LRISK: Systemic Liquidity Risk in Mutual Funds *

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Abstract

This paper introduces LRISK, a forward-looking measure of systemic liquidity risk in mutual funds that quantifies the aggregate price pressure on financial markets conditional on a systemic redemption shock. The model captures the mechanics of fire sale spillovers by integrating three key amplification channels: flow commonality, where correlated redemptions cause simultaneous selling pressure across funds; portfolio similarity, where overlapping holdings concentrate this pressure on the same assets; and liquidity spirals, where selling actively degrades asset liquidity. We apply this measure to U.S. corporate bond funds from 2011 to 2024 and validate it by showing that LRISK-implied price pressure predicts the cross-section of bond returns during the COVID-19 crisis. At the aggregate level, LRISK acts as an early warning signal forecasting market distress up to two quarters in advance. Finally, LRISK helps explain variation in the adoption of redemption in kind as a fund liquidity management tool.

Keywords: Systemic risk, fire sale, mutual funds, liquidity mismatch, contagion, bond market

JEL Classifications: G01, G12, G23, G28

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1 Introduction

The growing share of financial assets held by non-banking financial intermediaries (NBFIs) has shifted the focus of macroprudential policy from bank leverage to the liquidity mismatch inherent in open-ended mutual funds.[1] These funds offer daily redemptions to investors while holding illiquid securities, such as corporate bonds, creating a vulnerability to investor runs (Chen et al., 2010; Goldstein et al., 2017). When redemption shocks force funds to liquidate positions, the correlated selling of overlapping holdings can trigger fire sales (Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 1992).

Recent events, ranging from the COVID-19 market turmoil to the UK Gilt crisis in 2022, demonstrate that these fire sales are not merely theoretical (e.g., Falato et al., 2020; Ma et al., 2022; Pinter et al., 2024). The existence of this spillover channel, empirically validated in both equity and debt markets (Coval and Stafford, 2007; Falato et al., 2021), amplifies market fragility and poses a threat to financial stability. In this context, the management of systemic liquidity risk[2] in the mutual fund sector has become a priority for the Financial Stability Board (FSB) and the European Systemic Risk Board (ESRB), highlighting the need for enhanced monitoring and regulation of liquidity mismatches. Yet, measures to quantify this risk in the mutual fund sector remains elusive.

In this paper, we introduce LRISK, a dynamic and forward-looking measure of systemic liquidity risk in mutual funds. LRISK quantifies the expected aggregate price pressure on financial markets conditional on a severe system-wide redemption shock. To achieve this, our framework integrates three key amplification channels relevant to the fund sector. First, we model the systemic shock by dynamically forecasting the extreme tail of aggregate fund flows, moving beyond static hypothetical shocks. Second, we model the transmission of

[1] NBFI entities comprise different types of entities–investment funds, insurance companies, pension funds and other financial intermediaries–that have diverse business models and are subject to different regulatory frameworks, some tighter than others. A growing share of financial activities are being undertaken by non-banking financial intermediaries (NBFIs), which held 56% of total financial assets of advanced economies at the end of 2023.

[2] Systemic liquidity risk, as defined by the International Monetary Fund (IMF, 2011), is the "risk of simultaneous liquidity difficulties at multiple financial institutions."

this shock to individual funds via flow betas, capturing the liability-side contagion arising from correlated flows (e.g., Ben-David et al., 2022; Puy, 2016) and cross-fund holdings (Fricke and Wilke, 2023). Third, we map projected sales to asset liquidity to estimate the resulting price pressure. Unlike models that assume a linear price impact (e.g., Duarte and Eisenbach, 2021), our framework generates nonlinear price declines by capturing the feedback loops inherent in a liquidity spiral.

Existing systemic risk measures, such as CoVaR (Adrian and Brunnermeier, 2016) and SRISK[3] (Brownlees and Engle, 2017), are often designed for banks, not asset managers. Furthermore, fire sales models typically define a systemic shock as a capital loss that forces deleveraging to meet a target (e.g., Duarte and Eisenbach, 2021; Greenwood et al., 2015). This mechanism, however, is ill-suited for mutual funds, where selling is driven by redemption requests rather than the need to restore capital ratios. Moreover, simpler fund-level liquidity metrics fail to capture the systemic nature of the risk, as they overlook the correlated, simultaneous selling that defines a crisis (Bouveret, 2017; Jiang et al., 2022; Sadka, 2010). We address these limitations by building on these frameworks to construct LRISK, a measure of systemic liquidity risk specifically tailored to the mutual fund sector.

We construct the LRISK measure for the U.S. corporate bond fund sector from 2011 to 2024. Our empirical analysis is based on granular fund portfolio holdings, monthly fund flow data, and asset-level liquidity characteristics derived from the Center for Research in Security Prices (CRSP), the Trade Reporting and Compliance Engine (TRACE), and Datastream. The resulting aggregate time series reveals distinct phases of systemic fragility but does not exhibit a strong upward trend over the period. This reflects two opposing forces: while the market footprint of U.S. mutual bond funds has expanded significantly, this structural vulnerability has been largely offset by a general improvement in market liquidity conditions. Crucially, LRISK behaves as a countercyclical indicator. It tends to increase during periods of relative market calm and conversely decreases following a

[3]While conceptually related to the SRISK measure for banks, LRISK is specifically tailored to the unique vulnerabilities of the asset management sector.

crisis, as the immediate probability of a new systemic redemption shock diminishes. The measure reached its historical maximum in March 2020, reflecting a sudden deterioration in asset liquidity during the COVID-19 turmoil. Finally, we note that systemic liquidity risk is almost exclusively driven by the corporate bond segment, with sovereign bonds contributing negligibly.

We conduct a comprehensive validation and application of the LRISK measure. First, we test the micro-foundations of our model by using granular bond data from the COVID-19 crisis to determine whether the expected individual price pressure predicted by LRISK explains cross-sectional differences in realized bond returns. Second, we assess the relevance of the measure for individual financial institutions by examining whether a fund's ex-ante exposure to systemic fire sales predicts its subsequent underperformance during periods of aggregate redemption stress. Third, we evaluate the forward-looking properties of the aggregate LRISK, testing its ability to serve as an early warning indicator for future credit market distress. Finally, we investigate the tools available to fund managers to mitigate this risk. Specifically, we analyze whether funds with higher exposure to systemic liquidity risk are more likely to adopt liquidity management tools (LMTs), such as the option to redeem in kind.

Our results provide robust evidence that LRISK captures the vulnerabilities emanating from the liquidity mismatch in the mutual fund sector. At the asset level, we find that bonds with higher expected price pressure suffered significantly larger drawdowns during the COVID-19 shock. At the fund level, ex-ante exposure to fire sale spillovers predicts lower returns conditional on a severe aggregate redemption shock. At the aggregate level, LRISK serves as a reliable early warning signal: increases in systemic liquidity risk precede widenings in the corporate bond default premium and deteriorations in market functioning by approximately two quarters. Furthermore, we show that this systemic risk influences fund management behavior, as funds with higher ex-ante LRISK exposure are significantly more likely to secure the option to redeem in kind. Collectively, these findings confirm the forward-looking nature of LRISK, indicating that it provides an accurate and relevant tool for the macroprudential monitoring of the rapidly growing asset management sector.

Related literature— This paper contributes to the literature on measuring liquidity risk by shifting the focus from fund-specific metrics to a systemic, forward-looking framework. Existing studies typically focus on asset-side liquidity as a proxy for risk, employing widely used measures such as effective bid-ask spreads, the Amihud illiquidity ratio, imputed round-trip costs (Jiang et al., 2022), or liquidity-bucket ratios (Metadjer and Moloney, 2017). Other papers, such as Aramonte et al. (2020), measure a fund's sensitivity to aggregate market liquidity (e.g., Pástor and Stambaugh, 2003; Acharya et al., 2013). Additionally, Bouveret (2017) and Bouveret and Yu (2017) have developed methodologies to identify vulnerable fund categories, drawing inspiration from the Liquidity Coverage Ratio used for banks under Basel III liquidity regulatory requirements.[4] However, these approaches remain largely static or backward-looking. LRISK differs fundamentally by quantifying liquidity risk in a systemic context. We build a forward-looking index that not only stress-tests individual funds in isolation but estimates the aggregate price pressure generated by their joint behavior conditional on a systemic tail event.

By studying the role of systemic liquidity risk in corporate bond fire sales, we further contribute to the literature on the determinants and outcomes of fire sales in financial markets (Shleifer and Vishny, 1992; Falato et al., 2020; Pinter et al., 2024). While prior work has separately identified the strategic drivers of fund flows (Diamond and Dybvig, 1983; Massa et al., 1999; Barber et al., 2005; Ferson and Kim, 2012; Goldstein et al., 2017; Ben-David et al., 2022), their interaction with fund liquidity (Chen et al., 2010; Hanouna et al., 2015), and specific contagion mechanisms in the corporate bond market (Ma et al., 2022; Fukker et al., 2022; Coppola, 2025), these channels are typically studied in isolation. We distinguish our work by proposing the first comprehensive and fully tractable framework that integrates these distinct strands into a unified model of systemic risk in mutual funds.

[4]This approach has influenced the ESMA stress simulation framework (ESMA, 2019).

Specifically, our approach simultaneously captures liability-side contagion (flow commonality), asset-side contagion (overlapping holdings), and endogenous price spirals. By doing so, we move beyond theoretical stylized facts and empirical analyses limited to specific stress episodes (e.g., the COVID-19 turmoil) to produce a dynamic, forward-looking monitoring tool that is directly applicable for macroprudential regulation.

Finally, our article is linked to the recent literature studying the effects of liquidity management tools by mutual funds. Recent papers have studied the role of using swing pricing and anti-dilution levies through swing pricing (Capponi et al., 2020; Jin et al., 2022; Dunne et al., 2022; Baena and Garcia, 2022), engaging in interfund lending programs to mitigate asset fire sales after extreme investor redemptions (Agarwal and Zhao, 2019), and finally maintaining the right to redeem investors "in kind" (Agarwal et al., 2023). We contribute to this literature by showing that in corporate bond funds, fire sale risk exposure predicts the probability of adopting redemption in kind beyond classic fund-level traits, such as portfolio liquidity.

The remainder of the paper proceeds as follows. Section 2 introduces the LRISK measure and explains how to estimate it using commonly-available data. Section 3, shows how LRISK performs as a systemic risk indicator and its effectiveness as a predictive tool, and its relation to the use of liquidity management tools by funds. Section 4 concludes.

2 LRISK

2.1 The Model

We develop a measure of systemic liquidity risk for investment funds, LRISK, that quantifies the aggregate price pressure on financial markets conditional on a systemic redemption shock. Our framework integrates three key amplification channels: flow commonality, where correlated redemptions cause simultaneous selling pressure across funds, portfolio similarity, where overlapping holdings concentrate this pressure on the same assets, and a liquidity spiral, where selling actively degrades market conditions.

The aggregate LRISK at time t for a universe of N investment funds and J assets is defined as the expected, asset-weighted price pressure, conditional on a systemic market outflow event $\mathcal{S}$:

$$LRISK_t = \frac{1}{A_t} \sum_{j=1}^{J} A_{j,t} \cdot \mathbb{E}_t \left[PP_{j,t+1} \mid \mathcal{S} \right] \tag{1}$$

where, $A_{j,t}$ is the total market value of asset j, $A_t = \sum_{j=1}^{J} A_{j,t}$ is the total value of all assets, and $PP_{j,t+1}$ is the price pressure on asset j. The conditioning event, $\mathcal{S}$ represents a systemic shock where aggregate net fund flows reach a critical threshold C_t (i.e., $\mathcal{S} \equiv F_{m,t+1} = C_t$).

2.1.1 Price Pressure Specification

The price pressure on asset j depends on the total sales volume relative to market size and the asset's liquidity. We model this relationship based on two core ideas. First, we assume asset sales have a price impact that is linear in the volume sold, a standard assumption in empirical fire-sale studies (e.g., Kyle, 1985; Duarte and Eisenbach, 2021). Second, we explicitly model liquidity as endogenous to the fire sale itself, positing that liquidity decreases linearly with sales volume. This reflects a liquidity spiral where sales actively worsen market conditions.

Therefore, coordination failure in liquidation strategies leads to disproportionately high systemic stress.

Formally, the price pressure is :

$$PP_{j,t+1} = \left(\frac{V_{j,t+1}}{A_{j,t+1}}\right) \cdot (1 - \text{Liq}_{j,t+1}) \tag{2}$$

where $V_{j,t+1} = \sum_{n=1}^{N} v_{n,j,t+1}^{s}$ is the total sales volume of asset j, and $\text{Liq}_{j,t+1} \in [0,1]$ is the market liquidity score. The amount sold by fund n, $v_{n,j,t+1}^{s}$, depends on its total redemptions $F_{n,t+1}$ and its chosen liquidation strategy s. Let J_n^s be the set of assets fund n liquidates under strategy s. We define liquidation weights $w_{n,j,t+1}^{s}$ as the fraction of the total outflow $\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$ met by selling asset j, such that $v_{n,j,t+1}^{s} = w_{n,j,t+1}^{s}\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$. These weights satisfy $\sum_{j\in J_n^s} w_{n,j,t+1}^{s} = 1$, and $w_{n,j,t+1}^{s} = 0$ for $j \notin J_n^s$.

We model the endogenous liquidity as:

$$(1 - \text{Liq}_{j,t+1}) = (1 - \text{Liq}_{j,t}) + \gamma \left(\frac{V_{j,t+1}}{A_{j,t}}\right) \tag{3}$$

The parameter $\gamma \geq 0$ is the liquidity spiral parameter, governing how severely sales impact liquidity.

Substituting Equation (3) into (2) yields:

$$PP_{j,t+1} = \left(\frac{V_{j,t+1}}{A_{j,t+1}}\right) \left[(1 - \text{Liq}_{j,t}) + \gamma \left(\frac{V_{j,t+1}}{A_{j,t+1}}\right)\right] \tag{4}$$

Expanding this shows that our linear assumptions derive a quadratic price pressure function, which implies that the marginal price impact of additional sales increases non-linearly:

$$PP_{j,t+1} = (1 - \text{Liq}_{j,t}) \left(\frac{V_{j,t+1}}{A_{j,t+1}}\right) + \gamma \left(\frac{V_{j,t+1}}{A_{j,t+1}}\right)^2 \tag{5}$$

Our objective is to calculate the conditional expectation $\mathbb{E}_t[PP_{j,t+1}|\mathcal{S}]$. Applying the expectation operator to Equation (5):

$$\mathbb{E}_t[PP_{j,t+1}|\mathcal{S}] = (1 - \text{Liq}_{j,t}) \cdot \mathbb{E}_t \left[\frac{V_{j,t+1}}{A_{j,t+1}} \middle| \mathcal{S} \right] + \gamma \, \mathbb{E}_t \left[\left(\frac{V_{j,t+1}}{A_{j,t+1}} \right)^2 \middle| \mathcal{S} \right] \tag{6}$$

To make this expression computable, we rely on several assumptions. First, we use observable time-t data as the best predictor for time-$t+1$ characteristics: $A_{j,t+1} \approx A_{j,t}$ and the liquidation strategy $w^s_{n,j,t+1} \approx w^s_{n,j,t}$ is known at t. Second, under the systemic event $\mathcal{S}$, the dominant uncertainty is the single, common shock to aggregate fund flows $F_{m,t+1}$, with individual fund redemptions proportional to this shock via the conditional flow beta $\beta_{n,t+1|t}$. Third, we make the standard approximation that the risk is dominated by the shock's magnitude, not its variance, approximating $\mathbb{E}[V^2_{j,t+1}|\mathcal{S}] \approx (\mathbb{E}_t[V_{j,t+1}|\mathcal{S}])^2$.[5]

Under these assumptions, the expected sales volume is linear in the expected aggregate shock $F_{m,t+1}$:

$$V^{\text{E}}_{j,t} = \mathbb{E}_t\left[V_{j,t+1} \mid \mathcal{S}\right] = \underbrace{\left(\sum_{n=1}^{N} w^s_{n,j,t} \beta_{n,t+1|t} \right)}_{\equiv \Psi_{j,t}} \cdot \mathbb{E}_t\left[F_{m,t+1} \mid \mathcal{S}\right] \tag{7}$$

where $\Psi_{j,t}$ is the aggregate sensitivity of asset j's sales. Substituting $V^{\text{E}}_{j,t}$ into Equation (5) and applying the variance approximation yields the final, tractable expression for expected price pressure:

$$\mathbb{E}_t\left[PP_{j,t+1} \mid \mathcal{S}\right] = (1 - \text{Liq}_{j,t}) \left(\frac{V^{\text{E}}_{j,t}}{A_{j,t}} \right) + \gamma \left(\frac{V^{\text{E}}_{j,t}}{A_{j,t}} \right)^2 \tag{8}$$

This formula captures amplification through flow commonality and portfolio similarity (via $V^{\text{E}}_{j,t}$) and the liquidity spiral (via γ).

[5]By setting $\mathbb{E}[X^2] \approx (\mathbb{E}[X])^2$, we abstract from the impact of variance ($\mathbb{E}[X^2] = (\mathbb{E}[X])^2 + \text{Var}(X)$). Jensen's inequality implies our measure is a lower bound on the true expected pressure incorporating variance.

2.1.2 Fund Managers' Responses to Redemptions

To meet investor redemptions, fund managers must liquidate part of their portfolios. In practice, however, individual funds operate with limited information: they do not observe the holdings of other funds, nor do they know their peers' expected redemptions. As a result, managers cannot coordinate their liquidation decisions and must form expectations about asset-level liquidity costs based solely on their own information.

Funds typically rely on market-based liquidity scores to estimate the cost of selling asset j. These scores, often based on indicators like bid-ask spreads or trading volume, reflect the fund's belief about how easily an asset can be sold without significant price impact. While some managers may also consider their own market footprint—approximated by $\frac{v_{n,j,t}}{A_{j,t}}$—this term is generally small unless the fund holds large positions in thinly traded markets. Consequently, market-based liquidity scores (i.e, $\mathrm{Liq}_{j,t}$) remain the primary determinant of perceived liquidation cost. Importantly, these individual (and naive) expectations do not internalize the aggregate selling by other funds, leading to a systematic underestimation of price pressure during systemic events.

We focus on two stylized liquidation strategies (s) determining the set of assets sold (J_n^s) and the weights ($w_{n,j,t}^s$):

(i) Proportional liquidation (i.e., horizontal slicing): Managers liquidate a uniform fraction of all portfolio holdings, preserving the fund's asset allocation structure. Formally, $w_{n,j,t}^s = w_{n,j,t}$, where $w_{n,j,t}$ is the initial portfolio weight. This behavior is often observed in practice, especially for passively managed funds. It is also supported by many empirical findings in Morris et al. (2017), Shek et al. (2018), and Dötz and Weth (2019), especially during crisis episodes (Jiang et al., 2021). We use this strategy as our baseline assumption.

(ii) Liquidity-based liquidation (i.e., vertical slicing): Managers sell assets sequentially in order of decreasing liquidity. The process continues until expected redemptions $\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$ are met. This approach minimizes immediate costs and is consistent with some empirical evidence (e.g., Chernenko and Sunderam, 2016; Zeng, 2017; Choi et al., 2020; Ma et al., 2022). The marginal asset index k is defined by:

$$k := \min \left\{ k \in \{1, \ldots, K\} \;\middle|\; \sum_{j=1}^{k} v^s_{n,j,t} \geq \mathbb{E}_t \left[F_{n,t+1} \;\middle|\; \mathcal{S} \right] \right\} \tag{9}$$

Only the most liquid assets $j \leq k$ are included in the liquidation bucket. This strategy concentrates selling pressure on the most liquid segments of the market. We also compute LRISK based on this alternative strategy and compare the results with our baseline assumption.

Each of these strategies represents a different trade-off between immediate cost minimization and structural stability of the portfolio. Both approaches are individually rational but can lead to inefficient aggregate outcomes, particularly when many funds react similarly to the same liquidity signals. The lack of coordination and limited foresight regarding aggregate redemptions generates excess price pressure, contributing to systemic risk.

To contrast these decentralized responses with the system-wide optimum, we consider a coordinated planner's problem in Section 2.1.5, which internalizes the externalities generated by overlapping portfolios and correlated redemptions.

2.1.3 Marginal Contribution to LRISK

A key feature of our framework is the ability to attribute systemic risk to individual institutions. We define the marginal contribution to LRISK for fund n, denoted $\Delta_n LRISK_t$, as the incremental impact of its participation in the systemic fire sale. This is measured by the difference between the system-wide risk including all funds and the hypothetical risk recalculated excluding fund n:

$$\Delta_n LRISK_t = LRISK_t - LRISK_t^{-n} \tag{10}$$

where $LRISK_t$ is calculated using all N funds, and $LRISK_t^{-n}$ is recalculated using only the other $N-1$ funds. This approach measures the fund's full incremental contribution to systemic risk within our model, including non-linear interaction effects.

2.1.4 Portfolio Impact of Systemic Fire Sales

While $\Delta_n LRISK_t$ quantifies a fund's contribution to system-wide price impact, systemic events also impose costs on funds through the devaluation of their existing holdings, irrespective of their own sales. We define the Exposure-LRISK ($\mathcal{E}_n LRISK_t$) for fund n as the total expected percentage loss on its initial portfolio due to the market-wide repricing caused by aggregate fire sales. It is calculated by weighting the system-wide expected price pressure on each asset by the fund's initial holding weight:

$$\mathcal{E}_n LRISK_t = \sum_{j=1}^{J} w_{n,j,t} \cdot \mathbb{E}_t \left[PP_{j,t+1} \,|\, \mathcal{S} \right] \tag{11}$$

where $w_{n,j,t}$ is the portfolio weight of asset j in fund n at time t (before the shock), and $\mathbb{E}_t \left[PP_{j,t+1} \,|\, \mathcal{S} \right]$ is the system-wide expected price pressure derived in Equation (8). $\mathcal{E}_n LRISK_t$ captures the fund's vulnerability to systemic contagion through its asset exposures.

2.1.5 Coordinated Redemption Strategy and Systemic Risk Minimization

In a system-wide stress scenario ($\mathcal{S}$), uncoordinated liquidation strategies can amplify fire sales. A central planner might seek to coordinate liquidations across funds and balance the mitigation of immediate systemic impact ($LRISK_t$) against the preservation of funds' post-sale liquidity buffers, ensuring ongoing resilience.

This trade-off can be modeled by choosing coordinated liquidation weights $\{w^*_{n,j,t}\}$ to minimize a combined objective function. We define the liquidity buffer penalty for fund n, $\Phi_n(\cdot)$, as the liquidity-weighted value of assets remaining after sales, which penalizes reducing holdings of liquid assets:

$$\Phi_n\left(\{w^*_{n,j,t}\}\right) := \sum_{j=1}^{J}(1 - \text{Liq}_{j,t})\left(h_{n,j,t} - v^*_{n,j,t}\right) \tag{12}$$

where $v^*_{n,j,t} = w^*_{n,j,t}\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$ is the value sold and $h_{n,j,t}$ is the initial holding value.

Using our derived quadratic price pressure from Equation (5) for $LRISK_t$ and adapting the liquidity buffer penalty $\Phi_n(\cdot)$ from Equation (12), the planner solves:

$$\min_{\{w^*_{n,j,t}\}} \quad \underbrace{LRISK_t}_{\text{Systemic Impact}} + \lambda \cdot \underbrace{\sum_{n=1}^{N}\Phi_n\left(\{w^*_{n,j,t}\}\right)}_{\text{Aggregate Liquidity Buffer Penalty}} \tag{13}$$

$$\text{s.t.} \quad \sum_{j=1}^{J} w^*_{n,j,t} = 1 \quad \forall n \in \{1, \ldots, N\} \tag{14}$$

$$v^*_{n,j,t} \leq h_{n,j,t} \quad \forall \quad n, j, t \tag{15}$$

where $LRISK_t$ depends implicitly on $\{w^*_{n,j,t}\}$ via the total expected sales $V^{*,\mathrm{E}}_{j,t} = \sum_{n=1}^{N} v^*_{n,j,t}$. The parameter $\lambda \geq 0$ governs the planner's preference for preserving liquidity buffers (discouraging sales of liquid assets) versus minimizing the immediate fire-sale impact captured by $LRISK_t$.

The optimal coordinated strategy $w^*_{n,j,t}$ depends on λ. A low λ prioritizes minimizing immediate $LRISK_t$, concentrating sales on the most liquid assets (resembling a system-optimized vertical slicing) but depleting buffers. A high λ prioritizes preserving buffers, leading to a more proportional selling pattern across assets (shifting towards a horizontal slicing strategy) even if it increases immediate price pressure. This optimization provides a benchmark for evaluating interventions, highlighting the trade-off between mitigating immediate externalities and maintaining longer-term resilience.

2.2 LRISK Calibration

2.2.1 Fund Universe

To calibrate the model, we construct a granular dataset of U.S. corporate bond fund holdings using the Center for Research in Securities Prices (CRSP) Mutual Fund database, covering the period from January 2011 to June 2024. We follow Jiang et al. (2021) by selecting corporate bond funds based on the objective codes provided by the CRSP: a fund must have either a Lipper objective code in the set (A, BBB, HY, SII, SID, IID), a Strategic Insight objective code in the set (CGN, CHQ, CHY, CIM, CMQ, CPR, CSM), a Wiesenberger objective code in the set (CBD, CHY), have "IC" as the first 2 characters of its CRSP objective code, or have "I" as the first character of its CRSP objective code and have a Lipper asset code "TX". We then filter out funds that at no point have at least 50 percent of their portfolio invested in corporate bonds, and those whose TNA never surpasses 5 million USD. Finally, we drop fund-months where the holdings in CRSP cover less than 90 percent of the TNA and when our asset liquidity data covers less than two-thirds of the holdings. Our final sample consists of 1,479 unique funds.

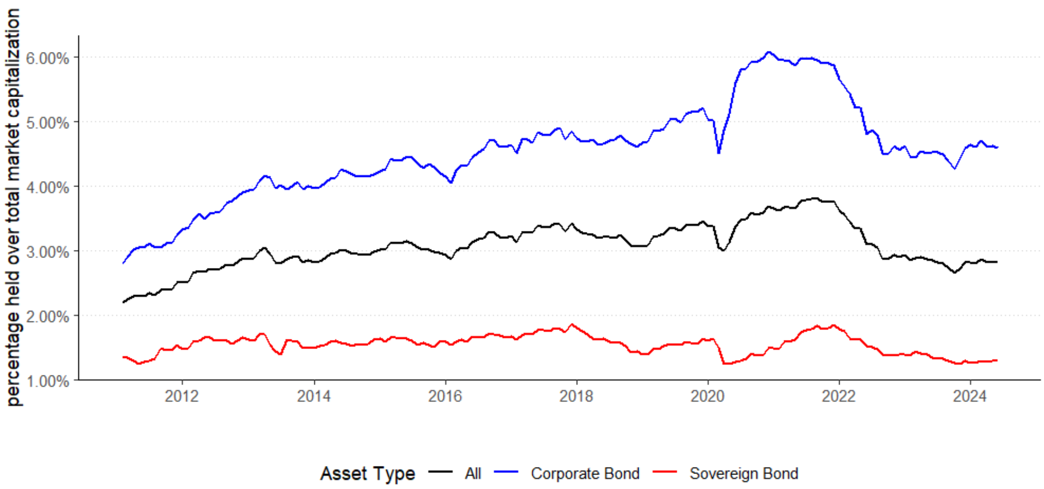
We further obtain monthly TNA and returns data from CRSP, which we use to compute monthly fund flows as a percentage of TNA:

$$Flows_{n,t} = \frac{TNA_{n,t} - (TNA_{n,t-1} \cdot (1 + R_{n,t}))}{TNA_{n,t-1}} \tag{16}$$

with $R_{n,t}$ the returns of fund n at month t, and $TNA_{n,t}$ the total net assets of fund n at month t. Aggregate flows are computed as the sum of fund flows, weighted by fund size.

Fund-level statistics are detailed in Appendix A. The distribution of TNA is positively skewed. While the median fund size is $287 million, the mean TNA is substantially higher at $1,631 million, indicating that the sample is dominated by a few large funds. Regarding asset allocation, the portfolios are concentrated in corporate bonds. The median holding of corporate bonds is 85.99%. Conversely, holdings of government bonds and cash remain relatively low, with medians of 2.13% and 1.69%, respectively. This confirms that funds operate with limited immediate liquidity buffers, increasing their reliance on market depth for managing potential redemptions. The low percentage of purely liquid assets underscores the importance of accurately modeling the liquidity risk embedded within the corporate bond fund sector.

Figure 1: Fund Footprint



Note: The figure shows the monthly holdings of our sample of mutual funds relative to the total market capitalization of U.S. corporate and sovereign bonds. Market capitalization figures are derived from the Flow of Funds' marketable securities liabilities, retrieved from Federal Reserve Economic Data (FRED database).

Figure 1 illustrates the evolution of the U.S corporate bond funds' footprint in the U.S. corporate and sovereign bond markets since 2011, measured as the share of outstanding marketable debt held by our sample of mutual funds. The footprint in the corporate bond market expanded materially, doubling from approximately 3% in 2012 to a peak of 6% at the end of 2020. This structural shift highlights that mutual funds have become increasingly critical marginal holders of corporate credit. Notably, the volatility observed around 2020 reflects the severe crisis dynamics: a initial liquidity squeeze triggering outflows and sales, followed by a stabilization driven by policy interventions. In contrast, the footprint in the sovereign bond market exhibits a much more stable trend, fluctuating within a narrow band.

This divergence reflects the deep and highly liquid nature of the U.S. Treasury market, where mutual funds play a comparatively smaller role.

2.2.2 Asset Liquidity

Our asset liquidity measure is derived from the bid-ask spread of securities within U.S. corporate bond fund portfolios. The liquidity of a security is not directly observable, and there is no single indicator that can account for all of its dimensions (transaction cost, depth, breadth, execution speed, resilience). Although the bid-ask spread represents only the transaction cost component of liquidity, it remains one of the most widely used indicators in the bond market (Bao et al., 2011; Edwards et al., 2007). We use the effective bid-ask spread measure, i.e. spreads from actual transactions recorded in the TRACE platform.[6] Bid-ask spread measures also have the advantage of being available for a large proportion of the securities held by our sample of funds, and over a significant time horizon.

We start by using the transactions in the Trade Reporting and Compliance Engine (TRACE) which covers corporate bonds. We clean these transactions following the procedure detailed in Dick-Nielsen (2014). We compute the bid-ask spread as the difference between the weighted average dealer ask price and weighted-average dealer bid prices, and then average these daily spreads per month, following Jiang et al. (2021). This covers about 75% of assets held by US corporate bonds. For securities not covered by TRACE, we use quoted bid-ask spreads from Datastream. This covers mainly sovereign bonds, non-US corporate bonds, stocks and ETF shares. The observed bid-ask spreads are winsorized at the asset-class level (using the 2.5% and 97.5% quantiles) to mitigate the impact of potential outliers. Moreover, we classify cash, US treasury bills and money market shares as perfectly liquid ($\text{Liq}_j = 1$). Finally, we impute remaining missing values using the 95^{th} percentile of the distribution of the observed bid-ask spreads within the respective asset class. This

[6] This measure is considered to be a superior measure of liquidity compared to the quoted spread Díaz and Escribano (2022), which reflects the spread of the willingness to buy or sell and has limitations in the bond market where low volumes and bilateral negotiations complicate its interpretation.

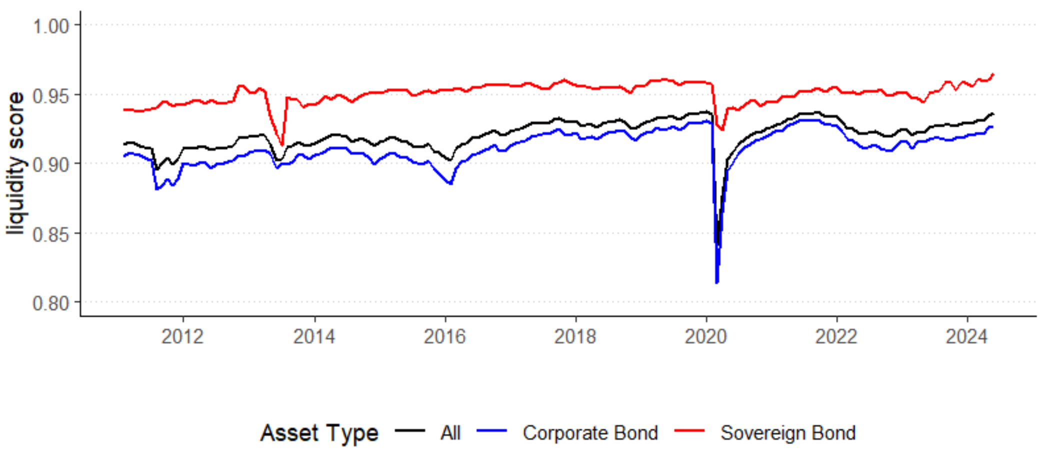
approach acknowledges that the absence of reported market data is often correlated with lower liquidity.

Finally, the bid-ask spread for each security j is converted into a normalized liquidity score $\text{Liq}_j \in [0,1]$. The liquidity score is constructed such that a higher value indicates greater liquidity (i.e., a lower bid-ask spread). We employ a minimun-maximum scaling function defined as:

$$\text{Liq}_j = 1 - \frac{\text{BAS}_j - \text{BAS}_{\text{min}}}{\text{BAS}_{\text{max}} - \text{BAS}_{\text{min}}} \tag{17}$$

The minimum bid-ask spread (BAS_{min}) is set to 0, representing perfect liquidity. The maximum spread (BAS_{max}) is set at 3.71 percent which is determined based on the observed maximum bid-ask spread (post winsorization) in our sample from 2011 to 2024. This normalization maps a zero bid-ask spread to $\text{Liq}_j = 1$ (perfectly liquid) and a BA-spread of 3.71 percent to $\text{Liq}_j = 0$ (illiquid asset).

Figure 2: Liquidity Score



Note: The figure displays the monthly mean of the liquidity score of assets held by our sample of mutual funds, weighted by the total holdings of funds in each asset type.

Figure 2 tracks the average liquidity score of assets held by mutual funds over time. Over the sample period, we observe a structural improvement in aggregate market liquidity. However, this broad trend masks significant heterogeneity. Corporate bonds exhibit structurally lower and more volatile liquidity compared to sovereign debt. This fragility becomes particularly acute during stress episodes: the sharp deterioration observed in 2020 illustrates how liquidity in the corporate segment can diminish abruptly. By contrast, sovereign bonds remain highly liquid throughout, providing a stabilizing anchor for fund portfolios.

Finally, to accurately estimate the price pressure exerted by fund sales, we address missing data in the bond market value outstanding (MV) based on the approach detailed in Appendix D.

2.2.3 Estimating Flow Betas and Aggregate Outflows

The LRISK measure requires estimates of the conditional flow betas ($\beta_{n,t+1|t}$) and the expected aggregate outflow under systemic stress ($\mathbb{E}_t[F_{m,t+1}|\mathcal{S}]$).

We estimate the time-varying sensitivity of individual fund flows ($F_{n,t}$) to aggregate market flows ($F_{m,t}$) using the Dynamic Conditional Correlation (DCC) GARCH model (Engle, 2002). We model the conditional variances ($\sigma^2_{i,t}$) of the flow series using a GARCH(1,1) specification and their conditional correlation matrix ($\mathbf{R}_t$) using the standard DCC(1,1) process. Let $\mathbf{H}_t$ be the conditional covariance matrix of the flows $[F_{n,t}, F_{m,t}]'$. It is constructed as $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$, where $\mathbf{D}_t = \text{diag}(\sigma_{n,t}, \sigma_{m,t})$ contains the conditional standard deviations. The time-t forecast of the conditional flow beta for $t+1$ is then derived directly from the elements of the forecasted covariance matrix $\mathbf{H}_{t+1|t}$:

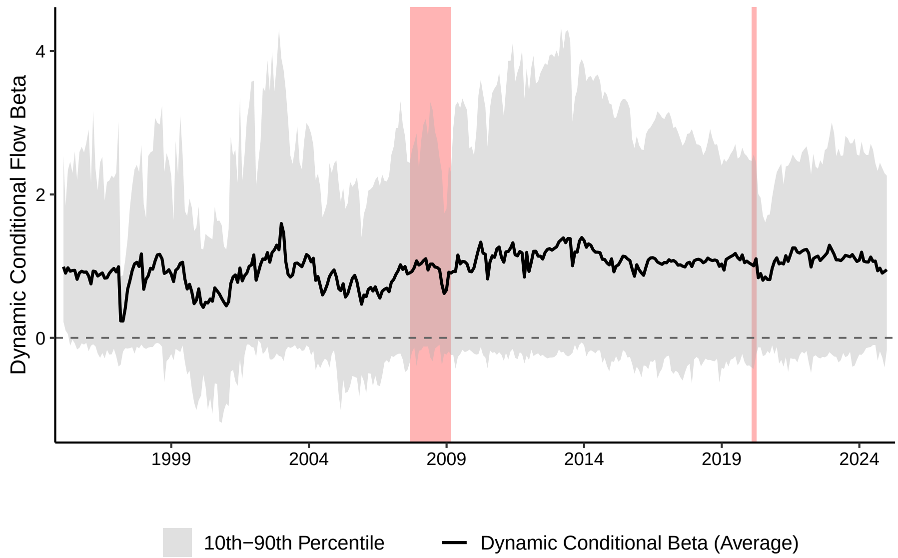
$$\beta_{n,t+1|t} = \frac{[\mathbf{H}_{t+1|t}]_{nm}}{[\mathbf{H}_{t+1|t}]_{mm}} \tag{18}$$

where $[\mathbf{H}_{t+1|t}]_{nm}$ is the forecasted conditional covariance between fund n and market flows, and $[\mathbf{H}_{t+1|t}]_{mm}$ is the forecasted conditional variance of market flows.

Figure 3 displays the cross-sectional distribution of these estimated flow betas over time. The solid line represents the cross-sectional average, while the shaded area captures the heterogeneity across the fund universe (10th to 90th percentiles). We observe that the average sensitivity is positive and close to one. Furthermore, the sensitivity of individual funds to aggregate flows is heterogeneous and changes over time. These variations have direct implications for the final LRISK measure. Indeed, periods where the distribution increases or widens imply a higher potential for simultaneous selling pressure in the fund sector.

To validate that these dynamic betas effectively capture forward-looking vulnerability on the liability side, we perform a predictive analysis in Appendix (Table A.3). We regress individual fund flows on their lagged flow beta ($\beta_{n,t|t-1}$), interacting this measure with a redemption shock dummy that identifies months of aggregate market stress. The results show a negative and statistically significant interaction term, confirming that funds with higher ex-ante flow betas experience disproportionately larger outflows specifically during periods of systemic stress. This confirms that the dynamic conditional flow beta is a relevant ex-ante measure of tail outflow risk.

Figure 3: Dynamic Conditional Flow Beta



***Note:** The figure illustrates the evolution of funds' dynamic conditional flow betas ($\beta_{n,t+1|t}$) from 1995 to 2024. The solid black line represents the cross-sectional average beta at each point in time. The grey shaded area represents the inter-percentile range (10th to 90th percentiles), highlighting the cross-sectional dispersion in flow sensitivity. For each month, individual betas are winsorized at the 1% and 99% level.*

The LRISK measure is conditional on a systemic aggregate outflow event $\mathcal{S} \equiv \{F_{m,t+1} =$

$C_{t+1}\}$. To capture the time-varying nature of systemic risk, we model this threshold dynamically using the Conditional Autoregressive Value at Risk (CaViaR) framework (Engle and Manganelli, 2004). Specifically, we employ the Symmetric Absolute Value (SAV) specification to directly model an extreme quantile of the aggregate flow distribution, setting $\theta = 0.005$ (the 0.5% quantile) to represent a severe systemic event:

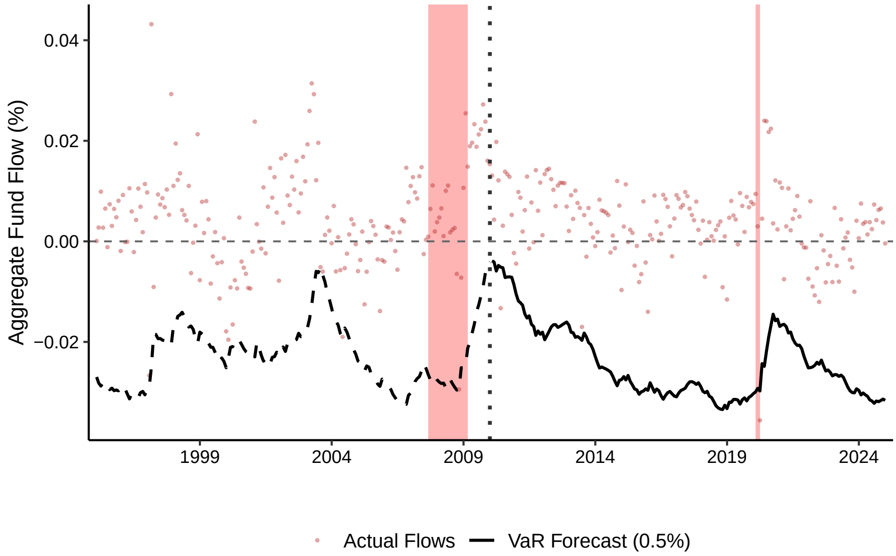
$$C_{t+1} = Q_{0.005,t+1} = \beta_0 + \beta_1 Q_{0.005,t} + \beta_2 |F_{m,t}| \tag{19}$$

The parameters $(\beta_0, \beta_1, \beta_2)$ are estimated via quantile regression using aggregate flow data up to 2010. We then generate out-of-sample forecasts for the dynamic threshold $C_{t+1} = Q_{0.005,t+1}$ from 2010 onwards. We use this forecasted extreme quantile $\mathbb{E}_t [F_{m,t+1} \mid \mathcal{S}] = C_{t+1}$ in our LRISK calculation (Equation 8). This approach focuses on the price impact generated as the system breaches this severe stress threshold.[7]

Figure 4 plots the aggregate fund flows alongside the forecasted 0.5% tail risk threshold. The model captures the cyclicality of flow risk. The forecasted magnitude of tail outflows tends to increase (the threshold becomes more negative) during periods of relative calm, reflecting the accumulation of risk. Conversely, the threshold decreases (moves closer to zero) following realized crisis events, as observed after the large outflows in 2008 and 2020. This property allows the measure to anticipate potential stress by signaling elevated risk levels before a crisis materializes.

[7]Using the VaR threshold directly, particularly an extreme one like the 0.5% quantile, simplifies the estimation compared to calculating the Expected Shortfall ($F_{m,t+1} < C_{t+1}$), while still capturing the impact of a severe systemic event.

Figure 4: Forecasted Tail Redemptions



Note: The figure shows the evolution of monthly aggregate fund flows (grey dots) and the forecasted 0.5% Value-at-Risk threshold (solid and dashed black lines) from 1995 to 2024. The dashed black line (1995–2010) represents the in-sample estimation period, while the solid black line (2010–2024) represents the out-of-sample forecast used to compute LRISK.

2.2.4 Aggregate LRISK

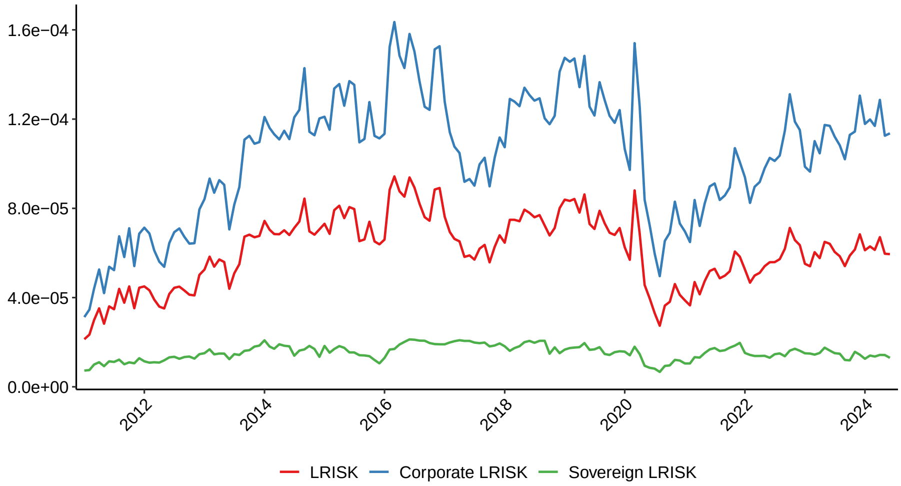
We first calibrate the price pressure function used to construct the LRISK, in which the liquidity is endogenous to the fire sale. In Equation 3, the parameter γ captures the sensitivity of market liquidity to selling flows. In Table A.2, we empirically estimate this parameter by regressing realized bond liquidity scores on realized selling pressure (under the proportional liquidation hypothesis) during the COVID-19 crisis. The results yield a statistically significant coefficient close to 2 across all specifications, confirming the existence of a liquidity spiral. To remain conservative in our baseline calibration, we set $\gamma = 1.5$. Figure A.1 shows that while the absolute level of LRISK scales with γ, the identification of periods with high systemic liquidity risk is robust to this parameter choice.

Figure 5 presents the time series of the aggregate LRISK measure for the U.S. corporate bond fund sector from 2011 to 2024. Our main specification relies on the proportional liquidation approach combined with dynamic outflows. Over the full sample, the measure exhibits only a limited upward trend, reflecting the interplay of two opposing forces: while the market footprint of U.S. corporate bond funds has expanded significantly (see Figure 1), this structural vulnerability was largely counterbalanced by an overall improvement in market liquidity conditions between 2011 and 2020 (see Figure 2). Within this broader stability, however, we observe distinct phases. The aggregate LRISK rises clearly between 2011 and 2015, driven primarily by the accumulation of tail risk in fund flows (see Figure 4). Furthermore, the measure peaks in March 2020, mostly reflecting a sudden deterioration in asset liquidity.

Our choice of the liquidation strategy is guided by Figure A.2, which compares our baseline proportional liquidation strategy against the alternative liquidity-based liquidation. It shows that under a vertical slicing assumption, where funds sell their most liquid assets first, the estimated systemic risk is negligible, even during the extreme stress of March 2020. This strategy effectively protects the market from fire sales by draining cash and Treasury buffers. However, this lack of impact contradicts the severe price impact on the corporate bond market segment observed during the crisis (e.g., Ma et al., 2022; Coppola, 2025). In contrast, the proportional selling strategy generates significant price pressure consistent with realized market distress. To properly capture systemic fragility, we thus assume that funds tend to sell both liquid and illiquid assets from their portfolio during market stress episodes (i.e., proportional redemptions). This assumption is also supported by other evidence in the literature (e.g., Morris et al., 2017; Shek et al., 2018; Jiang et al., 2021; Dötz and Weth, 2019).

Finally, the LRISK decomposition in Figure 5 shows that systemic liquidity risk is almost exclusively driven by the price pressure on corporate bonds (see the Corporate LRISK). Sovereign bond holdings contribute almost nothing to the aggregate measure due to their high liquidity and size.

Figure 5: Aggregate LRISK



***Note:** The figure displays the monthly evolution of the Aggregate LRISK (red line) for the U.S. corporate bond fund sector from 2011 to 2024. The measure is calculated using the baseline specification: proportional liquidation and dynamic tail outflows, with $\gamma = 1.5$. The measure is decomposed into the contributions from corporate bonds (blue line) and sovereign bonds (green line).*

3 Empirical Results

In this section, we conduct a series of empirical tests to evaluate the reliability of LRISK as a systemic risk indicator and its effectiveness as a predictive tool. Our empirical strategy involves three steps, moving from asset-level to system-wide financial implications. First, we validate the transmission mechanism underlying our model by testing whether the asset-specific price pressures implied by the LRISK can explain cross-sectional differences in bond returns during a period of realized stress, specifically the COVID-19 market turmoil. Second, we assess the relevance of the measure for individual financial institutions by examining whether a fund's ex-ante exposure to systemic liquidity risk predicts its subsequent underperformance during aggregate redemption shocks. Third, we evaluate the forward-looking properties of the aggregate LRISK measure, testing its ability to serve as an early warning indicator for future distress in the corporate bond market. Finally, we link fund's ex-ante exposure to systemic liquidity risk to the use of formal liquidity management tools.

3.1 Predictive Analyses

3.1.1 Expected Price Pressure and Bond Returns during the COVID-19 Crisis

We first test the micro-foundation of our model: does the asset-level price pressure predicted by our framework explain bond returns during a systemic crisis? We focus on the COVID-19 market turmoil of early 2020, a period characterized by severe liquidity stress in the corporate bond market segment and massive mutual fund outflows.

We estimate the expected price pressure ($\mathbb{E}_{t-1}[PP_{j,t}|\mathcal{S}]$) for each corporate bond j in our sample as of January 2020, using the methodology described in Section 2.1. We then regress the realized maximum drawdown of these bonds, computed from daily prices, during the peak of the crisis (February-March 2020) on our ex-ante pressure measure. The regression specification is:

$$\text{MaxDrawdown}_{j,t\to t+1} = \beta\cdot\mathbb{E}_{t-1}[PP_{j,t}|\mathcal{S}]+\gamma\cdot\text{Controls}_{j,t-1}+\alpha_{\text{Type}}+\alpha_{\text{Seniority}}+\alpha_{\text{Issuer}}+\epsilon_j \quad (20)$$

where $\text{MaxDrawdown}_{j,t\to t+1}$ is the maximum percentage loss in bond value over the February-March 2020 period. Controls_j is a vector of bond-level characteristics including modified duration, time to maturity, and issue size. We use fixed effects for bond type, seniority, and issuer to absorb unobserved heterogeneity and credit risk factors unrelated to systemic liquidity pressure.

Table 1 reports standardized regression coefficients. We find a positive and statistically significant coefficient on expected price pressure across all specifications. This indicates that bonds with higher predicted fire-sale exposure suffered larger drawdowns, even after controlling for standard risk characteristics. The effect is economically substantial: a one standard deviation increase in expected price pressure is associated with an increase in drawdown ranging from 0.8% (Column 3) to 3.5% (Column 1). To ensure these results are not driven solely by the concentration of ownership, we conduct robustness checks in Table A.4 by controlling for the percentage of each bond held by U.S. investment funds. While this slightly mitigates the magnitude of the coefficients (ranging from 0.4% to 2.7%), they remain statistically significant. Overall, these findings provide robust evidence that the flow-driven price pressure mechanism captured by LRISK was a significant driver of bond returns during the COVID-19 shock.

Table 1: Covid-19: Bond maximum drawdown & LRISK

This table presents the predictive power of the LRISK framework on realized bond market fragility. The dependent variable is the bond-level maximum drawdown calculated from daily prices over the peak of the COVID-19 market turmoil (February–March 2020). The variable of interest is the expected price pressure, estimated ex-ante using data available as of January 2020. Columns (1)–(4) use individual fixed effects for Bond Type, Debt Seniority, and Issuer. Column (5) presents the strictest specification, including a interactive fixed effect (Bond Type × Debt Seniority × Issuer) alongside bond-specific controls. All numerical independent variables are winsorized at the 1% and 99% levels. Standardized regression coefficients are displayed. HAC standard errors are reported in parentheses. *, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.**

	Dependent variable:				
	Maximum drawdown: February-March 2020				
	(1)	(2)	(3)	(4)	(5)
Exp. price pressure$_{t-1}$	0.035***	0.033***	0.008***	0.009***	0.011***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Modified duration$_{t-1}$	0.030***	0.033***	0.085***	0.085***	0.088***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Life to maturity$_{t-1}$	0.035***	0.034***	−0.009**	−0.010***	−0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Size (log)$_{t-1}$	−0.001	−0.005***	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FE: Bond type (BT)	Yes	No	No	Yes	Yes
FE: Debt seniority (DS)	No	Yes	No	Yes	Yes
FE: Issuer	No	No	Yes	Yes	Yes
FE: BT X DS X Issuer	No	No	No	No	Yes
Observations	12,860	12,860	12,860	12,860	12,860
R^2	0.303	0.298	0.914	0.916	0.935
Adjusted R^2	0.303	0.296	0.884	0.887	0.905

3.1.2 Exposure LRISK and Fund Returns

Next, we examine the implications of fire-sale spillovers for investment funds themselves. We test whether a fund's specific vulnerability to systemic liquidity risk, measured by its

Exposure-LRISK ($\mathcal{E}_n$LRISK, see Equation 11), predicts its performance during periods of aggregate stress.

We estimate predictive panel regressions of monthly fund returns ($R_{n,t}$) on the lagged $\mathcal{E}_n$LRISK measure. To focus on periods of risk materialization, we interact our lagged measure with a redemption shock (RS_t) dummy variable, set to one in months where aggregate outflows exceed the 95th historical percentile. The specification is defined as follows:

$$R_{n,t} = \beta_1 \mathcal{E}_n \text{LRISK}_{t-1} + \beta_2(\mathcal{E}_n \text{LRISK}_{t-1} \times RS_t) + \gamma \cdot \text{Controls}_{n,t-1} + \alpha_n + \lambda_t + \epsilon_{n,t} \quad (21)$$

where α_n represents fund fixed effects to control for time-invariant fund characteristics, and λ_t represents month-year fixed effects to control for aggregate shocks. The set of control variables includes lagged fund size, expense ratio, retail share, open status, age, and the fund's own flows ($Flows_{n,t}$ and $Flows_{n,t-1}$). Including own flows ensures that we capture spillover effects from the system rather than the direct price impact of the fund's own trading.

Table 2 presents the results. The coefficient of interest is the interaction term (β_2). We observe a negative and statistically significant coefficient across all specifications. This implies that funds with higher ex-ante exposure to fire-sale spillovers experience significantly worse returns during months of systemic redemption stress. The economic magnitude is substantial: a one standard deviation increase in ex-ante fire-sale exposure leads to an additional underperformance of around 1 percentage point during episodes of redemption shock. Furthermore, the positive coefficient on the non-interacted term (β_1) suggests that highly exposed funds outperform during normal periods. This is consistent with the idea that investors earn a risk premium for bearing systemic liquidity risk.

Table 2: Fund Return Regressions with Exposure LRISK

This table examines the predictive power of a fund's ex-ante exposure to fire-sale spillovers ($\mathcal{E}_n$LRISK$_{t-1}$, see Equation 11) on its subsequent performance, conditional on aggregate market stress, over the period 2011-2024. The dependent variable is the monthly fund return, winsorized at the 1% and 99% level. The main explanatory variables are the lagged Exposure LRISK, a dummy for a system-wide redemption shock (RS), computed from the historical percentile (5%) of aggregate flows, and their interaction term. $\mathcal{E}_n$LRISK$_{t-1}$ is scaled and winsorized at the 1% and 99% level. Columns (1) and (4) are baseline specifications without fixed effects. Columns (2) and (5) add fund fixed effects, and columns (3) and (6) include both fund and time fixed effects. Columns (4)–(6) further control for current and lagged fund flows. Standard errors are clustered by fund and time. All specifications include a set of lagged fund-specific controls: Size, Age, Expense Ratio, Retail share, and Open status. *, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.**

	Fund Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathcal{E}_n\text{LRISK}_{t-1}$	0.002***	0.001***	0.001**	0.002***	0.001***	0.001*
	(0.001)	(0.0003)	(0.0004)	(0.001)	(0.0003)	(0.0004)
Redemption Shock (RS)	−0.024***			−0.023***		
	(0.008)			(0.008)		
$\mathcal{E}_n\text{LRISK}_{t-1}$ x RS	−0.011***	−0.009***	−0.009***	−0.011***	−0.009***	−0.009***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Fund Flows (%)				0.042***	0.012***	0.011***
				(0.008)	(0.002)	(0.002)
Fund Flows$_{t-1}$(%)	−0.005	0.0002	−0.001	−0.018***	−0.003*	−0.004**
	(0.007)	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)
FE: Fund	No	Yes	Yes	No	Yes	Yes
FE: Month-Year	No	No	Yes	No	No	Yes
Controls: Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,136	73,136	73,136	73,136	73,136	73,136
R^2	0.143	0.631	0.635	0.157	0.632	0.636
Adjusted R^2	0.143	0.630	0.631	0.157	0.631	0.632

3.1.3 Early Warning Properties of Aggregate LRISK

Beyond fund-level validation, a key test for a systemic risk measure is its ability to forecast aggregate financial stability risks before they materialize. We evaluate the early-warning properties of the aggregate corporate LRISK regarding two dimensions of credit market stress: the Corporate Bond Default Premium (DP), defined as the difference in yield between BAA and AAA bonds, and the Corporate Bond Market Distress Index ($CMDI$), a comprehensive measure of the U.S. market functioning (Boyarchenko et al., 2025).[8]

Following the specification proposed by Allen et al. (2012) and Brownlees and Engle (2017), we estimate predictive regressions for the future monthly change in these stress indicators (ΔY_{t+h}) across several forecasting horizons, ranging from $h = 1$ to $h = 10$ months ahead. The regression measures the change in market conditions based on the change in the predictors h months before. The model controls for autoregressive dynamics and a broad set of macro-financial variables to isolate the incremental information content of LRISK:

$$\Delta Y_{t+h} = \alpha + \sum_{k=0}^{2} \beta_k \Delta \mathrm{LRISK}_{t-k} + \sum_{k=0}^{2} \phi_k \Delta Y_{t-k} + \delta \cdot \Delta \mathrm{Macro}_t + \epsilon_{t+h} \tag{22}$$

where Y_t represents either the Default Premium (DP) or the Corporate Bond Market Distress Index (CMDI). The control variables $\Delta \mathrm{Macro}_t$ includes changes in the term spread (i.e., 10-year minus 2-year Treasury yield), housing market activity (i.e., new privately-owned housing units started), S&P 500 returns, and the VIX. ϵ_{t+h} is a random error term assumed to be uncorrelated with the predictors. We evaluate the predictive power through the significance of the β_k coefficients and the increase in adjusted R^2 (ΔAdj. R^2) relative to a baseline model excluding LRISK. The model is estimated via OLS on data from January 2011 to June 2024, including two lags ($k = 2$). Statistical significance is assessed using Newey-West HAC standard errors.

Table 3 presents the results for the Corporate Bond Default Premium. We find that aggre-

[8]The CMDI incorporates measures of primary market issuance and pricing, secondary market pricing and liquidity conditions, and the relative pricing between traded and non traded bonds.

gate corporate LRISK contains significant predictive information for future credit spreads, particularly at medium-term horizons. Lagged monthly changes in LRISK (ΔLRISK$_{t-1}$ and ΔLRISK$_{t-2}$) exhibit positive and statistically significant coefficients at horizons of 4 to 7 months. This indicates that a buildup in systemic liquidity risk in the fund sector tends to precede a widening of credit spreads by approximately two quarters. The incremental explanatory power is substantial. Including LRISK as a predictive variable increases the adjusted R^2 by up to 3.1 percentage points (at Lead 7) over the baseline model.

Table 4 reports the results for the Corporate Bond Market Distress index. Similarly, LRISK appears to anticipate deteriorations in market functioning. The coefficients on lagged LRISK are positive and significant at multiple horizons (2, 3, 5, and 6 months ahead). This indicates that elevated systemic liquidity risk in investment funds acts a leading indicator of corporate bond market conditions. The ΔAdj. R^2 remains positive for the first 7 months, suggesting that LRISK is a early warning signal for market fragility.

Table 3: LRISK Predictive Regression for the Corporate Bond Default Premium

This table evaluates the early-warning properties of aggregate LRISK regarding future credit market distress, from 2011 to 2024. The dependent variable is the monthly change in the Corporate Bond Default Premium (ΔDP_{t+h}) across forecasting horizons h ranging from 1 to 10 months ahead. The model regresses future distress on current and lagged changes in aggregate LRISK, controlling for autoregressive dynamics and macro-financial variables (changes in Term Spread, Housing Market activity, S&P 500, and VIX). All variables are winsorized at the 1% and 99% level. To quantify the incremental predictive content of the proposed measure, the last row reports the ΔAdj. R^2, defined as the difference in adjusted explanatory power between the full specification and a baseline model that excludes LRISK. Newey–West robust standard errors are reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.**

	Dependent variable:									
	Δ Default Premium (DP)									
	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5	Lead 6	Lead 7	Lead 8	Lead 9	Lead 10
$\Delta LRISK_t$	−0.138	0.100	−0.049	0.050	0.150**	−0.075	0.236**	−0.136*	0.098	0.118
	(0.105)	(0.119)	(0.099)	(0.074)	(0.076)	(0.091)	(0.103)	(0.078)	(0.077)	(0.096)
$\Delta LRISK_{t-1}$	−0.060	−0.031	0.057	0.163**	−0.038	0.223*	−0.129	0.062	0.100	0.158**
	(0.099)	(0.079)	(0.067)	(0.080)	(0.082)	(0.117)	(0.084)	(0.093)	(0.102)	(0.069)
$\Delta LRISK_{t-2}$	0.015	0.002	0.171**	−0.038	0.210*	−0.136	0.071	0.114	0.178**	−0.129
	(0.067)	(0.061)	(0.079)	(0.094)	(0.114)	(0.094)	(0.079)	(0.087)	(0.080)	(0.086)
ΔDP_t	−0.358***	0.205***	−0.135	0.066	0.195**	−0.079	−0.078	0.012	0.066	0.097
	(0.092)	(0.079)	(0.091)	(0.091)	(0.086)	(0.088)	(0.099)	(0.082)	(0.076)	(0.094)
ΔDP_{t-1}	−0.057	−0.033	0.020	0.181***	0.027	−0.116	−0.059	0.042	0.114	−0.103
	(0.093)	(0.054)	(0.075)	(0.052)	(0.080)	(0.094)	(0.087)	(0.065)	(0.083)	(0.077)
ΔDP_{t-2}	−0.076	−0.040	0.134*	0.036	−0.060	−0.035	−0.082	0.135	−0.103	0.039
	(0.086)	(0.090)	(0.077)	(0.095)	(0.097)	(0.099)	(0.098)	(0.086)	(0.086)	(0.071)
ΔTerm Spread_t	−0.308***	−0.165**	−0.133*	0.150**	−0.003	−0.029	−0.066	−0.113	−0.00003	−0.010
	(0.074)	(0.082)	(0.070)	(0.069)	(0.071)	(0.098)	(0.076)	(0.086)	(0.077)	(0.065)
ΔHousing Market_t	−0.187	−0.043	0.255*	−0.019	0.080	−0.120	−0.131	0.258**	0.030	−0.201*
	(0.119)	(0.152)	(0.136)	(0.157)	(0.145)	(0.162)	(0.183)	(0.112)	(0.135)	(0.118)
$\Delta S\&P500_t$	−0.020	1.057**	−1.122	0.486	0.453	−0.919	0.116	0.418	0.476	0.244
	(0.417)	(0.429)	(0.685)	(0.450)	(0.809)	(0.568)	(0.511)	(0.491)	(0.440)	(0.576)
ΔVIX_t	0.002	0.006**	−0.006	0.004	−0.001	−0.006	0.004	0.003	0.0001	0.002
	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Constant	−0.009	−0.016*	0.003	−0.005	−0.010	0.006	−0.005	−0.013	−0.014	−0.008
	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.008)	(0.008)	(0.009)
Observations	161	160	159	158	157	156	155	154	153	152
R^2	0.262	0.066	0.114	0.065	0.081	0.073	0.073	0.084	0.072	0.080
Adj. R^2	0.213	0.003	0.054	0.002	0.019	0.010	0.008	0.020	0.007	0.014
Δ Adj. R^2	-0.003	-0.013	0.001	-0.002	0.024	0.030	0.031	0.003	0.011	0.017

Table 4: LRISK Predictive Regression for the Corporate Bond Market Distress

This table assesses the ability of aggregate LRISK to forecast future Corporate Bond Market Distress (CMDI, Boyarchenko et al., 2025) conditions. The dependent variable is the future monthly change in the liquidity index (ΔCMDI$_{t+h}$) across forecasting horizons h ranging from 1 to 10 months. The predictive regression models future liquidity as a function of current and lagged changes in aggregate LRISK. To isolate the specific information content of the proposed measure, the specification controls for autoregressive dynamics and macro-financial variables (changes in Term Spread, Housing Market activity, S&P 500, and VIX). All variables are winsorized at the 1% and 99% level. To quantify the incremental predictive content of the proposed measure, the last row reports the ΔAdj. R^2, defined as the difference in adjusted explanatory power between the full specification and a baseline model that excludes LRISK. Newey–West robust standard errors are reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.**

	Dependent variable:									
	Δ Corporate Bond Market Distress (CMDI)									
	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5	Lead 6	Lead 7	Lead 8	Lead 9	Lead 10
ΔLRISK$_t$	0.044	−0.040	−0.019	0.042	−0.015	0.043	0.063*	0.015	0.007	−0.011
	(0.028)	(0.034)	(0.018)	(0.026)	(0.019)	(0.028)	(0.037)	(0.023)	(0.026)	(0.021)
ΔLRISK$_{t-1}$	−0.021	−0.015	0.051**	−0.003	0.050*	0.075**	0.020	0.003	−0.015	−0.011
	(0.031)	(0.022)	(0.025)	(0.021)	(0.029)	(0.030)	(0.027)	(0.032)	(0.025)	(0.022)
ΔLRISK$_{t-2}$	−0.007	0.050*	−0.007	0.044	0.064**	0.014	0.014	−0.010	−0.008	−0.011
	(0.022)	(0.027)	(0.024)	(0.031)	(0.029)	(0.029)	(0.028)	(0.022)	(0.019)	(0.022)
ΔCMDI$_t$	0.143**	−0.038	−0.036	−0.085	−0.187**	−0.026	0.018	−0.098	−0.015	−0.149***
	(0.072)	(0.104)	(0.064)	(0.084)	(0.079)	(0.074)	(0.079)	(0.088)	(0.067)	(0.054)
ΔCMDI$_{t-1}$	−0.001	−0.023	−0.097	−0.162**	−0.007	0.014	−0.085	−0.017	−0.088*	−0.075
	(0.078)	(0.072)	(0.076)	(0.074)	(0.078)	(0.073)	(0.072)	(0.071)	(0.052)	(0.049)
ΔCMDI$_{t-2}$	−0.014	−0.153*	−0.149*	0.052	−0.001	−0.064	−0.027	−0.123*	−0.059	0.085
	(0.068)	(0.083)	(0.087)	(0.091)	(0.074)	(0.073)	(0.050)	(0.064)	(0.055)	(0.056)
ΔTerm Spread$_t$	−0.009	−0.012	−0.004	0.007	−0.040**	0.013	−0.0003	−0.026	−0.018	−0.008
	(0.022)	(0.021)	(0.019)	(0.017)	(0.016)	(0.024)	(0.014)	(0.024)	(0.017)	(0.016)
ΔHousing Market$_t$	−0.014	−0.060**	0.042	0.046*	−0.009	−0.021	−0.020	−0.009	0.087**	−0.069**
	(0.035)	(0.030)	(0.038)	(0.025)	(0.026)	(0.024)	(0.040)	(0.037)	(0.036)	(0.033)
ΔS&P500$_t$	−0.132	−0.114	−0.040	0.005	−0.017	−0.154	−0.053	0.136	0.183	−0.070
	(0.138)	(0.128)	(0.119)	(0.127)	(0.092)	(0.110)	(0.127)	(0.112)	(0.172)	(0.084)
ΔVIX$_t$	0.002	0.0001	0.001	−0.0003	−0.0003	−0.001	−0.0002	0.001	0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−0.0003	−0.001	−0.002	−0.003	−0.004	−0.001	−0.002	−0.005	−0.006*	−0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Observations	161	160	159	158	157	156	155	154	153	152
R^2	0.226	0.086	0.081	0.086	0.108	0.079	0.048	0.039	0.074	0.063
Adj. R^2	0.174	0.024	0.019	0.024	0.047	0.016	-0.018	-0.028	0.009	-0.004
Δ Adj. R^2	0.005	0.016	0.008	0.014	0.032	0.037	0.016	-0.018	-0.018	-0.018

3.2 LRISK and Fund Liquidity Management

In this final step, we link our fund-level LRISK exposure measure to the use of formal liquidity management tools. Such tools are mechanisms that funds can put in place ex ante to manage investor redemptions. If LRISK captures the underlying vulnerability of a fund to funding shocks and forced asset sales, then funds with higher LRISK should have stronger incentives to adopt contractual arrangements that mitigate liquidity stress and run risk.

Among U.S. mutual funds, some prominent examples of liquidity management tools are swing pricing, redemption gates, and temporary halts of redemptions, but in practice these are either almost never used or are very crude instruments. As reported in Form N-CEN, swing pricing is virtually never elected by U.S. mutual funds, and hard gates or suspensions tend to be employed only in extreme circumstances[9]. We therefore focus on redemption in kind, the contractual right that funds can reserve to meet redemption requests by delivering a basket of portfolio securities rather than cash. Under the Investment Company Act of 1940, rule 18f-1 allows a fund that has the right to redeem in kind to elect, by filing Form N-18F-1 with the SEC, to commit to pay in cash all redemptions by any shareholder of record up to the lesser of $250,000 or 1% of the fund's net asset value in any 90-day period, while retaining the option to satisfy amounts above this threshold in kind. The filing specifies the registrant, the series or classes covered, and records this election on an ongoing basis.

Prior work by Agarwal et al. (2023) shows that funds with this right use in-kind redemptions as a liquidity management tool and face weaker run incentives. To test whether funds with higher exposure to systemic liquidity risk are more likely to adopt these rights, we construct a panel of redemption-in-kind rights as follows. We first download all Form N-18F-1 filings from the SEC's EDGAR website. Because the layout and way funds are listed in these forms is often idiosyncratic, automated parsing is very imprecise; instead, for each filing we manually record the names of the funds to which the election applies,

[9] One reason for this is the (perceived) high reputational cost of suspending redemptions among mutual funds.

the filing date, and the CIK of the registrant, and, when no specific fund names are given, we interpret the election as applying to all funds under that CIK. We then match these fund names to Lipper fund names to obtain CUSIPs, first restricting to candidates with the same CIK and then taking the best name match, which we verify by hand. Next, we link the resulting Lipper CUSIPs to CRSP mutual fund identifiers and merge them with our fund-month $\mathcal{E}_n LRISK$ panel (see Equation 11). We obtain a quarterly dataset on 640 corporate bond funds spanning from 2011/03 to 2024/06. Using this dataset, we analyze how LRISK relates to the probability that a fund has an outstanding right to redeem in kind, estimating the following specification:

$$RIK_{n,t} = \beta_1 \mathcal{E}_n LRISK_{t-1} + \gamma \cdot \text{Controls}_{n,t-1} + \alpha_c + \lambda_t + \epsilon_{n,t} \tag{23}$$

where λ_t are month fixed effects to control for aggregate shocks, and finally α_c are fund company fixed effects to control for time-invariant fund group characteristics. This last fixed effect is crucial, since redemption-in-kind filings typically include multiple funds and often apply to all funds at once. Controls include fund-time specific covariates relevant to a fund's LRISK, namely its size as, age since its inception, its historic return volatility (standard deviation of its quarterly yield since inception) and the illiquidity of its holdings as measured by the percentage share of corporate bond holdings out of its whole portfolio.

Table 5 displays the results of the regressions, where the dependent variable is an indicator for whether the fund has elected the right to use RIK via Form N-18F-1. Across all specifications, LRISK enters with a positive and statistically significant coefficient of about 0.02, meaning that an increase of one standard deviation in the exposure LRISK of a fund is associated with a 2 percent increase in the odds of having the right to use RIK. These results indicate that funds with higher ex ante vulnerability to fire sale risk are more likely to secure the option to redeem in kind.

Table 5: Exposure LRISK and the Probability of Using Redemption-in-Kind

This table displays the relationship between a fund's specific Exposure-LRISK and the probability that the fund uses Redemption-in-kind. To isolate the specific information content of the proposed measure, the specifications control for fund group and time variables, as well as fund-level variables pertinent to its liquidity management. $\mathcal{E}_n$LRISK is winsorized at the 5% and 95% level. Standard errors clustered at the fund and date level are reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.**

	Dependent variable:				
	RIK				
	(1)	(2)	(3)	(4)	(5)
$\mathcal{E}_n\text{LRISK}_{t-1}$	0.018*	0.019*	0.021**	0.021**	0.024*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.014)
Corporate Bond Share_{t-1}(log)		−0.005	−0.003	−0.003	0.011
		(0.008)	(0.009)	(0.008)	(0.012)
TNA_{t-1}(log)			0.005	0.003	−0.008
			(0.006)	(0.007)	(0.008)
Return volatility_{t-1}(log)			−0.0004	−0.0003	−0.026**
			(0.011)	(0.011)	(0.012)
Fund age (log)			−0.003	0.002	−0.008
			(0.024)	(0.024)	(0.028)
Fund Group FEs	Yes	Yes	Yes	Yes	No
Time FEs	No	No	No	Yes	Yes
Observations	27,223	27,223	26,346	26,346	26,346
R^2	0.589	0.589	0.594	0.596	0.013
Adjusted R^2	0.586	0.586	0.592	0.593	0.011

4 Conclusions

This paper introduces the LRISK, a new forward-looking measure of systemic liquidity risk in mutual funds, and demonstrates its value for macroprudential oversight. By combining tail risk forecasts of aggregate flows, cross-fund flow contagion, overlapping holdings, and nonlinear price impact dynamics, LRISK captures the amplification mechanisms that make the mutual fund sector and financial markets vulnerable to fire sale spirals. Applied to U.S. corporate bond funds from 2011 to 2024, the measure identifies distinct phases of risk accumulation during relatively calm periods and its subsequent materialization during stress events.

Our empirical tests show that LRISK has strong micro- and macro-level validity. Assets with higher predicted price pressure experience larger losses during stress episodes, funds with greater ex-ante fire-sale exposure subsequently underperform in periods of elevated redemptions, and increases in aggregate LRISK precede by several quarters deteriorations in credit market conditions. Moreover, LRISK helps explain variation in fund liquidity-management choices, specifically predicting the adoption of redemption-in-kind provisions.

Taken together, these findings underscore the importance of monitoring liquidity mismatches and correlated redemption behavior in the rapidly expanding NBFI sector. LRISK provides a scalable, data-driven framework for quantifying systemic vulnerabilities in real time and offers a practical tool for policymakers seeking to assess and mitigate the fire sale risks posed by mutual funds.

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A Descriptive Statistics

Table A.1: Descriptive Statistics of Fund Holdings

Statistics are computed across the sample of fund-level observations between January 2011 and June 2024. TNA stands for total net assets. P5, P25, P50, P75, P95 denote the 5th, 25th, 50th (Median), 75th and 95th percentiles, respectively. All monetary values are in U.S. Dollars.

Variable	**Mean**	**P5**	**P25**	**P50**	**P75**	**P95**
TNA (M$)	1,532	0.10	72	275	1,029	163,941
Cash (%)	2.45	-7.20	0.12	1.45	3.87	15.80
% in Corporate Bonds	62.82	13.09	42.09	62.82	88.87	98
% in Government Bonds	14.9	0	0.28	6.12	23.29	64.56

B LRISK Measure–Calibration & Validation

Table A.2: Covid-19: Realized Bond Pressure and Bond Liquidity

This table presents the estimation of the liquidity spiral parameter (γ) from Equation (3) during the COVID-19 market turmoil (March 2020). The dependent variable is the bond liquidity score ($\text{Liq}_{j,t}$). The key regressor of interest is the realized bond pressure ($V_{j,t}/A_{j,t}$), calculated based on actual fund outflows in March 2020 and assuming a proportional liquidation strategy. Column (1) presents the baseline autoregressive specification (without intercept). Columns (2) through (6) introduce bond-specific controls and fixed effects. HAC standard errors are reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.**

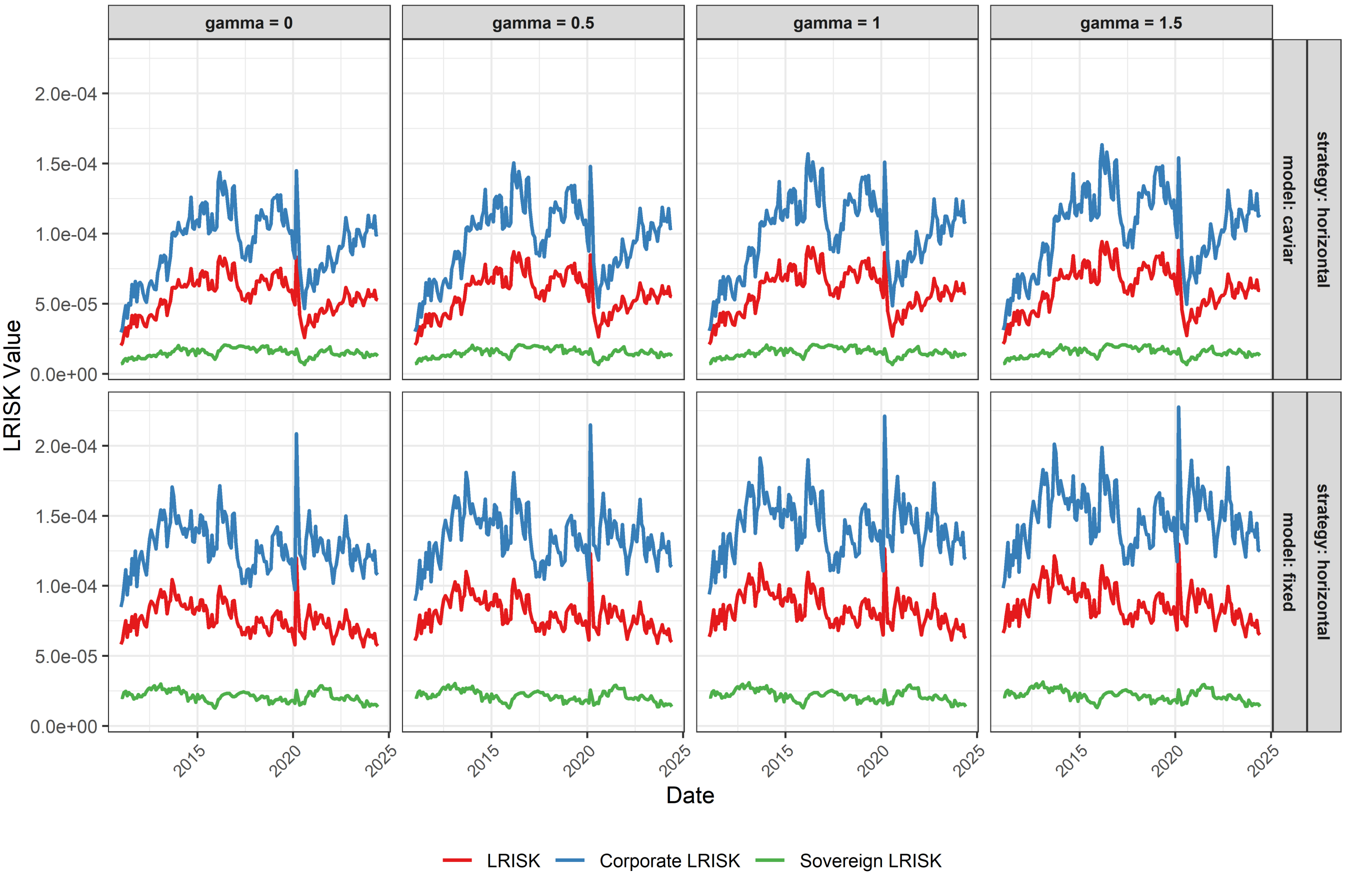
	Dependent variable:					
	Liquidity (t)					
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity_{t-1}	0.896***	1.540***	1.538***	1.546***	1.516***	1.516***
	(0.002)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
Realized V/A_t	−2.611***	−2.529***	−1.915***	−1.891***	−2.029***	−1.962***
	(0.288)	(0.285)	(0.269)	(0.266)	(0.290)	(0.295)
Modified duration_{t-1}		0.003***	0.002**	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Life to maturity_{t-1}		−0.004***	−0.003***	−0.004***	−0.004***	−0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size $(\log)_{t-1}$		0.003	0.005**	0.0001	0.003	0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FE: Bond type (BT)	No	Yes	No	No	Yes	Yes
FE: Debt seniority (DS)	No	No	Yes	No	Yes	Yes
FE: Issuer Type (IT)	No	No	No	Yes	Yes	Yes
FE: BT x DS x IT	No	No	No	No	No	Yes
Observations	11,733	11,733	11,733	11,733	11,733	11,733
R^2	0.319	0.415	0.417	0.419	0.424	0.428
Adjusted R^2	0.319	0.414	0.416	0.419	0.422	0.424

Table A.3: Fund Flow Regressions with Dynamic conditional Beta

This table examines the predictive power of a fund's ex-ante sensitivity to aggregate flows, the Dynamic Conditional Beta ($DCB_{t|t-1}$), on its subsequent net flows. The dependent variable is the monthly fund flow (as a percentage of TNA). The key explanatory variable is the interaction between the lagged DCB (estimated via a DCC-GARCH model) and a dummy for a system-wide redemption shock (RS). A negative coefficient on the interaction term indicates that funds with higher flow betas (ex-ante) experience disproportionately larger outflows during systemic redemption episodes, validating the flow commonality mechanism. The specifications progressively introduce fixed effects for Fund (controlling for time-invariant characteristics) and Month-Year (controlling for aggregate shocks). All models include fund-specific controls (lagged Fund Return, Size, Age, Expense Ratio, Retail share, Open status). Standard errors are clustered by fund and time. *, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.**

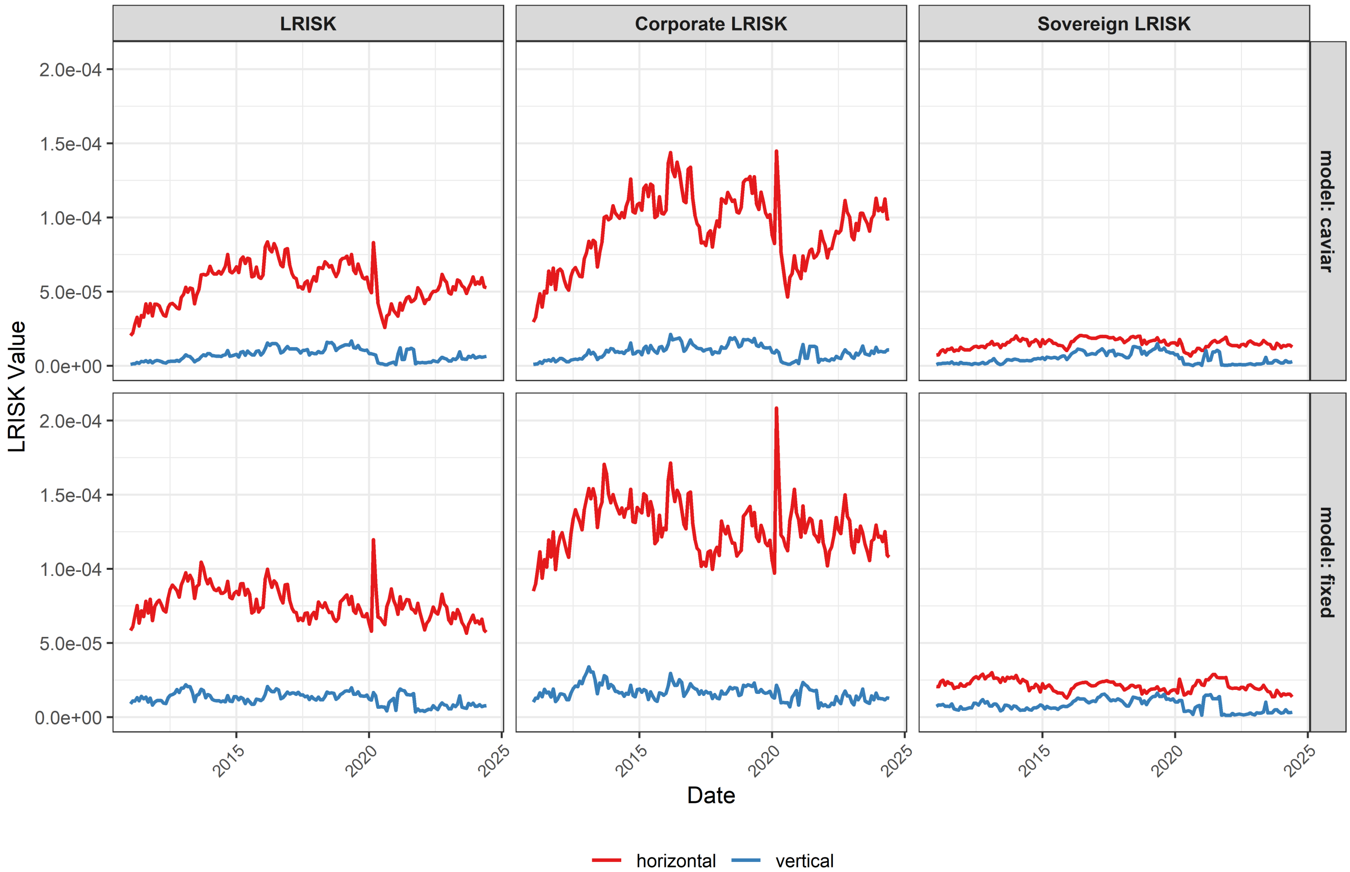
	Fund Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
$DCB_{t\|t-1}$	0.005***	0.005***	0.006***	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Redemption Shock (RS)	−0.010*			−0.002		
	(0.006)			(0.004)		
$DCB_{t\|t-1}$ x RS	−0.011***	−0.011***	−0.010***	−0.011***	−0.011***	−0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fund Return				0.350***	0.212***	0.181***
				(0.048)	(0.056)	(0.054)
Fund $Return_{t-1}$	0.232***	0.158***	0.136***	0.236***	0.151***	0.133***
	(0.059)	(0.045)	(0.044)	(0.046)	(0.042)	(0.041)
FE: Fund	No	Yes	Yes	No	Yes	Yes
FE: Month-Year	No	No	Yes	No	No	Yes
Controls: Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,136	73,136	73,136	73,136	73,136	73,136
R^2	0.060	0.109	0.172	0.072	0.111	0.173
Adjusted R^2	0.060	0.107	0.162	0.072	0.109	0.164

Figure A.1: Aggregate LRISK—Gamma Sensitivity



***Note:** The figure illustrates the sensitivity of the Aggregate LRISK measure to the liquidity spiral parameter γ, defined in Equation 3. Each panel displays the time series of Aggregate LRISK calculated using the baseline horizontal slicing (proportional liquidation strategy), but with a different value for γ (ranging from 0 to 1.5). The figure also compares the Aggregate LRISK calculated using dynamic tail outflows against fixed aggregate outflows (-3.5%). While the absolute magnitude of expected price pressure increases with γ, the time variations and the identification of stress periods remain robust across parameter choices. The baseline specification uses $\gamma = 1.5$, a conservative estimate relative to the empirical value of ≈ 2 derived in Table A.2.*

Figure A.2: Aggregate LRISK—Horizontal vs. Vertical Liquidation Strategy



Note: The figure decomposes the drivers of Aggregate LRISK by comparing different liquidation strategies (colors) and outflow models (rows). The top row uses the baseline dynamic outflow model, while the bottom row uses a static fixed outflow model (set to - 3.5%). The red line represents horizontal slicing (proportional liquidation), while the blue line represents vertical slicing (liquidity-based liquidation). The comparison shows that vertical slicing generates negligible price pressure, suggesting that a realistic measure of systemic fragility should assume proportional liquidation to capture the realized distress observed during crises.

C Additional Robustness Tests

Table A.4: Covid-19: Bond maximum drawdown & LRISK

This table presents the predictive power of the LRISK framework on realized bond market fragility. The dependent variable is the bond-level maximum drawdown calculated from daily prices over the peak of the COVID-19 market turmoil (February–March 2020). The variable of interest is the expected price pressure, estimated ex-ante using data available as of January 2020. Columns (1)–(4) use individual fixed effects for Bond Type, Debt Seniority, and Issuer. Column (5) presents the strictest specification, including a interactive fixed effect (Bond Type × Debt Seniority × Issuer) alongside bond-specific controls. All numerical independent variables are winsorized at the 1% and 99% levels. Standardized regression coefficients are reported. HAC standard errors are reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.**

	Dependent variable:				
	Maximum drawdown: February-March 2020				
	(1)	(2)	(3)	(4)	(5)
Exp. price pressure$_{t-1}$	0.027***	0.026***	0.004***	0.004***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fund coverage	0.016***	0.013***	0.006***	0.007***	0.007***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Modified duration$_{t-1}$	0.030***	0.034***	0.086***	0.085***	0.089***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Life to maturity$_{t-1}$	0.036***	0.035***	−0.010**	−0.010***	−0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Size (log)$_{t-1}$	0.001	−0.003**	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FE: Bond type (BT)	Yes	No	No	Yes	Yes
FE: Debt seniority (DS)	No	Yes	No	Yes	Yes
FE: Issuer	No	No	Yes	Yes	Yes
FE: BT X DS X Issuer	No	No	No	No	Yes
Observations	12,860	12,860	12,860	12,860	12,860
R^2	0.312	0.304	0.915	0.917	0.935
Adjusted R^2	0.311	0.302	0.885	0.888	0.906

D Imputation Strategy for Market Value Outstanding

Accurate calculation of asset-level sales pressure necessitates reliable data on the total market value outstanding (MV) of each security. When MV data is unavailable, we employ a two-step imputation strategy based on asset-class-specific characteristics. First, to manage the influence of outliers and define practical limits for estimation, we winsorize the observed MV values by asset type. The observed MV data are capped at the 2.5% and 97.5% levels. These bounds are used to constrain subsequent imputed values.[10]

We then calculate the asset-class-specific market coverage ratio (MCR) to estimate the proportion of the total outstanding amount that is held by our sample of funds. This ratio is defined as:

$$\mathrm{MCR}_{\mathrm{class}} = \frac{\sum_{j \in \mathrm{class}} \mathrm{Holdings}_j}{\sum_{j \in \mathrm{class}} \mathrm{MV}_j} \tag{24}$$

A lower MCR indicates that funds, in aggregate, hold only a small fraction of the total market. Conversely, a higher MCR indicates that the funds hold a substantial portion of the outstanding securities.

For an asset j with a missing MV, the imputed value ($\mathrm{MV}_{\mathrm{imputed}}$) is estimated by dividing the total absolute market value of that asset held by all funds ($\mathrm{Holdings}_j$) by the calculated coverage ratio ($\mathrm{MCR}_{\mathrm{class}}$):

$$\mathrm{MV}_{\mathrm{imputed},j} = \frac{\mathrm{Holdings}_j}{\mathrm{MCR}_{\mathrm{class}}} \tag{25}$$

This methodology relies on the assumption that MCR is consistent across securities within the same asset class, regardless of whether their MV is initially observed or missing. Finally, the imputed MV is checked against, and constrained by, the previously defined winsorized bounds to maintain consistency with the empirical distribution of observed MV values.

[10] If there is insufficient data within a specific asset class to reliably calculate these bounds, we substitute the bounds derived from the more extensive corporate bond category, ensuring a consistent and realistic range for all imputed values.