expected shortfall (ES), which is equal to the average net flows below the VaR. The ES approach includes extreme values observed when funds faced severe stress, while smoothing them out, by taking their average. In other words, the redemption shocks is calculated as the average worst outflows experienced by funds.

The ES is given by:

$$ES(\alpha) = \frac{1}{\alpha}\int_0^\alpha VaR(l)\,dl \tag{2}$$

or equivalently:

$$ES(\alpha) = E\big(Z\big|Z < VaR(\alpha)\big) \tag{3}$$

where Z represents observed net flows.

The redemption shock is defined under the homogeneity assumption: each fund in the same category faces the same outflows (in percent of their NAV), based on the distribution of all flows of funds within this category (IMF, 2018). It implies that for example all HY bond funds face the same outflows and all IG bond funds face the same outflows (which are different from HY flows). This approach allows different shocks across fund categories, which consider the different features of the fund categories (type of assets they invest in and types of investors), while ensuring that results can be compared within fund categories (ESMA, 2019). Another approach would have been to use a heterogeneity assumption, where the redemption shock is only calibrated on each individual fund flows. Yet this approach has several limits. First, it does not allow the comparison of outcome across funds for a redemption shock of the same magnitude. Second, if funds have not experienced large outflows the calibrated shock will not be meaningful and finally, by construction, the funds have been able to withstand the shock, which provide limited insights on their ability to do so in the future (See Bouveret (2017) and ESMA (2019) for further discussion of the calibration approaches).[1]

Measure of Highly Liquid Assets

The ability of funds to withstand shocks is estimated by comparing the redemptions to the level of high liquid assets. The objective is to assess vulnerabilities at fund-level. This approach is complemented by the liquidation approach, which estimates the amounts of asset sales by funds, irrespective of their levels of highly liquid assets, in order to derive the price impact of funds' sales on financial markets. The liquidation of securities by funds constitutes one channel through which funds can transmit shocks to the rest of the financial system.

Highly liquid assets for fund i are given by:

$$HLA^i = \sum_{k=1}^{n} \omega_{i,k} \times s_{i,k} \quad (4)$$

where $\omega_{i,k}$ are liquidity weights assigned to each security $s_{i,k}$ in the fund portfolio as discussed below.

There are different approaches that can be used to measure highly liquid assets and define such liquidity weights (ESMA, 2019). For example, in the U.S., since 2019, investment companies have to report to the Securities and Exchange Commission (SEC) the liquidity of their mutual funds in four different buckets from highly liquid to illiquid (SEC, 2018).

Here, we measure Highly liquid assets using the liquidity weights defined in the context of the Liquidity Coverage Ratio (LCR) for banks, in line with ESMA (2015), Bouveret (2017), ESMA (2019) and IMF (2019). For each asset class, liquidity weights are defined based on the type of assets and for fixed income instruments the credit quality. Liquidity weights are taken from the Basel Committee rather than domestic implementation of the LCR, to allow for comparability (Table 1).

[1] For robustness purposes, the liquidity stress test ran for the 2020 U.S. FSAP features both the homogeneity and the heterogeneity approaches, using different thresholds (1 percent, 5 percent and 10 percent). For further details see Appendix XIII in IMF (2020b).

Table 1. Liquidity Weights by Asset Class

		Liquidity weights
Cash		100%
Equities		50%
Fixed income instruments	Credit rating	
Sovereign bonds	AAA-AA	100%
	A	85%
	BBB	50%
	Below BBB	0%
Corporate bonds	AAA-AA	85%
	A	50%
	BBB	50%
	Below BBB	0%
Securitized	AAA-AA	85%
	A	0%
	BBB	0%
	Below BBB	0%

Source: Basel Committee

For each fund, the HLA measure is equal to the weighted average liquidity.

As in the 2017 Luxembourg FSAP (IMF, 2017), the ability of funds to withstand redemption shocks is measured by the Redemption Coverage Ratio (RCR) defined as follows:

$$RCR = \frac{Highly\ liquid\ assets}{Redemption\ shock} \tag{4}$$

When the RCR is below 1, the fund does not have enough highly liquid assets to cover redemptions without selling fewer liquid assets. In that case, the liquidity shortfall is defined as the difference between the redemption shock and the stock of highly liquid assets:

$$Liquidity\ shortfall = Redemption\ shock - Highly\ liquid\ assets \tag{5}$$

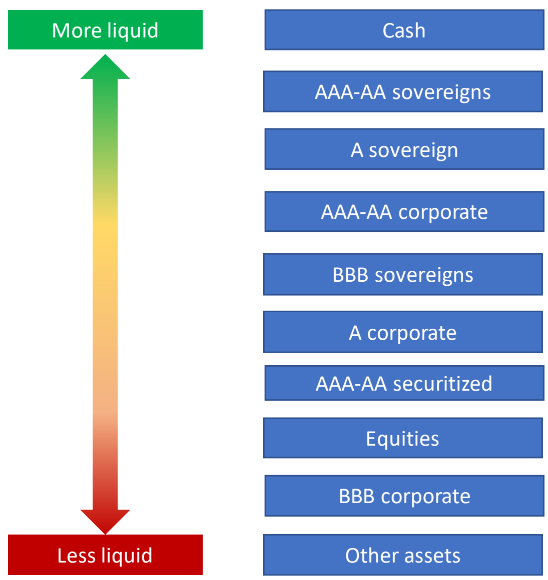
C. Sales and Market Impact

The HQLA approach defined previously does not allow for the estimation of the price impact of sales by funds, since the analysis ends with the comparison of HQLA to redemptions. Therefore, we complement it with the estimation of the price impact of sales by funds. Once investors redemptions occur, fund managers have to dispose of assets (or use cash) to meet redemptions. Following the redemption shocks, fund managers have to sell some of the fund assets to meet investors' redemptions. Different liquidation strategies can be used: vertical slicing (pro rata)—where the manager sells each asset class in proportion of their weight in the fund's portfolio—waterfall (where most liquid assets are sold first), or a mixed approach where cash is used first and then the manager follows a slicing approach.

The choice of the liquidation strategy can have a sizeable impact on remaining investors. Under the slicing approach, the manager maintains the liquidity profile of the portfolio, in line with the investment policy, but this might require selling assets which are less liquid. Such sales could result in losses due to higher trading costs compared with more liquid assets (Girardi et al., 2017).

Under the waterfall approach, the manager sells the most liquid assets first, which mitigates the price impact of sales but generates costs for remaining investors as they are left with a portfolio which is less liquid than initially. When the waterfall approach is used, the liquidation strategy is based on the ordering stemming from high quality liquid asset (HQLA) liquidity weights (cash then AAA-AA sovereign bonds, A sovereign bonds, AAA-AA corporate bonds, BBB sovereign bonds, A corporate bonds, AAA-AA securitized assets, and BBB corporate bonds). When assets with positive liquidity weights have been entirely sold, managers use unrated sovereign bonds, corporate bonds and finally securitized assets (Figure 4).

Figure 4. Waterfall Liquidation Strategy



Generally, asset managers use the slicing approach since it preserves the liquidity profile of the portfolio and keeps it in line with the investment policy. However, in some cases the waterfall approach can be better for both redeeming and remaining investors as well as for the market as large (AMIC, 2019; Blackrock, 2019). The effect of the waterfall approach on the protection of investors can be ambiguous. When using a waterfall approach, the price impact of sales will be lower than under the slicing approach, since funds sell their most liquid assets first. On the one hand, remaining investors will experience higher returns than under the slicing approach due to the limited price impact of sales. On the other hand, remaining investors end up with a less liquid fund, which could create additional challenges if redemptions were to continue. In addition, the waterfall approach can result in changes in the portfolio structure of the fund, which could create challenges for fund managers since the portfolio structure should remain aligned with the investment policy of the fund as defined in its prospectus. The diversity of practices across funds and across normal and stress periods mirrors the findings from the literature, which do not point to a specific liquidation approach, but rather to flexible approaches used by fund managers.

Price Impact of Funds Sales

Given a redemption shock and a liquidation strategy, funds have to sell a given amount of securities across different asset classes. To estimate the price impact of the sales, the volume of sales is compared to market depth, which measures the absorption capacity of the market. Following Cont and Schaaning (2017), market depth is equal to:

$$MD(\tau) = c\frac{ADV}{\sigma}\sqrt{\tau} \tag{6}$$

The market depth over a time horizon τ , $MD(\tau)$, is a function of a scaling factor c, times the ratio between the average daily trading volumes ADV and the asset volatility σ, multiplied by the square root of the time horizon $\sqrt{\tau}$. The market depth is therefore higher, when the time horizon is longer, i.e. it is possible to sell a higher volume of bonds over a longer period of time. The higher the market depth, the lower the price impact of trades, as markets are able to absorb high volumes without large price discounts.

The estimation of the parameters follows the approach used by Cont and Schaaning (2017) and Coen et al. (2019), using high-level data on trading volumes and bond indices to estimate the volatility. For each asset class, the daily volatility is computed over different periods representing normal trading conditions and stressed trading conditions (September–December 2008). Table 2 shows the corresponding measures of market liquidity obtained.

The price impact measures in Table 2 are calculated at asset class level and not at security-level. For example, under normal conditions, the sales of USD 1 billion of IG corporate bonds would lead to a decline in bond prices of around 4 basis points and 8 basis points under stressed conditions. On average bond funds, invest in around 100 bonds, which implies that bond funds would need to sell USD 10 million of each bond, resulting in a decline in prices of 4 and 8 basis points respectively. At security-level, the price impact of trades can be substantially higher, especially for corporate bonds as they trade very infrequently.

Table 2. Price Impact Measures by Asset Classes

Asset class	ADV (US$ bn)	Average volatility	2008 Volatility	Normal trading conditions: Market Depth (US$ bn)	Normal trading conditions: Impact of $ 1bn of sale (in bps)	Stressed trading conditions: Market Depth (US$ bn)	Stressed trading conditions: Impact of $ 1bn of sale (in bps)
UST	545	0.28%	0.55%	77,857	0.1	39,636	0.3
Corp. IG	21	0.30%	0.65%	2,800	3.6	1,292	7.7
Corp. HY	12	0.31%	1.07%	1,548	6.5	449	22.3
Leveraged loans	3	0.18%	0.64%	556	18.0	156	64.0
EM debt	8	0.40%	1.36%	750	13.3	221	45.3
Municipal bonds	11	0.19%	0.64%	2,316	4.3	688	14.5
Securitized Agencies	220	0.19%	0.44%	46,316	0.2	20,000	0.5
Securitized	2	0.11%	0.27%	727	13.8	296	33.8
Equities	320	1.12%	3.60%	11,429	0.9	3,556	2.8

Sources: Refinitiv Datastream, SIFMA, JPMorgan, EMTA, IMF staff
Note: 2008 volatility estimated over September-December 2008

Given a liquidation strategy and a redemption shock, we estimate the price impact by comparing the sales by asset classes to market depth.

$$PI(\tau) = \frac{Sales}{MD} \tag{7}$$

For example, if sales of IG corporate bonds amount to USD 10 billion, under normal trading conditions, market depth is USD 2,800 billion, implying a price impact of 0.36 percent or 36 basis points.

D. Contagion Analysis

The contagion analysis uses two types of models to assess the interconnectedness between funds and fund categories: a dependence approach using flows and a spillover approach using funds returns. Both approaches aim at identifying fund categories which are vulnerable (more likely to be in distress when other funds are in distress), or systemic (when in distress, other fund categories are more likely to be in distress).

The dependence approach estimates the expected outflows that a fund (fund A) would face if another fund (fund B) were to experience large outflows. The larger the expected outflows, the more vulnerable fund A is, and the more systemic fund B is.

The spillover approach measures how much of shocks to fund A's returns have an effect on the volatility of fund B's returns and the other way around. If both funds tend to propagate shocks to each other, they are highly interconnected. In addition, if fund B transmits more shocks to fund A than it receives from fund A, then fund B is a net transmitter a shock (hence more systemic) and fund A is a net receiver (hence more vulnerable).

Dependence Across Fund Categories Using Copulas (Flows in Distress, FiD)

When a fund experiences large redemption, other funds might also face outflows from investors. For example, in December 2018 both HY and loan funds had large outflows, as investors were concerned with credit risk in riskier markets. At the same time, government funds recorded inflows as a result of a flight to safety. In that context, it is crucial to assess how distress in one type of funds—defined as large outflows—can be associated with distress in other types of funds, so as to ensure that contagion effects remain limited.

One simple measure of the dependence between net flows across funds is the correlation coefficient. However, correlation is a very rough representation of the dependence structure since one number (the correlation coefficient) summarizes all the dependence between funds (see Segoviano and Goodhart, 2009). In particular, during stress periods, outflows across funds might be very different from what would be observed during normal periods. In that context, the modelling of the dependence structure needs to be richer, for example by allowing higher dependence during stress periods (i.e. large outflows) than during normal times (i.e. average flows).

Copulas can be used to model the dependence structure across fund flows. Copulas are mathematical functions that link distributions together, allowing for the modelling of complex dependence structures. Each fund is characterized by its distribution of flows, and the dependence between fund flows is characterized by the copula. Given a distribution of flows for fund A and fund B, a copula can be used to link the two distributions together. Once the copula is estimated, it can be used to compute joint probabilities, such as the probability that fund A and fund B face outflows larger than 5 percent at the same time.

We estimate the dependence structure across fund categories by computing the expected net flows conditional on another fund category being in distress. Formally, our dependence measure (Flows in Distress, FiD) for funds of category A condition on stress for funds of category B ($FiDp_{B\to A}$) is given by:

$$FiDp_{B\to A} = E(f_A | f_B < \alpha) \tag{7}$$

The FiD measure is equal to the conditional expectation of net flows for funds A (f_A) when funds B (f_B) are in distress, defined as net flows below a certain threshold α. When the FiD measure is low, it implies that when fund B is in distress, fund A is likely to face large outflows (given by value of the conditional expectation), since net flows would be negative (outflows).

We rely on copulas to model the dependence structure between net flows across funds. Copulas have been used to model dependence for various applications in finance over the last twenty years, including market and credit risk management (Jouanin et al., 2004), pricing of a basket of derivatives (Li, 2000. More recently, copulas have been used to assess systemic risk, including the joint probability of distress for entities (Segoviano and Goodhart, 2009; Oh and Patton, 2018)

According to Sklar's theorem, given H, a n-dimensional cumulative density function with one-dimensional marginals $F_1, \ldots, F_n$, then there exists a copula C such that

$$H(x_1, \ldots, x_n) = C\big(F(x_1), \ldots, F(x_n)\big), \forall (x_1, \ldots, x_n) \in \mathbb{R}^n \tag{8}$$

In other words, given a series of distributions of flows for funds (called marginal distributions), it is always possible to model the dependence structure between those distributions using a copula. The copula captures the dependence structure of the joint cumulative density function.

The dependence measure is given by:

$$FiD_{B\to A} = E(f_A|f_B < \alpha) = \int_{-\infty}^{+\infty} \int_{-\infty}^{\alpha} xh(x,y)dxdy \tag{9}$$

Where h is the joint density function of net flows for funds A and B.

Following Kole et al. (2007), we choose a Student t-copula to model the dependence structure across fund flows. Using a portfolio of stocks, bonds and real estate, Kole et al. (2007) show that the t-Copula has a better goodness of fit than the correlation-based Gaussian copula or extreme-value based copulas such as Gumbel. Unlike the Gaussian copula, the t-copula allows for tail dependence, implying that when a fund faces large outflows, another fund is more likely to face outflows at the same time, while in normal time the dependence is lower. This modelling is in line with observations of very large outflows for some fund categories during stress periods, while during more normal times, dependence between flows is low. As a robustness check, a Gaussian copula is also used (Appendix B).

The Student t-copula with ν degrees of freedom, is given by:

$$C^t_{\nu,\Sigma}(u_{1,}, \dots, u_{n,}) = t_{\nu,\Sigma}(t_\nu^{-1}(u_1), \dots, t_\nu^{-1}(u_n)) \tag{10}$$

with $t_{\nu,\Sigma}$ the joint cumulative density function of the multivariate distribution and $u_{i,} = F(x_i)$. The copula requires the input parameter Σ which represents the correlation matrix:

$$\Sigma = \begin{pmatrix} 1 & \cdots & \rho_{1,n} \\ \vdots & \ddots & \vdots \\ \rho_{n,1} & \cdots & 1 \end{pmatrix} \tag{11}$$

In our estimation, we first use a parametric approach for the marginal distribution. The logistic distribution provides the best fit for the distribution of flows by types. The probability density function is given by:

$$f(x;\mu,s) = \frac{e^{-\frac{x-\mu}{s}}}{s\left(1+e^{-\frac{x-\mu}{s}}\right)^2} \tag{12}$$

With μ the mean and s the scale parameter. Both parameters are estimated by maximum likelihood.

The parameters of the Student copula are also estimated by maximum likelihood, using observable correlations among series as input for Σ (see Yan (2007) for details about the estimation procedure). The FiD is finally calculated using Monte Carlo simulations (100,000 simulations), but using numerical integration gives similar results.

Spillovers Across Fund Categories

The copula approach presented in the previous section is useful to perform ‘what if’ analyses but it does not provide insights on the directional connectedness between funds. To complement the dependence approach, we also use the spillover approach of Diebold and Yilmaz (2014), labelled DY thereafter, which have been used extensively in IMF FSAPs to assess market-based directional interconnectedness across institutions, usually banks or insurance companies (Malik and Xu, 2017; Bricco and Xu, 2019). The DY approach provides estimates of directional effects, which complement the Copula approach. In that context, we use the DY framework to estimate volatility spillovers within fund categories. The DY framework provides a range of measures of interconnectedness between entities within the system, which can be used for risk monitoring and identification of vulnerable and systemic funds.

The DY framework estimates how much of the volatility of fund’s returns can be explained by shocks from other funds and how much of those volatilities can pass to other funds. The method provides a directional shock transmission dependence measures between funds by the decomposition of returns’ variance: it is directional because fund A’s contribution to the forecast error’s variance of fund B can be higher than fund’s B contribution to the forecast error’s variance of fund A, implying that fund A is a net shock transmitter to fund B, while fund B is a net shock receiver.

More precisely, a financial spillover (or interconnectedness) from fund A to fund B is defined as the share of the variation in fund B’s returns shocks that can be attributed to (contemporaneous or preceding) shocks to fund A’s returns. This concept stresses idiosyncratic shocks and excludes co-movement across markets that is driven by common factors.

The DY approach is based on three different measures of interconnectedness:

i) Pairwise directional connectedness (interlinkages between two entities or markets). For example, how shocks to fund A contribute to the variance of fund B

ii) System-wide connectedness (overall level of connectedness in the system). For example, how shocks are transmitted within fixed income funds.

iii) System-wide directional spillovers (how individual shocks are transmitted to the system and how shocks to the system are transmitted to individual entities). For example, how shocks to fixed income funds are transmitted to a specific fund and how shocks to this specific fund are transmitted to the system.

DY use a Vector Autoregression (VAR) model based on the standard deviations of the market returns to estimate the different measures of connectedness. The VAR is then used to decompose forecast error variances: how much of the variation in the volatility (i.e. the forecast error variance) of fund A can be attributed to other funds.

Formally, the VAR model is given by:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{13}$$

where x_t is a vector of return volatility and p is the number of lags.

After estimating the VAR, the generalized forecast error variance is decomposed into parts attributed to the various variables in the system.

Variable j's contribution to variable i's H-step-ahead generalized forecast error variance is given by:

$$\theta_{i,j}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A'_h e_i)} \tag{14}$$

where Σ is the covariance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zeros otherwise.

For the purpose of our analysis, we follow DY and perform the VAR estimation on a system of log-volatilities of financial indices with automatic selection of the lasso (least absolute shrinkage and selection operator) penalty. The lasso penalty is used to shrink the regression coefficients towards zero to improve the prediction accuracy and interpretability of the coefficients (see Zou and Hastie 2005).

The four system connectedness measures can then be directly computed:

Total connectedness:

$$C^H = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{i,j}^{g}(H)} \tag{15}$$

Inward connectedness (extent to which shocks to the system affect fund i):

$$C_{i\leftarrow .}^{H} = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{i,j}^{g}(H)} \tag{16}$$

Outward connectedness (extent to which shocks to fund i affect the system):

$$C_{.\leftarrow i}^{H} = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{j,i}^{g}(H)} \tag{17}$$

Net connectedness (difference between shocks to and from the system):

$$C^H = C_{.\leftarrow i}^{H} - C_{i\leftarrow .}^{H} \tag{18}$$

We can also compute pairwise directional connectedness: (net spillovers between fund i and j)

$$C_{i \leftarrow j}^{H} = \tilde{\theta}_{i,j}^{g}(H) \tag{19}$$

Spillovers measures can then be estimated based on a sample of funds belonging to different categories.

IV. Risks and Vulnerabilities in the U.S. Mutual Fund Industry

A. Sample of Funds and Assumptions Used

The emphasis is on fixed income mutual funds, since they invest in a range of fixed income assets with varying degrees of liquidity. Other types of entities such as hedge funds, private funds or separate managed accounts, which can also have a large footprint in fixed income markets are not included in the analysis, due to data gaps.

Based on commercial data, the sample includes 2,743 funds for a net asset value of about USD 6.4 trillion as of end-2019, covering the entire mutual fund universe tracked by the Investment Company Institute (see Appendix A for details). The sample is subdivided into nine categories reflecting the type of instruments mutual funds invest in. As shown in Table 3, the categories are IG and HY corporates, loan funds (exposed to leveraged loans), global bond funds, EM funds, government bond funds, municipal bond funds, mixed funds (investing in equities and bonds) and multi-sector funds (which invest in different countries and across fixed income categories, see also Cortes and Sanfilippo; 2020).

Table 3. Sample of Funds

Fund category	Net asset Value (US $ bn)	Number of funds
Corp. IG	2,427	608
Mixed funds	1,752	792
Municipal	799	567
Multisector	432	182
Government	326	161
Corp. HY	257	192
Global	247	87
Loan funds	91	58
EM funds	66	96
Total	6,398	2,743

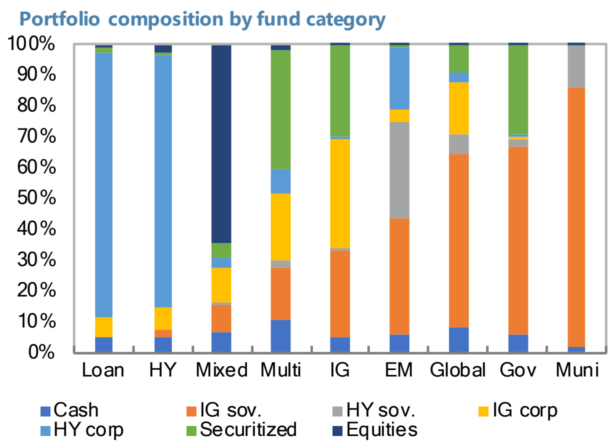
Sources: Morningstar, ICI, IMF staff calculations

For each fund, we collect monthly data on fund net asset value, monthly net flows over 2007–2019, along with portfolio composition and credit quality of their fixed income portfolio.

Figure 5 shows the portfolio composition by fund category: HY and loan funds invest mainly in non-IG securities, while government and municipal bond funds invest mainly in IG sovereign bonds. The large differences in portfolio composition across fund categories reflect the different investment policies pursued by funds. Overall, most funds have relatively limited cash buffers (around 5 percent) as fund managers prefer to be almost fully invested in order to achieve better performance (given low returns on cash).

One exception relates to the multi-sector fund category which includes multisector bond and nontraditional bond funds (Annex A). For some of those funds, the high cash buffers can be explained by the use of derivatives such as interest rate swaps and CDSs, as funds keep cash to be able to meet variation margins on their derivatives' positions. Based on sample of funds with assets close to USD 1trillion, Cortes and Sanfilippo (2020) document that such funds are more likely to engage in leveraged derivatives trades.

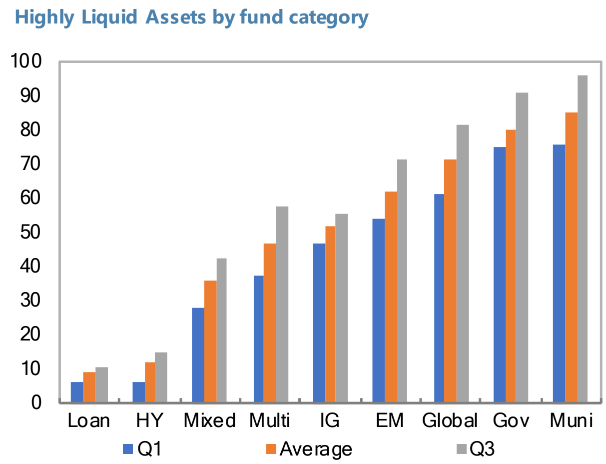
Figure 1. Portfolio Composition



Note: HY corporate bonds include leveraged loans. Data as of December 2019.
Sources: Morningstar, IMF staff.

For each fund, we compute the share of highly liquid assets using the portfolio composition and applying the LCR liquidity weights. Figure 6 indicates that the level of HQLA is very heterogeneous across fund categories, with HQLA ranging from around 6 percent of NAV for HY and loan funds up to more than 80 percent for government and municipal bond funds. However, within fund categories the levels of HQLA are very homogeneous, with funds in the first and third quartile having relatively similar HQLA.

Figure 6. Highly Liquid Assets by Fund Categories



Note: HQLA in % of NAV.
Sources: Morningstar, IMF staff.

The distribution of net flows for each fund category is obtained by merging monthly net flows for each fund in a given category. The redemption shock is calibrated at the 3 percent expected shortfall (the average of the lowest net flows below the 3rd percentile, i.e. the average of the largest outflows) in line with ESMA (2019), resulting in redemption shocks ranging from 7 percent of NAV for municipal funds to 17 percent for EM bond funds (Table 4).[2]

By using historical data by fund category, the redemption shock is different for each category and identical for each fund within each category, making it possible to compare funds while considering different redemptions patterns. Since net flows are merged across funds within a category, this method also allows some funds to be subject to a higher shock than they had experienced in the past.

[2] Using other calibration approaches (VaR) or different threshold yield similar conclusions as shown in Appendix XIII in IMF (2020b).

Table 4. Redemption Shocks

Fund category	Redemption shock in % of NAV
Municipal	7
Mixed funds	9
Corp. IG	13
Multisector	13
Loan funds	13
Global	14
Government	14
HY	15
EM funds	17

Note: Net outflows in % of NAV.
Sources: Morningstar, IMF staff.

Overall, funds within a category appear to be quite homogeneous when looking at their portfolio composition (asset type and credit quality), HQLA measure or distribution of net flows, while funds are very heterogeneous across categories.

For the dependence analysis, monthly net flows are aggregated by fund categories (i.e. allowing netting effects within a category with inflows in one fund compensating outflows in another one).

For the spillover analysis, we use weekly returns for the ten largest funds of each category, implying a sample of 90 funds.

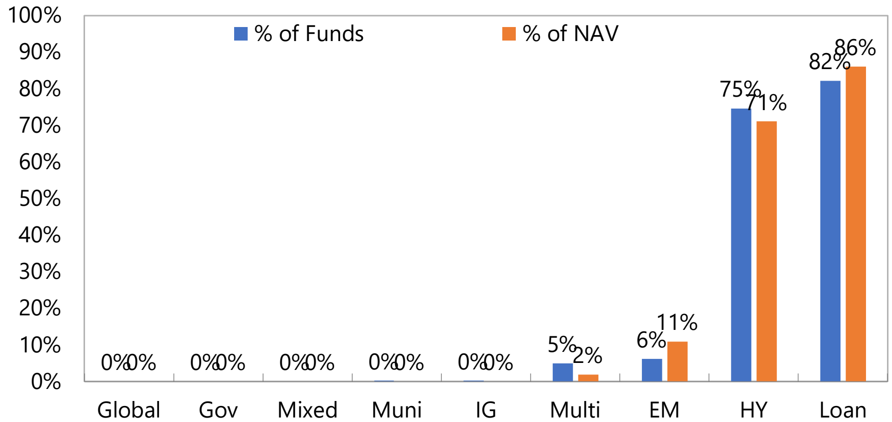
B. Liquidity Stress Test

Overall, nearly all funds would be able to withstand severe redemptions, as more than 90 percent of the funds would have enough highly liquid assets to meet investors' redemptions (Figure 7).

Yet, most funds exposed to HY and leveraged loans would not have enough highly liquid assets and would need to sell less liquid securities in their portfolio, assuming that they do not use any liquidity risk management tools. The results are related to the high exposure of HY and loan funds towards less liquid asset classes (HY corporate bonds which include leveraged loans), which have a liquidity weight of zero for HQLA calculations. This finding is in line with previous studies (IMF, 2017; IMF, 2019; and ESMA, 2019), which also show that funds exposed to less liquid assets are more vulnerable than other funds. The results are similar when reported by number of funds or share of NAV, indicating that vulnerabilities are not only for small funds within each category.

The fund categories identified as most vulnerable in the liquidity stress tests are also the smaller ones in terms of NAV in the sample (Table 3).

Figure 7. Results of the Liquidity Stress Tests



Note: Share of funds (by category) whose Redemption Coverage Ratio (highly liquid assets to redemption) is below one .
Sources: Morningstar, IMF staff.

C. Price Impact

Asset sales by mutual funds to meet redemptions could have a sizeable impact on markets, depending the size of the shock, the related asset sales and the underlying market depth.

For a given redemption shock, the impact on underlying markets is larger when funds use vertical slicing (pro-rata) than when using a waterfall approach, where they sell their most liquid assets first.

Under the slicing approach—where funds sell securities in proportion of their weights in the portfolio—mutual funds exposed to less liquid asset classes (such as EM bonds, HY corporate bonds or leveraged loans) would sell large amounts of bonds compared to the size of the market, which would create some significant downward pressure on prices given the limited absorption capacity of the underlying markets. Under the waterfall approach, the price impact would be more muted, since funds would sell first their most liquid assets. However, remaining investors would end up with a less liquid portfolio, which could amplify the first-mover advantage (i.e., the incentive to redeem before other investors as trading costs are not passed on redeeming investors). At fund-level there is a trade-off between reducing the price impact of sales (thereby preserving the returns of the fund) and maintaining the portfolio allocation in line with the investment objective.

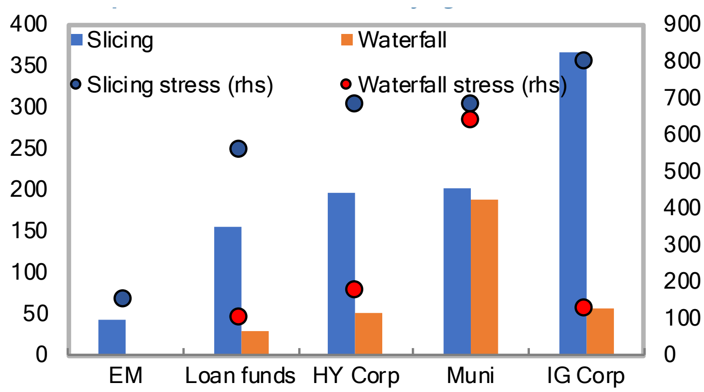
Overall, prices would experience large declines, especially under stressed conditions. Across asset classes, the price impact of sales from mutual funds ranges between 50 to 200 basis points in normal times, and between 150 to 700 bps during stress periods under the slicing approach (Figure 8 and Table 5).

The high price impact on IG corporate bond markets is related to the size of IG bond funds (USD 2,427bn in our sample): under the slicing approach, IG bond funds would sell around USD 100bn of corporate bonds, which would result in sharp decline in prices (Table 5).

For funds exposed to less liquid assets (EM, or loan funds), the volume of sales would be limited in absolute amounts with less than USD 10 bn, which explains that even though the underlying markets are less liquid than IG bonds, the price impact is lower.

If funds sell their most liquid assets first (waterfall approach), the price impact on underlying markets is muted (less than 100 bps under normal conditions and less than 200 bps under stress for most asset classes).

Figure 8. Price Impact of Asset Sales



Note: Price impact of asset sales by liquidation strategy, in bps. The chart shows the impact of sales for each category of funds on its underlying market (EM bond fund sales impact on EM bond market etc.)
Sources: Morningstar, IMF staff.

Table 5. Price Impact for Selected Fund Categories

Fund category	Slicing			Waterfall		
	Volume of sales	Normal	Stressed	Volume of sales	Normal	Stressed
EM	3	43	147	-	-	-
HY Corp	30	196	678	8	50	173
IG Corp	103	368	796	16	57	124
Loan funds	9	156	556	2	29	102
Muni	47	202	679	44	188	634

Note: Volumes of sales in US$bn and price impact of sales on the underlying market (in basis points)
Source: IMF staff

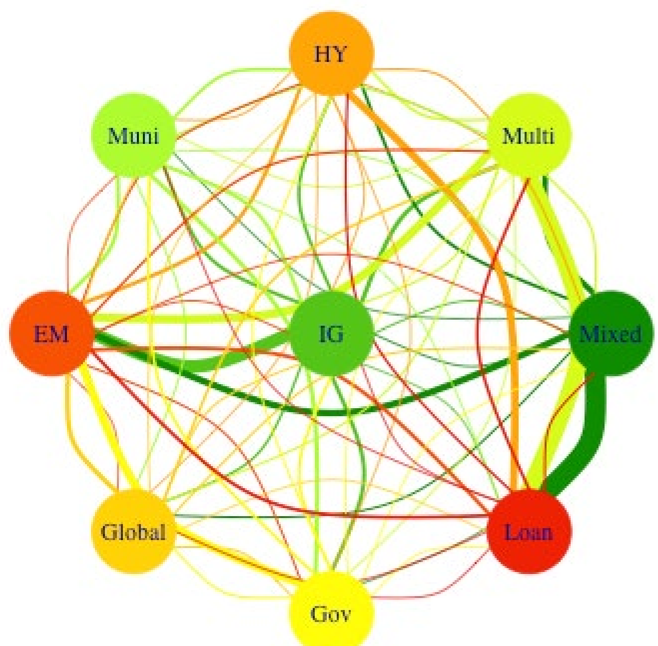
D. Contagion Analysis

The outcome of the contagion analysis shows that some specific fund categories are more vulnerable than others. Funds investing in less liquid asset classes (HY, EM or loan funds) tend to be more vulnerable to shocks to other funds (outflows or volatility shocks). On the other hand, shocks to IG corporate bond funds, government and municipal bonds funds are associated with higher levels of stress in the system, through either larger redemptions for other funds (FiD approach) or higher volatility of returns (DY approach).

Flows in Distress

Some fund categories are potentially more vulnerable to distress in the fund industry. Figure 9 shows the expected net flows, when other fund categories are in distress (i.e., facing large outflows). In that context, EM bonds funds are likely to experience large outflows, as indicated by wide edges stemming from IG and the larger values in the columns of Table 6. This could be explained by the riskier nature of EM bond funds compared to other fund categories: when volatility rises, EM funds are more likely to experience outflows. This result is in line with Arslanalp et al. (2020), which show that EM bond funds are highly sensitive to global factors. IG corporate bond funds are also particularly vulnerable to distress affecting municipal and government bond funds, as IG expected net flows would be below the 5th percentile.

Figure 9. Expected Net Flows Conditional on Distress (Net Flows)



Note: 1./ Nodes' colors (from red to dark green) depend on the expected net outflows (in percent of NAV) when they are in distress: the reddest Loan category has the largest expected net flow in percent of NAV when it is in distress; the greenest Mixed category has the lowest expected net flow in percent of NAV when it is in distress.
2./ Edges' widths depend on the scale of expected impact (expected net flow in percent of NAV) on other fund categories when one is in distress and colors are the same as that of the impact sender: the thickest dark green edge between Mixed and Loan categories indicates the largest expected outflow in percent of NAV will happen in the category of Loan when Mixed category is in distress.
3./ Positive net flows are omitted.
Source: Morningstar, IMF staff calculation.

Table 5. Expected Net Flows Conditional on Distress

Impact on other funds

Funds in distress

Net flows	IG	Mixed	Multi	HY	Muni	EM	Global	Gov	Loan	To (AVG)
IG	-2.2	-0.5	-2.3	-1.7	-1.8	-4.6	-1.0	-2.1	-0.1	-1.8
Mixed	-0.2	-1.7	-2.9	-1.6	0.2	-3.2	-0.6	0.8	-5.6	-1.6
Multi	-0.7	-1.0	-3.7	-1.3	-0.1	-3.7	-0.6	-0.1	-5.3	-1.6
HY	-0.3	-0.5	-0.7	-4.5	-0.3	-2.1	0.8	0.0	-3.4	-0.8
Muni	-1.9	-0.1	-0.8	-1.6	-3.0	-2.1	-0.4	-2.3	3.7	-0.7
EM	-0.4	-0.4	-1.1	-0.8	0.0	-5.0	-0.1	-0.7	-2.0	-0.7
Global	-0.5	-0.6	-1.2	0.1	-0.2	-2.4	-4.4	-0.5	1.1	-0.5
Gov	-1.4	0.3	-0.1	-0.5	-1.5	-3.7	-0.7	-4.2	4.8	-0.3
Loan	0.6	-0.6	-1.5	-1.0	1.2	-1.7	1.0	1.2	-11.0	-0.1
From (AVG)	-0.6	-0.4	-1.3	-1.1	-0.3	-2.9	-0.2	-0.5	-0.9	

Net flows
>0
[-1%,0]
[-1%,-3%]
<-3%

Note: Expected net flows conditional on distress in % of NAV. Grey cells show net flows for funds in distress.

Sources: Morningstar, IMF staff.

Some fund categories are identified as more systemic than others. When some fund categories are in distress, other funds might also be in distress at the same time, indicating the systemic nature of the first category. Systemic categories include IG corporate bond funds, multi-strategy bond funds and to a lesser extent municipal bond funds, mixed funds and government bond funds. For example, in the case of IG bond funds, where they are in distress, three other fund categories would face outflows around or higher than 2 percent (Municipal, multi and EM bond funds), which correspond to the 5th percentile of their net flows distribution.

Fund categories which are most exposed to liquidity risk such as HY, EM and loan funds are not systemic since when they are in distress, other fund categories do not experience large outflows, partly due to substitution effects, with investors moving out of those funds into safer funds. For example, when loan funds are in distress, municipal and government bond funds would experience inflows.

Given that the size of the fund categories is very heterogeneous, we compute the cumulated expected net flows in USD for each category conditional on another category being in distress. Table 7 below shows that Municipal bond funds generate the largest impact (USD 59 billion in outflows), which is due to the relatively large outflows from IG funds (close to 2 percent of NAV), the largest category in the sample. This pattern can also be seen in Figure 10, where the edge originating from Municipal bond funds towards IG is the largest. For the same reason, government bond funds have also a large aggregate impact. IG and multi strategy bond funds have a similar impact, yet it is due to a more widespread impact across fund categories: fewer edges with large width but more edges with medium width (Figure 10).

Table 6. Expected Net Flows Conditional on Distress (in USD billion)

Impact on other funds →

Funds in distress ↑

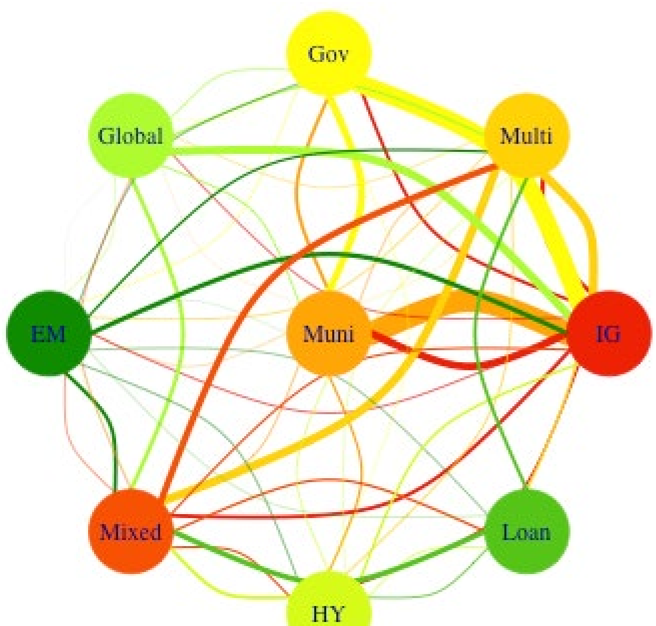
Net flows	Muni	IG	Multi	Gov	Global	EM	Mixed	HY	Loan	Cumulated flows (net)
Muni	-24	-46	-2	-7	-1	-1	-2	-5	5	-59
IG	-15	-52	-9	-7	-3	-3	-7	-4	0	-47
Multi	-1	-17	-16	0	-2	-2	-17	-3	-5	-47
Gov	-15	-37	0	-14	-1	-2	5	-1	5	-46
Global	-3	-17	-4	-2	-11	-2	-8	0	2	-34
EM	-1	-10	-5	-2	0	-3	-8	-2	-2	-29
Mixed	1	-4	-13	3	-2	-2	-30	-4	-5	-27
HY	-2	-5	-1	0	2	-1	-7	-11	-2	-17
Loan	10	14	-7	4	3	-1	-11	-3	-10	8
From (AVG)	-3	-15	-5	-1	0	-2	-7	-3	0	

Net flows in US$ bn
>0
[0;-10]
[-10;-20]
<-20

Note: Expected net flows conditional on distress in US$ bn. Grey cells show outflows for funds in distress. Cumulated flows exclude net flows from the funds in distress. Negative values indicate outflows.

Sources: Morningstar, IMF staff.

Figure 10. Expected Net Flows Conditional on Distress (in USD billion).



Note: 1./ Nodes' colors (from red to dark green) depend on the expected net outflows (in USD billion) when they are in distress: the reddest IG category has the largest expected net flow in USD billion when it is in distress; the greenest EM category has the lowest expected net flow in USD billion when it is in distress.
2./ Edges' widths depend on the scale of expected impact (expected net flow in USD billion) on other fund categories when one is in distress and edges' colors are the same as that of the impact sender: the thickest orange edge between Muni and IG categories indicates the largest expected outflow in USD billion will happen in the category of IG when Muni category is in distress.
3./ Positive net flows are omitted.
Source: Morningstar, IMF staff calculation.

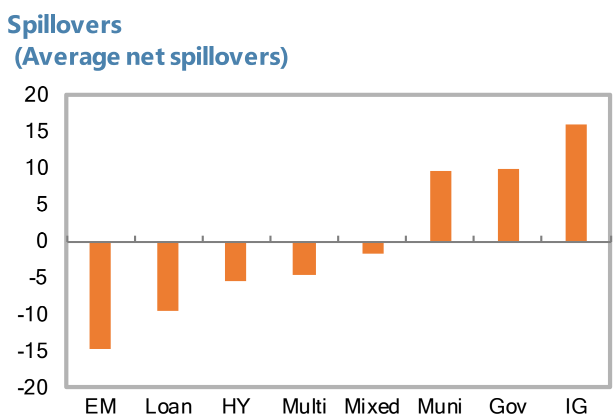
Overall, the FiD analysis complements the liquidity stress tests and provide a more comprehensive picture of vulnerabilities within U.S. mutual funds.

Fund categories identified as vulnerable in the liquidity stress test, especially HY and EM bond funds are also more likely to experience outflows when other funds are in distress. Other fund categories such as IG or municipal bond funds, for which the liquidity stress test points to limited liquidity mismatch, are nevertheless at risk of outflows when other fund categories are in distress. Given their size and their market footprint, these fund categories can propagate shocks within the fund complex, even though at fund-level they are able to cope with investors' redemptions. Such analyses provide a framework for risk monitoring within the fund industry.

Spillover Analysis

The interconnectedness analysis based on funds' returns yield similar results than the FiD approach based on flows. Using net spillovers (the difference between the transmission of shocks to the system and the reception of shocks from the system), funds exposed to less liquid asset classes (EM, loan and HY bond funds) appear to be net receivers of spillovers from other funds and hence more vulnerable than other fund categories (Figure 9). On the other side, IG, municipal and government bond funds are net senders of spillovers to the rest of the fund industry, which can be due to third factor effects, as stress in the underlying asset classes (IG, municipal and government bonds) is likely to occur jointly with stress in less liquid markets.

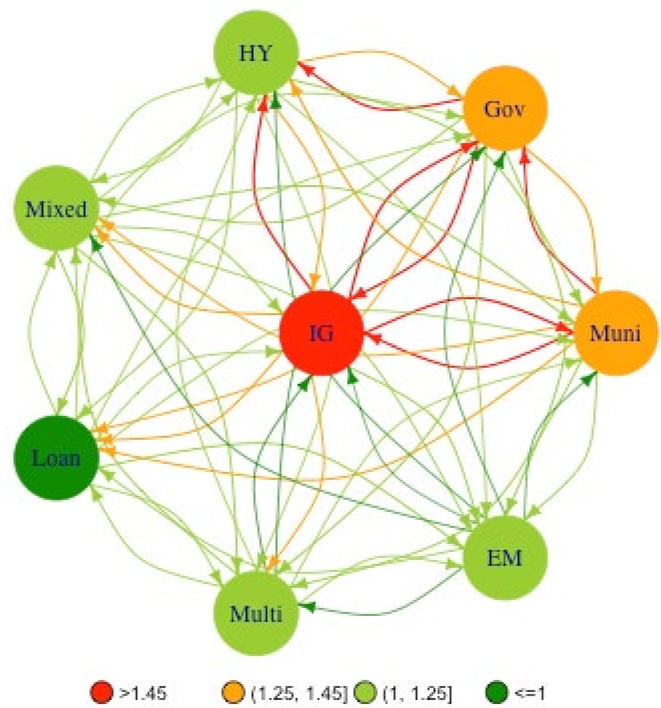
Figure 11. Net Spillovers by Fund Categories



Note: Average spillovers by fund categories defined as the average of the net spillovers (outward minus inward spillovers).
Sources: Morningstar, IMF staff.

Looking at spillovers within fund categories, Similarly, IG bond funds may be more vulnerable to spillovers from municipal and government bond funds (Table 8), as seen by the red arrows originating from those two funds categories and pointing IG bond funds in Figure 12. At the same time, IG bond funds are the main transmitter of shocks to other funds, with a high impact on Municipal, government and HY bond funds (first row in Table 8 and red arrows originating from IG bond funds).

Figure 12. Average Spillovers by Fund Categories



Note: 1./ arrows are indicating spillover senders and receivers;
2./ colors of edges and nodes depend on the scale of spill over, which is indicated by legends: for example, EM category (in blue) has spillover to itself between 1 and 1.25 and has a spillover on Muni category less than 1 (green arrow to Muni).
Source: Morningstar and IMF staff calculation.

Table 7. Average Spillovers

Heat map : Relative Average Spillovers

		To:								
		IG	Muni	Gov	HY	Mixed	Loan	Multi	EM	To (avg)
From:	IG	1.5	1.6	1.6	1.6	1.3	1.4	1.3	1.2	1.4
	Muni	1.5	1.4	1.5	1.4	1.3	1.3	1.2	1.1	1.3
	Gov	1.5	1.4	1.4	1.5	1.1	1.3	1.2	1.2	1.3
	HY	1.3	1.2	1.3	1.1	1.0	1.1	1.0	1.0	1.1
	Mixed	1.1	1.2	1.0	1.1	1.2	1.2	1.2	1.1	1.1
	Loan	1.0	1.0	1.0	1.1	1.1	1.0	1.1	1.2	1.1
	Multi	1.0	1.0	1.0	1.0	1.2	1.1	1.0	1.1	1.1
	EM	0.8	0.8	0.9	0.9	1.0	1.1	1.0	1.0	0.9
	From (avg)	1.2	1.2	1.2	1.2	1.1	1.2	1.1	1.1	

<1
[1;1.25]
[1.25;1.5]
>1.5

Note: Average spillovers from and to funds within each categories.
Sources: Morningstar, Authors' calculations.

The findings based on the interconnectedness analysis applied on returns volatility are consistent with the results based on the funds in distress approach presented previously. One possible explanation relates to the importance of the flow-return relationship for funds' investors studied in the literature. Funds performance tends to predict flows in the next period as investors rebalance their portfolio based on funds' past returns. Conversely, outflows are more likely to generate downward pressure on the NAV for funds invested in less liquid asset classes due to the liquidation costs, which in turn can lead to further outflows.

V. The COVID-19 Crisis

The acute liquidity stress that occurred in March 2020 featured very large outflows from bond mutual funds, in the U.S. and in the rest of the world, amid a sharp deterioration of market liquidity. Our previous analyses can be put into context of the March liquidity crisis. During the month of March 2020, IG bond funds in our sample experienced outflows of more than 5.6 percent of NAV, way above the previous peak of 2.9 percent in October 2008.

Liquidity Stress Test

Regarding the liquidity stress test, the addition of data up to September 2020 do not change significantly the results. As shown in table 9 below, the calibration of the redemption shock remains similar for almost all fund categories, even when outflows experienced in March 2020 are included. This can be explained by the method used: net flows at individual fund level (within a fund category) are used for the distribution of net flows. It implies that extreme flows experienced by funds before the COVID-19 crisis are included. Although, fund categories on the aggregate experienced larger outflows in 2020 than in the past, the largest outflows at fund level observed in 2020 were not that different from what we observed over 2007–2019.

Table 9. Comparison of Redemption Shocks

Fund category	Redemption shock in % of NAV	Redemption shock in % of NAV incl. 2020 data
Municipal	7	7
Mixed funds	9	9
Corp. IG	13	13
Multisector	13	15
Loan funds	13	15
Global	14	14
Government	14	15
HY	15	16
EM funds	17	19

Note: Net outflows in % of NAV.
Sources: Morningstar, IMF staff.

Macrofinancial Scenario

It is possible to use the period of stress observed in March 2020 to calibrate a macrofinancial scenario and apply it to the sample of funds along the lines of Bouveret (2017) and IMF (2020b). We use changes in yields for fixed income assets and equity prices observed during the 4-18 March period of intense stress (Table 10) to estimate the impact of the crisis on individual fund returns, using each individual fund portfolio composition and duration.

Table 10. Changes in Valuation over March 4–18, 2020

Asset class	Change	Unit
Equities	-23	%
IG Gov.	-40	bps
EM Gov	421	bps
Corp IG	170	bps
Corp HY	359	bps
Municipal	90	bps

Sources: Refinitv Datastream, IMF staff calculations

Given the deterioration of funds returns (as reported in Table 11), we assume that investors redeem some of their fund shares, based on the estimated flow-return relationship (See appendix C for details). For some funds such as loan funds, the estimated outflows are very small which is due to the very low duration of loan funds portfolio, while for funds invested in bonds with longer maturity and high stress (such as EM bond funds), estimated redemptions aggregated by fund categories would be high.

Table 11. Estimated Fund Returns and Investor Outflows

	Return shock	Redemption shock	Redemptions US$ bn
EM	-17%	-16.3%	-7.9
Global	-8%	-1.7%	-1.9
Gov	-2%	-0.3%	-0.8
HY	-8%	-5.7%	-12.8
IG	-5%	-3.6%	-76.0
Loan	-1%	-1.0%	-0.7
Mixed	-15%	-3.9%	-55.0
Multi	-5%	-1.5%	-5.4
Muni	-4%	-2.5%	-19.3

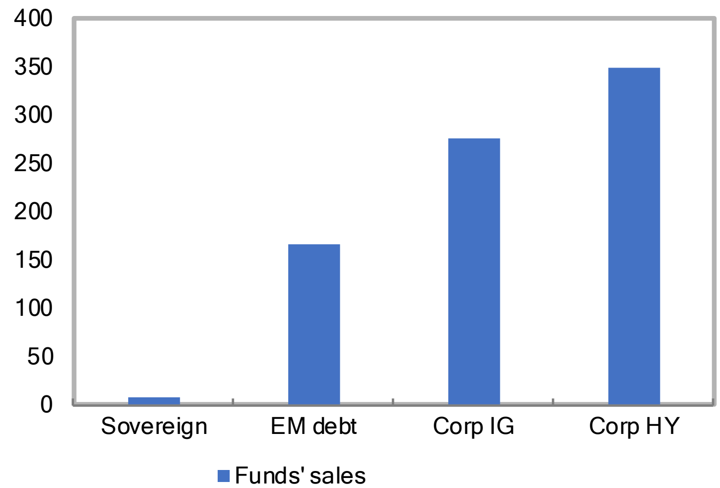
Sources: Refinitv Datastream, IMF staff calculations

Given the level of outflows, we estimate the volume of asset sales by fund managers, assuming that fund managers use a slicing approach to meet redemptions. Finally, the volumes of sales are used to estimate the price impact due to fund sales, using the methodology detailed previously, using measures of market depth under stress conditions.

Overall, the impact of funds' sales on markets would be larger on corporate bonds, with a 3.5 percent decline in prices for HY and 2.8 percent for IG bonds (Figure 13) than sovereign markets. To put those estimates in perspective, over 4-18 March, the market value of HY bonds declined by 15 percent and IG by around 10 percent. Therefore, the additional decline in prices due to fund sales would account for around 30 percent of the shock observed. In absolute amounts, given funds exposures in our sample (USD 1,094bn to IG and USD 360bn to HY), losses due to fund sales would amount to around USD 30bn for IG bonds and USD 13bn for HY bonds.

Figure 2. Price Impact of Funds' Sales by Asset Class

Price impact of asset sales in the macrofinancial scenario



Note: Price decline by asset class, in bps.
Sources: Morningstar, IMF staff.

The price impact estimates are in line with the analysis done in the October 2020 Global Financial Stability Report (IMF, 2020c), although a different methodology was used. In the GFSR (Box 1.2), bonds sold by funds experiencing high outflows, had returns around 2 percentage point lower than other bonds, which is in in the range of the estimates we provided.

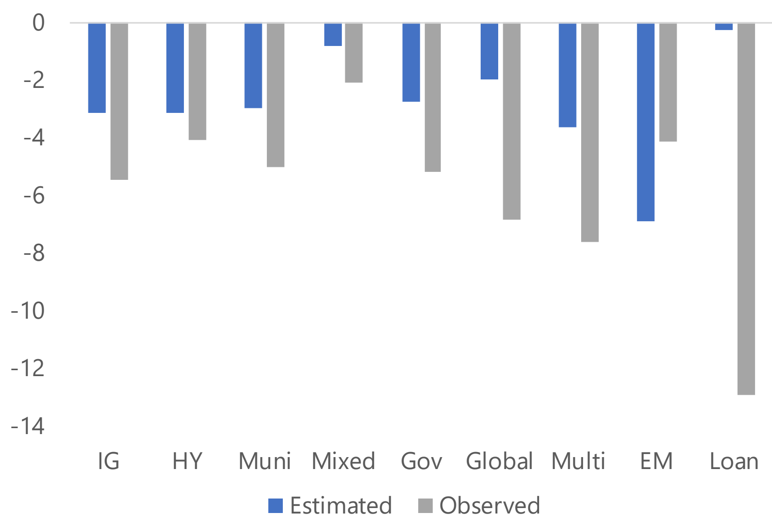
This analysis shows that sales by fund experiencing outflows can have a significant impact on financial markets and could constitute a transmission channel of shocks to the financial system.

Flows in Distress

We can also use the FiD framework to calculate what could be the expected net flows, when some bond funds face their historical worst outflows. This analysis focused on IG bonds funds, given that they account for the larger share in our sample and because they experience their worst outflows in March.

For illustrative purposes, we use 2007–2019 data on flows and assume that IG bonds funds face net flows below the 0.1 percentile to compute the expected net flows for all the other fund categories. Figure 14 shows the calculated value (in blue) and the observed values in March 2020. Observed outflows were relatively close to estimated values for HY and municipal bonds funds, while for other categories, actual outflows were larger than predicted by the model.

Figure 14. March 2020 Outflows and Projected Values



Source: IMF staff.

Since the copula provides the entire dependence structure of flows within fund categories, it is also possible to calculate the joint probability of all fund categories being in distress, measured by using different percentiles of net flows in line with Cortes et al. (2018). The joint probability that f_A and f_B are simultaneously in distress (net flows below α) is given by:

$$P(f_A \leq \alpha, f_B \leq \alpha) = \int_{-\infty}^{\alpha} \int_{-\infty}^{\alpha} p(x,y)dxdy \tag{20}$$

where x and y are two random variable representing fund A and B net flows.
We provide estimates of the joint probability of all fund categories being in distress at different levels using two sample of 100 observations each: September 2011 to December 2019 and February 2012 to May 2020. The second sample includes the liquidity crisis of March and April 2020. Table 12 shows that the joint probability of distress is lower in the first sample than in the second one, reflecting the acute simultaneous stress faced by funds in March 2020 due to the 'dash for cash'. The results also show how FiD can change over time, suggesting the need to update estimates to reflect the evolving dependence structure within fund flows.

Table 12. Joint Probability of Distress

Distress level	2011-2019 sample	2012-2020 sample
1%	0.49%	0.85%
5%	0.58%	0.99%
10%	0.74%	1.20%

Note: Joint probability of all fund categories being in distress

Sources: Morningstar, IMF staff calculations

While the COVID-19 outbreak was an exceptional external shock outside of the financial system, the following liquidity crisis has put severe pressure on financial institutions including mutual funds. Mutual funds have been able to meet redemptions and no fund had to suspend redemptions, partly due to swift and massive intervention by the Federal Reserve to support financial institutions and markets. Overall, this liquidity crisis provides evidence on how vulnerabilities within the mutual fund industry can crystallize during stress periods, and how funds can transmit shocks to the financial system through asset sales.

VI. Policy Discussion

The analyses presented previously point to a range of potential vulnerabilities within the U.S. bond fund industry. To mitigate those risks a range of policy options could be contemplated.

Funds' Ability to Withstand Redemptions Shocks

As we discussed in liquidity stress test part, most funds exposed to HY and leveraged loans have relatively low levels of high liquid assets and can therefore be vulnerable to large redemption shocks. In line with the 2017 FSB recommendations, there are different options to limit the potential liquidity mismatch for those fund categories.

Firstly, regulators should ensure that risk management frameworks are being applied in a robust and effective manner. Beside supervisory reporting (as currently done to the SEC through form N-PORT), some fund categories could be subject to liquidity stress test requirements (as is currently the case for Money Market Funds and for derivatives exposures of some mutual funds). In that context, enhanced guidance for frequent and rigorous stress testing and appropriate disclosures of risks should be provided to support the funds' liquidity risk management and to identify the vulnerable funds for closer inspection (IMF, 2019). While stress tests could be performed by asset managers, the analysis could be complemented by SEC-led stress tests (IMF, 2020a).

Another option is to structure funds so that the liquidity on the liability side is matched with the liquidity on the asset side. Given the low level of liquidity for HY bonds and especially leveraged loans (where transactions can take 10 to 20 days to settle), changing the redemption frequency of such funds could be an option. For example, the redemption frequency could be increased to one week or one month.

In addition, the availability of the widest possible set of liquidity management tools (such as gates, deferring redemptions, swing pricing) should be supported and encouraged. While swing pricing is available for U.S. mutual funds, so far no mutual fund has implemented it. Besides, the authorities should monitor developments and seek to provide timely and reliable valuations of assets in their portfolio (IMF, 2020c).

Funds' Role in Transmitting Shocks to the Financial System

As discussed in section IV, simultaneous sales of assets from mutual funds can have a large price impart on financial markets, especially when those assets are less liquid (HY bonds or leveraged loans) or when the market footprint of mutual funds is high (IG corporate bonds).

Policymakers can help mitigate the negative externalities linked to funds' sales by making sure that funds have enough liquid buffers (to reduce the sale of their less liquid assets) and also by ensuring that fund managers take into account their impact on the market when contemplating liquidation methods (for example by requiring asset managers to run simultaneous stress tests across the fund categories they manage).

Interconnectedness Within the Fund Sector

The contagion and spillover analyses have shown that some fund categories are more connected than others, implying that stress in one category is likely to spread to connected categories. In that context, such interlinkages within the fund industry should be further analyzed and in particular, authorities could estimate whether those interlinkages reduce risks through diversification or if they increase risks. Market-based and flow-based analyses should also be complemented by balance sheets and off-balance sheet exposures analysis. Following up on a recent report by the SEC (SEC, 2020) which sheds light on the importance of these interlinkages across markets and across different types of financial institutions, such interconnectedness could be studied further. Macrofinancial stress simulations could be a useful tool, since a scenario could be used to estimate the impact on the different part of the financial system and identify key vulnerabilities.

VII. CONCLUSION

While bond mutual funds contribute to credit intermediation, they are subject to potential liquidity mismatch as they offer daily redemptions to investors while investing in a range of assets with varying degrees of liquidity.

In this article, we use a range of analytical techniques to assess the ability of U.S. mutual funds to withstand liquidity shock, and we estimate the transmission channels to financial markets and to mutual funds. Overall, while most funds are able to cope with severe redemption shock, their asset sales could propagate stress by putting downward pressure on asset prices, and thereby transmit shocks to the financial system.

In addition, we perform a range of contagion and interconnectedness analysis to identify fund categories which are more vulnerable than others, as well as funds categories which are more likely to spread distress to other funds. We obtain robust results based on the copula-dependence approach and the Diebold-Yilmaz interconnectedness framework: IG corporate bonds funds, municipal bond funds and government bond funds are more likely to spread distress to other fund categories than HY, EM and loan funds, which in turn are more vulnerable to distress in other parts of the mutual fund industry. Such different levels of interconnectedness within the fund industry show that from a macrofinancial perspective, dependencies between fund categories need to be taken into account to measure risks for the financial system.

In order to improve the resilience of vulnerable funds, the risk management frameworks should be warranted, the availability of liquidity management tools (such as gates/ deferring redemptions, swing pricing) should be available, and support of timely and reliable valuations of assets should be provided.

Besides, policymakers can help mitigate potential fire sales by reducing liquidity mismatch and providing contemplate liquidity provision for key funds. System wide stress test will be strongly recommended to identify the vulnerable funds for closer inspection.

Looking forward, our analysis can be used to perform what-if scenarios and identify key parts of the mutual fund industry, which might call for closer monitoring. Given the size and diversity of the asset management industry, the tools developed in this paper are relevant for regulatory and supervisory institutions as well as risk managers. Such tools could be used to perform liquidity stress test at individual fund level or macrofinancial stress tests.

In addition, given the diversity of the fund industry, the contagion analysis presented in this paper can be used to identify specific fund strategies which are more important from an interconnectedness perspective and might require further monitoring. Beyond the fund industry, the Flows in Distress framework could be applied to a range of other entities such as banks (to estimate expected deposit outflows conditional on bank runs for example) or countries in the context of capital flows (to estimate expected capital outflows conditional on another country facing massive outflows.

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Appendix A. Sample of Funds and Additional Information Regarding the Liquidity Stress Test

1. Sample of Funds

The sample of funds is based on available data from Morningstar. The sample includes all U.S. mutual funds that belong to the following Morningstar global broad category group: Allocation, Taxable Bond and Municipal Bond. Target dates funds are excluded since they are not included in ICI categories. The remaining 2,743 funds were split into 43 fund Morningstar Global categories, which were then mapped into the Investment Company Institute (ICI) categories using the correspondence table below (Table A1). For the purpose of the stress tests, nine categories of funds are used, mainly based on the type of assets the funds invest in.

Table A1. Correspondence Table

Global Broad category group	Global category	ICI category	Fund category
Allocation	US Fund Allocation--15% to 30% Equity	Mixed	Mixed
	US Fund Allocation--30% to 50% Equity	Mixed	Mixed
	US Fund Allocation--50% to 70% Equity	Mixed	Mixed
	US Fund Allocation--70% to 85% Equity	Mixed	Mixed
	US Fund Allocation--85%+ Equity	Mixed	Mixed
	US Fund Convertibles	Mixed	Mixed
	US Fund Tactical Allocation	Mixed	Mixed
	US Fund World Allocation	Mixed	Mixed
Municipal	US Fund High Yield Muni	Muni	Muni
	US Fund Muni California Intermediate	Muni	Muni
	US Fund Muni California Long	Muni	Muni
	US Fund Muni Massachusetts	Muni	Muni
	US Fund Muni Minnesota	Muni	Muni
	US Fund Muni National Interm	Muni	Muni
	US Fund Muni National Long	Muni	Muni
	US Fund Muni National Short	Muni	Muni
	US Fund Muni New Jersey	Muni	Muni
	US Fund Muni New York Intermediate	Muni	Muni
	US Fund Muni New York Long	Muni	Muni
	US Fund Muni Ohio	Muni	Muni
	US Fund Muni Pennsylvania	Muni	Muni
	US Fund Muni Single State Interm	Muni	Muni
	US Fund Muni Single State Long	Muni	Muni
	US Fund Muni Single State Short	Muni	Muni
	US Fund Muni Target Maturity	Muni	Muni
Taxable Bond	US Fund Emerging Markets Bond	Global	EM
	US Fund Emerging-Markets Local-Currency Bond	Global	EM
	US Fund World Bond	Global	Global
	US Fund World Bond-USD Hedged	Global	Global
	US Fund Inflation-Protected Bond	Gov	Gov
	US Fund Intermediate Government	Gov	Gov
	US Fund Long Government	Gov	Gov
	US Fund Short Government	Gov	Gov
	US Fund High Yield Bond	HY	HY
	US Fund Bank Loan	HY	Loan
	US Fund Intermediate Core Bond	IG	IG
	US Fund Intermediate Core-Plus Bond	IG	IG
	US Fund Long-Term Bond	IG	IG
	US Fund Preferred Stock	IG	IG
	US Fund Short-Term Bond	IG	IG
	US Fund Ultrashort Bond	IG	IG
	US Fund Corporate Bond	IG	IG
	US Fund Multisector Bond	Multi	Multi
	US Fund Nontraditional Bond	Multi	Multi

The nine categories are mixed, municipal, EM, HY, IG, loan, government, multi-strategy funds and global funds.

Table A2 displays the sample of funds compared to the ICI universe.

Table A2. Sample of Funds

Fund category	Net asset value (US$ bn)		Number of funds	
	Sample	ICI	Sample	ICI
Corp. IG	2,427	2,118	608	593
Corp. HY	347	334	250	255
Govt	325	341	161	194
Multisector	433	291	182	95
Global	247	541	183	347
Municipal	799	793	567	554
Mixed funds	1,752	1,532	792	772
Total	6,319	5,951	2,743	2,810

Sources: Morningstar, ICI, IMF staff calculations

2. Data

For each fund in the sample, monthly data on flows, net asset value, portfolio composition and returns are retrieved over the 2017–2019 period. The sample of fund is based only on funds that were still alive as of end-2019.

Computation of net flows: For each fund, net flows in percent of NAV (f_t) are computed using the following formula:

$$f_t = \frac{FLOWS_t}{NAV_{t-1}}$$

Net flows whose absolute value is above 50 percent were excluded as they are likely related to reporting mistakes.

Portfolio composition: For each fund, the latest portfolio composition is retrieved. At the highest level, the portfolio is split into four categories: cash, equities, bonds and other. The fixed income portfolio (cash and bonds) is then split into further categories: government, municipal, corporate, securitized, cash and equivalents, and derivatives (Table A3). Each subcategory is subsequently split into further asset classes as detailed in Morningstar (2016).

Table A3. Morningstar Portfolio Composition

Asset allocation	Fixed income classification
Equities	
Cash	Cash and equivalents
Bonds	Government Municipal Corporate Securitized Derivatives
Other	

Source: Morningstar

Credit quality: For each fund, the latest data on credit quality are retrieved, i.e., the share of the bond portfolio split by credit rating. Morningstar does not provide the credit rating data by type of fixed income instrument (government, corporate bond, etc.). Therefore, credit rating by instrument is estimated by allocating the highest credit rating first to the government portfolio, then to corporate bonds and finally to securitized products.

Treatment of mutual funds using derivatives and leverage: When funds use derivatives and leverage Morningstar asset allocation weights will always add up to 100 percent, but the cash part will have negative values. In those cases, cash is set up equal to 0 percent, and put a 100 percent limit on the other parts of the portfolio. When the funds reports cash allocation above 100 percent, the cash is bounded to 100 percent.

Appendix B. Robustness Checks for the Flows in Distress Approach

Gaussian copula

We use a Student copula to model the dependence between fund net flows, as this copula allows for tail dependence between flows. In other words, when outflows for one fund category are large, other funds could face larger outflows than predicated on correlation.

As a robustness check, we also perform the estimation using a Gaussian copula, where the correlation parameters are equal to the observed correlation among net flows by fund categories.

Table B1 shows the initial results using the Student copula and Table B2 for the Gaussian copula. As expected, expected net flows are larger when using the Student copula, due to the tail dependence.

Figures B1 and B2 show that results are qualitatively similar: IG, mixed and multisector bond funds are the fund categories with the largest (average) effects on other funds, while EM, HY and loan funds remain the most vulnerable fund categories.

Table B1. Expected Net Flows (Student Copula)

Impact on other funds

Funds in distress

Net flows	IG	HY	Muni	Mixed	Gov	Global	Multi	EM	Loan	To (AVG)
IG	-2.2	-1.7	-1.8	-0.5	-2.1	-1.0	-2.3	-4.6	-0.1	-1.8
HY	-0.3	-4.5	-0.3	-0.5	0.0	0.8	-0.7	-2.1	-3.4	-0.8
Muni	-1.9	-1.6	-3.0	-0.1	-2.3	-0.4	-0.8	-2.1	3.7	-0.7
Mixed	-0.2	-1.6	0.2	-1.7	0.8	-0.6	-2.9	-3.2	-5.6	-1.6
Gov	-1.4	-0.5	-1.5	0.3	-4.2	-0.7	-0.1	-3.7	4.8	-0.3
Global	-0.5	0.1	-0.2	-0.6	-0.5	-4.4	-1.2	-2.4	1.1	-0.5
Multi	-0.7	-1.3	-0.1	-1.0	-0.1	-0.6	-3.7	-3.7	-5.3	-1.6
EM	-0.4	-0.8	0.0	-0.4	-0.7	-0.1	-1.1	-5.0	-2.0	-0.7
Loan	0.6	-1.0	1.2	-0.6	1.2	1.0	-1.5	-1.7	-11.0	-0.1
From (AVG)	-0.6	-1.1	-0.3	-0.4	-0.5	-0.2	-1.3	-2.9	-0.9	

Net flows
>0
[-1%,0]
[-1%,-3%]
<-3%

Note: Expected net flows conditional on distress in % of NAV. Grey cells show net flows for funds in distress.

Sources: Morningstar, IMF staff.

Table B2. Expected Net Flows (Gaussian Copula)

Impact on other funds

Funds in distress

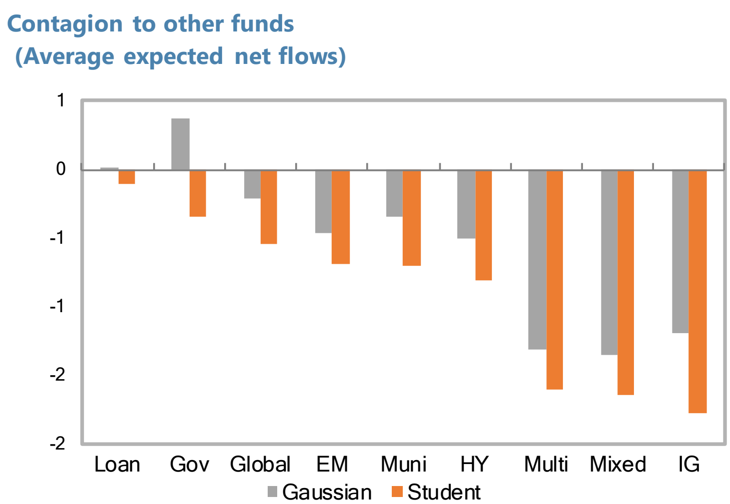
Net flows	IG	HY	Muni	Mixed	Gov	Global	Multi	EM	Loan	To (AVG)
IG	-2.2	-1.5	-1.7	-0.4	-1.6	-0.1	-1.6	-2.9	0.2	-1.2
HY	-0.2	-4.5	-0.1	-0.3	-0.1	0.9	-0.4	-1.1	-2.8	-0.5
Muni	-1.6	-0.9	-2.9	-0.2	-1.7	0.1	-0.3	-1.7	3.5	-0.3
Mixed	-0.1	-0.9	0.2	-1.7	0.8	-1.0	-2.7	-3.1	-4.0	-1.3
Gov	-0.9	-0.4	-1.2	0.3	-4.2	1.3	0.6	-1.8	5.0	0.4
Global	0.1	0.4	0.0	-0.6	0.3	-4.3	-0.8	-1.3	0.2	-0.2
Multi	-0.6	-1.0	0.0	-0.9	0.0	-0.3	-3.7	-3.1	-4.5	-1.3
EM	-0.2	-0.6	-0.1	-0.4	-0.5	0.2	-0.9	-5.0	-1.2	-0.5
Loan	0.6	-1.0	1.1	-0.5	1.1	0.8	-1.1	-0.9	-11.0	0.0
From (AVG)	-0.4	-0.7	-0.2	-0.4	-0.2	0.2	-0.9	-2.0	-0.4	

Net flows
>0
[-1%,0]
[-1%,-3%]
<-3%

Note: Expected net flows conditional on distress in % of NAV. Grey cells show net flows for funds in distress.

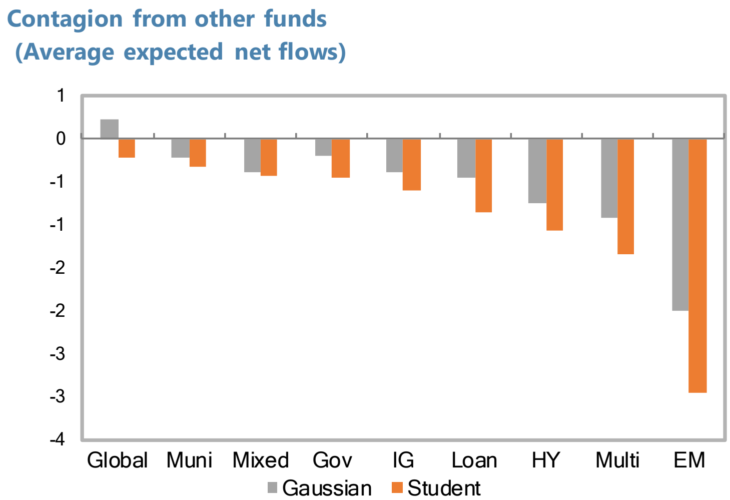
Sources: Morningstar, IMF staff.

Figure B1. Contagion to Other Funds



Note: Average expected net flows conditional on one fund category being in distress.
Sources: Morningstar, IMF staff.

Figure B2. Contagion from Other Funds



Note: Average expected net flows conditional on other fund categories being in distress.
Sources: Morningstar, IMF staff.

Appendix C. Methodology Used for the Macrofinancial Scenario

The macrofinancial scenario includes several components as detailed in Bouveret (2017) and in Appendix XII of IMF (2020b).

First, a scenario is designed, then the value of the macrofinancial variables are used to compute individual funds' returns based on each fund portfolio composition.

Second, we estimate the flow-return relationship for each fund category. This relationship shows that investors tend to react to past returns, which inflows for funds with high returns and outflows from funds with low (and negative returns).

Given the estimated returns stemming from the macrofinancial scenario, and the flow-return relationship, net flows are projected for each fund. Once the flows are known, the volume of sales by asset classes and funds is obtained by assuming that managers follow a slicing approach (i.e. they sell each asset in their portfolio in proportion of their share).

When asset sales are known, we use market depth measures to estimate the price impact of funds sales.