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 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. Empirically, LRISK proves valuable across three dimensions: at the micro level, LRISK-implied price pressure predicts the cross-section of bond returns during the COVID-19 crisis; at the fund level, high LRISK exposure predicts underperformance during redemption shocks and explains the adoption of redemption in kind; and at the aggregate level, it acts as an early warning signal forecasting market distress up to two quarters in advance. Finally, a system-wide optimization shows that a central planner could overcome the spillovers of uncoordinated liquidations, suggesting that macroprudential tools could be designed to mitigate systemic liquidity risk.

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, indicate 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 ex ante in the mutual fund sector remains elusive.[3]

In this paper, we introduce LRISK, a dynamic and forward-looking measure designed to quantify the systemic liquidity risk in the mutual fund sector. Unlike banks, which typically sell assets to meet leverage constraints, mutual funds are subject to investor redemptions, a distinct mechanism that renders traditional systemic risk frameworks unsuitable for this industry. LRISK captures this specific vulnerability within a tractable framework that traces the propagation of a redemption shock dynamically. The model operates in three steps. First, it forecasts the magnitude of a

[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."

[3]See the European Central Bank (2026) report of the FSC high level task force on NBFI, which emphasizes that the current regulatory framework is not adequately designed to mitigate systemic risks ex ante. Consequently, the Eurosystem calls for strengthening the macroprudential lens in the regulation of non-bank financial intermediation, advocating for the development of new systemic tools such as an ex ante liquidity instrument for open-ended funds and the implementation of system-wide stress testing.

systemic tail event in aggregate fund flows. Second, it estimates how this aggregate shock is transmitted to individual funds—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)—leading to accumulated forced sales. Third, it maps these projected sales to asset-level liquidity in order to quantify the resulting price pressure on the market.[4] By doing so, LRISK builds on existing systemic risk frameworks developed for the banking sector, such as SRISK (Brownlees and Engle, 2017) and fire-sale spillover models (Duarte and Eisenbach, 2021), and adapts them to the specificities of 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 LRISK 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 substantially, this structural vulnerability has been largely offset by a general improvement in market liquidity conditions. Importantly, LRISK behaves as a countercyclical indicator. It tends to increase during periods of relative market calm and conversely decreases following a crisis, as the immediate probability of a new systemic redemption shock diminishes. The measure reached a peak 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

[4]This approach addresses the limitations of simpler fund-level liquidity metrics, which fail to capture the systemic nature of the risk by overlooking the correlated, simultaneous selling that defines a crisis (Bouveret, 2017; Jiang et al., 2022; Sadka, 2010).

serve as an early warning indicator for future credit market distress. Fourth, 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. Finally, we use the framework to characterize the trade-off between systemic price pressure and fund-level resilience under optimized liquidation strategies, and to quantify the gains from coordinating sales relative to decentralized fund behavior.

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. Moreover, we show that this 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. At the aggregate level, LRISK serves as a reliable early warning signal: increases in systemic liquidity risk precede deteriorations in market functioning by approximately two quarters. Finally, our optimization exercise shows that coordinated liquidation can substantially improve on decentralized fund sales, sharply reducing systemic price pressure while preserving liquidity buffers. 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 and 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., Acharya et al., 2013; Pástor and Stambaugh, 2003). 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.[5]

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

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 (Falato et al., 2020; Pinter et al., 2024; Shleifer and Vishny, 1992). While prior work has separately identified the strategic drivers of fund flows (Barber et al., 2005; Ben-David et al., 2022; Diamond and Dybvig, 1983; Ferson and Kim, 2012; Goldstein et al., 2017; Massa et al., 1999), their interaction with fund liquidity (Chen et al., 2010; Hanouna et al., 2015), and specific contagion mechanisms in the corporate bond market (Coppola, 2025; Darmouni et al., 2022; Fukker et al., 2022; Ma et al., 2022), these channels are typically studied in isolation. We distinguish our work by proposing a comprehensive and tractable framework that integrates these distinct strands into a unified model of systemic risk in the mutual fund sector. Specifically, our approach simultaneously captures liability-side contagion (flow commonality), asset-side contagion (overlapping holdings), and endogenous liquidity 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 and 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 (Baena and Garcia, 2022; Capponi et al., 2020; Dunne et al., 2022; Jin et al., 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, its effectiveness as a predictive tool. Section 4 analyses regulatory implications, examining the relation between LRISK and the use of formal liquidity management tools, and then studying how coordinated liquidation compares with decentralized fund-level sales. Section 5 concludes.

2 LRISK Construction

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 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 :

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

where $V_{j,t+1} = \sum_{n=1}^{N} v^s_{n,j,t+1}$ 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, $v^s_{n,j,t+1}$, depends on its total redemptions $F_{n,t+1}$ and its chosen liquidation strategy s. Let J^s_n be the set of assets fund n liquidates under strategy s. We define liquidation weights $w^s_{n,j,t+1}$ as the fraction of the total outflow $\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$ met by selling asset j, such that $v^s_{n,j,t+1} = w^s_{n,j,t+1}\mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$. These weights satisfy $\sum_{j \in J^s_n} w^s_{n,j,t+1} = 1$, and $w^s_{n,j,t+1} = 0$ for $j \notin J^s_n$. Finally, κ is a normalization coefficient that translates pressure into an expected percentage price drop.

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:

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

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:

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

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

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

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 $\mathbb{E}[V^2_{j,t+1}|\mathcal{S}] \approx (\mathbb{E}_t[V_{j,t+1}|\mathcal{S}])^2$.[6]

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

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

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

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

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

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

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

unless the fund holds large positions in thinly traded markets. Consequently, market-based liquidity scores (i.e, $\text{Liq}_{j,t}$) 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 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 scenario and empirically validate this assumption in Appendix C.1.

(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:

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

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 Portfolio Impact of Systemic Fire Sales

Systemic events 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 expected price pressure on each asset by the fund's initial holding weight:

$$\mathcal{E}_n LRISK_t = \sum_{j=1}^{J} w_{n,j,t} \cdot \mathbb{E}_t \left[PP_{j,t+1} \,|\, \mathcal{S} \right] \tag{10}$$

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 expected price pressure derived in Equation (8). $\mathcal{E}_n LRISK_t$ captures the fund's vulnerability to contagion through its asset exposures.

2.1.4 Coordinated Redemption Strategy and Systemic Risk Minimization

In a global stress scenario ($\mathcal{S}$), uncoordinated liquidation strategies often lead to inefficient outcomes. While individual managers might prefer to sell liquid assets first to minimize immediate costs, such behavior can lead to concentrated selling pressures or deplete the system's liquidity buffers unevenly. A central planner can seek to coordinate liquidations to minimize the aggregate systemic impact ($LRISK_t$) while ensuring that post-sale liquidity is maintained and well-balanced across the system, with a particular focus on the resilience of larger institutions.

To formalize this, we define the liquidity resilience ratio (LRR_n^*) for fund n as the share of liquid assets remaining in the portfolio after the coordinated liquidation:

$$LRR_n^*(\{w_{n,j,t}^*\}) = \frac{\sum_{j=1}^{J} \mathrm{Liq}_{j,t} \left(h_{n,j,t} - v_{n,j,t}^* \right)}{TNA_{n,t} - \mathbb{E}_t[F_{n,t+1} | \mathcal{S}]} \tag{11}$$

where $v^*_{n,j,t} = w^*_{n,j,t} \mathbb{E}_t[F_{n,t+1}|\mathcal{S}]$ is the value of asset j sold by fund n, and $h_{n,j,t}$ is the initial holding value. This ratio captures the fund's post-sale portfolio liquidity. To account for both the aggregate level of resilience and its distribution across funds, the planner penalizes the squared deviation of each fund's ratio from a resilience target (1.0), weighted by the fund's relative size (TNA).

The planner solves a multi-objective optimization problem that balances aggregate risk mitigation with a TNA-weighted resilience penalty:

$$\min_{\{w^*_{n,j,t}\}} \quad \underbrace{LRISK_t}_{\text{Systemic Impact}} \quad +\lambda \cdot \quad \underbrace{\sum_{n=1}^{N} \omega_{n,t}(1 - LRR^*_n)^2}_{\text{TNA-Weighted Resilience Penalty}} \tag{12}$$

$$\text{s.t.} \quad \sum_{j=1}^{J} w^*_{n,j,t} = 1 \quad \forall n \in \{1, \ldots, N\} \tag{13}$$

$$v^*_{n,j,t} \leq h_{n,j,t} \quad \forall \quad n, j, t \tag{14}$$

Where $w_{n,t}$ represents the relative size of fund n, defined as its TNA relative to the aggregate TNA of all funds in the sample. The first term measures the reduction in systemic risk, while the second term captures the post-sale liquidity gap. The constraints ensure that each fund meets its total expected redemption requirement and cannot sell more of a specific asset than it currently holds.

The parameter $\lambda \geq 0$ governs the trade-off. A low λ pushes the system toward an optimized vertical slicing strategy, liquidating the most liquid assets while ensuring a sufficient selling dispersion to minimize $LRISK_t$. A high λ prioritizes a well-balanced system, forcing funds to preserve their liquidity buffers, therefore moving toward a coordinated horizontal slicing strategy.

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.

Appendix A presents our sample selection, and fund-level statistics are detailed in Appendix B. The distribution of TNA is positively skewed. While the median fund size is $483 million, the mean TNA is substantially higher at $2,135 million, indicating that the sample is dominated by a few large funds. Regarding asset allocation, the portfolios are concentrated in corporate bonds, with a median holding of 61.15%. Conversely, holdings of government bonds and cash remain relatively low, with medians of 6.37% and 1.42%, 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.

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).[7] 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 TRACE. 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

[7]We prioritize the use of the effective bid-ask spread measure, i.e. spreads from actual transactions recorded in the TRACE platform. 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.

daily spreads per month, following Jiang et al. (2021). This covers about 75% of assets held by US corporate bonds funds. 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. To address remaining missing bid-ask spreads, we employ an imputation strategy that reflects the illiquidity premium associated with missing market data, described in Appendix F[8].

Subsequently, 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:

$$\text{Liq}_j = 1 - \frac{\text{BAS}_j - \text{BAS}_{\text{min}}}{\text{BAS}_{\text{max}} - \text{BAS}_{\text{min}}} \tag{15}$$

The minimum bid-ask spread (BAS_{min}) is set to 0, representing perfect liquidity. The maximum spread (BAS_{max}) is set at 3.43 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 3.43 percent to $\text{Liq}_j = 0$ (illiquid asset).

Figure A.3 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.

[8]To accurately estimate the price pressure exerted by fund sales, we further impute (rare) missing data in the bond market value outstanding based on the approach detailed in the second subsection of Appendix F.

2.2.3 Modeling Extreme Fund Outflows

The LRISK measure requires estimates of expected tail outflows. Existing models rely on the flow-performance relationship, where an initial aggregate market shock reduces fund returns and induces investor outflows (Darmouni et al., 2022; Fricke and Fricke, 2021). In contrast to these return-driven frameworks, we choose to model the extreme outflows directly, for two primary reasons. First, return-driven frameworks are subject to endogeneity and double counting issues. Observed extreme historical returns, used as an initial shock, already embed the price impact of the fire sales that occurred during the crisis. Simulating an additional round of asset fire sales double counts the systemic price impact. Second, a severe redemption shock does not necessarily originate from a prior decline in asset prices. During periods of macroeconomic stress, such as the COVID-19 dash for cash, some investors liquidated bond fund shares to meet external liquidity needs rather than in response to poor relative fund performance (Ma et al., 2022). Relying on the flow-performance relationship risks underestimating these pure liquidity shocks.

We propose a two-step approach to model fund-level tail outflow risk: first, we estimate the conditional flow betas ($\beta_{n,t+1|t}$), and second, we estimate 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 $\mathbf{D}_t = \mathrm{diag}(\sigma_{n,t}, \sigma_{m,t})$ 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 $\mathbf{H}_{t+1|t}$:

$$\beta_{n,t+1|t} = \frac{[\mathbf{H}_{t+1|t}]_{nm}}{[\mathbf{H}_{t+1|t}]_{mm}} \tag{16}$$

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 A.4 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 C (Table A.5). 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.

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:

$$C_{t+1} = Q_{0.005,t+1} = \beta_0 + \beta_1 Q_{0.005,t} + \beta_2 |F_{m,t}| \tag{17}$$

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.[9]

Figure A.5 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

[9] 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.

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.

2.2.4 Liquidity Spiral (γ)

A central amplification mechanism in the LRISK framework is the liquidity spiral, where flow-driven selling pressure actively degrades the liquidity of the underlying assets. This effect is governed by the parameter γ, which measures the sensitivity of asset liquidity to fire sales. Having established horizontal slicing as a valid baseline for manager behavior during a systemic shock in Appendix C.1, we use this insight to empirically calibrate γ.

Estimating the causal impact of sales on liquidity using OLS is subject to endogeneity bias. As highlighted by Edmans et al. (2012), observable trades often reflect discretionary decisions by managers rather than exogenous shocks. During a crisis, active fund managers may avoid selling assets experiencing the most severe liquidity shocks, or conversely, liquidate bonds based on private information regarding their future fundamentals. This endogenous selection creates a correlation between the error term and actual sales, thereby attenuating the OLS coefficient.

To solve this identification challenge, we employ an instrumental variable (IV) approach closely aligned with the fire-sale literature (e.g., Coval and Stafford, 2007; Edmans et al., 2012). We instrument the actual sales of bond j as a fraction of its total outstanding amount, $Actual(V/A)_{j,t}$, using the theoretical projected sales based on the horizontal slicing assumption, $Projected(V/A)_{j,t}$. The instrument is constructed by interacting pre-shock (January 2020) portfolio weights with the aggregate realized outflows of the funds during the February-March 2020 window. It enables to isolate the exogenous component of selling pressure, thereby purging it of real-time managerial discretion.

We estimate the following two-stage least squares (2SLS) model at the bond level:

$$Actual(V/A)_{j,t} = \alpha_1 + \theta Projected(V/A)_{j,t} + \delta_1 Controls_{j,t-1} + u_{j,t} \tag{18}$$

$$\Delta Liquidity_{j,t} = \alpha_2 + \gamma \widehat{Actual(V/A)}_{j,t} + \delta_2 Controls_{j,t-1} + \epsilon_{j,t} \tag{19}$$

where $\Delta Liquidity_{j,t}$ is the change in the bond's liquidity score from January to March 2020. The control variables include lagged asset liquidity, the log of bond duration, bond maturity, and amount outstanding. To absorb unobserved differences in liquidity provision across different segments of the market, we include fixed effects for bond type and seniority. Standard errors are clustered at the issuer level.

Table A.3 reports the estimation results. Column (1) presents a biased OLS coefficient associated with actual sales of -0.93. Column (2) presents the reduced-form regression, confirming that our exogenous instrument directly predicts the deterioration in bond liquidity. Columns (3) and (4) report the IV estimates. In particular, Column 4 report a coefficient on instrumented actual sales of -1.87, which is statistically significant at the 1% level. The first-stage F-statistic is 213.5, confirming the relevance of the horizontal slicing projection. Based on these results, we calibrate the liquidity spiral parameter of the LRISK model to $\gamma = 1.87$. This parameter is subsequently integrated into Equation 8 to compute the expected price pressure generated by a global redemption shock.

2.2.5 LRISK Normalization (κ)

The final step in our empirical calibration is to scale the dimensionless price pressure variable into an interpretable metric of expected price depreciation, allowing the aggregate LRISK measure to be expressed in percentage terms. This mapping is governed by the normalization coefficient κ. To estimate this parameter, we construct the actual price pressure ($ActualPP_{j,t}$) for each bond using Equation 8. We populate the equation with the actual realized sales of the bond (V/A), its lagged liquidity ($Liq_{j,t-1}$), and the empirically calibrated liquidity spiral parameter γ from the previous section.

Similar to the γ estimation, regressing realized bond returns on actual price pressure using OLS is subject to endogeneity and measurement error. Therefore, we use a similar instrumental variable framework. We construct the exogenous instrument, projected price pressure ($ProjectedPP_{j,t}$), by replacing the actual sales volume in Equation 8 with the projected sales volume derived from the horizontal slicing assumption. We estimate the following 2SLS model:

$$ActualPP_{j,t} = \alpha_3 + \phi ProjectedPP_{j,t} + \delta_3 Controls_{j,t-1} + v_{j,t} \tag{20}$$

$$Return_{j,t} = \alpha_4 + \beta \widehat{ActualPP}_{j,t} + \delta_4 Controls_{j,t-1} + \epsilon_{j,t} \tag{21}$$

where $Return_{j,t}$ is the cumulative mid-price return of bond j over the February to March 2020 crisis period. The control variables include the lagged liquidity of the bond. During market crashes, illiquid bonds experience severe price declines independent of mutual fund liquidations. By explicitly controlling for lagged liquidity, we ensure that our κ coefficient captures the causal impact of the flow-driven fire sale. We maintain the same controls and fixed effects used in the γ regressions.

Table A.4 presents the estimation results. Column (1) presents a biased OLS coefficient associated with actual price pressure of -2.28. Column (2) reports the reduced-form estimate, confirming that the projected price pressure instrument directly predicts the cross-section of bond returns. Columns (3) and (4) report the IV estimates. The coefficient on instrumented actual price pressure (κ) is -4.65 (Column 4), statistically significant at the 1% level. The first-stage F-statistic of 126.8 confirms that the instrument remains robust after the price pressure transformation. Consistent with our findings in the γ estimation, the IV specification reveals a substantially larger effect than the OLS benchmark.

3 LRISK Validation

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. Having computed aggregate, fund-level and asset-level LRISK measures, we first 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.

3.1 Aggregate LRISK

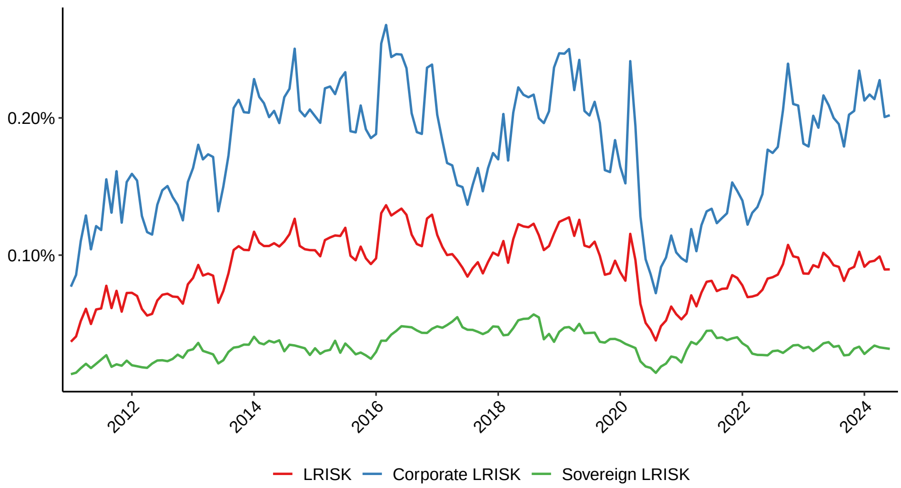
With our calibrated price pressure function, we construct the LRISK. Figure 1 presents the time series of the aggregate LRISK measure for the U.S. corporate bond fund sector from 2011 to 2024. Our main specification relies on the proportional liquidation approach combined with dynamic outflows. Over 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 A.1), this structural vulnerability was largely counterbalanced by an overall improvement in market liquidity conditions between 2011 and 2020 (see Figure A.3). 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 A.5). Furthermore, the measure peaks at 0.25% in March 2020[10], mostly reflecting a sudden deterioration in asset liquidity. Finally, the LRISK decomposition 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 A.2 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. It also highlights a divergence in aggregate LRISK dynamics between the horizontal and vertical slicing liquidation strategies. For horizontal slicing (top two rows), LRISK levels remain stable as γ increases from 0 to 2. This lack of sensitivity suggests that price pressure under proportional liquidation is primarily driven by linear impact costs, as outflows are diversified proportionally across all assets in the portfolio weight. In contrast, vertical slicing (bottom two rows) is highly sensitive to variations in γ. At $\gamma = 0$, aggregate price pressure is near-zero because funds manage outflows by liquidating only highly tradable, liquid assets with negligible impact costs. However, higher γ values strongly increase the non-linear, quadratic component of the price pressure. When outflows get large enough to exhaust a fund's buffer of liquid assets, concentrated selling must shift to less liquid corporate bonds. This concentrated pressure, coupled with a higher γ amplifier, triggers a spike in price

[10] This figure represents the average effect of expected fire sales across the entire U.S. corporate bond market. While this magnitude may appear modest, it masks substantial heterogeneity across individual bonds. Furthermore, it only reflects the impact of fire sales originating from U.S. corporate bond funds, ignoring other procyclical holders, such as multi-asset funds.

impact, leading to the rise in aggregate and corporate LRISK observed for $\gamma = 1$ and $\gamma = 2$.

Figure 1: 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 $\gamma = 1.87$. The measure is decomposed into the contributions from corporate bonds (blue line) and sovereign bonds (green line).

3.2 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:

$$\text{MaxDrawdown}_{j,t\to t+1} = \beta \cdot \mathbb{E}_{t-1}[PP_{j,t}|\mathcal{S}] + \gamma \cdot \text{Controls}_{j,t-1} + \alpha_{\text{Type}} + \alpha_{\text{Seniority}} + \alpha_{\text{Issuer}} + \epsilon_j \quad (22)$$

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 bond characteristics. The effect is economically substantial: a one standard deviation increase in expected price pressure is associated with an increase in drawdown ranging from 0.6% (Column 3) to 3.6% (Column 1). To ensure these results are not driven solely by the concentration of ownership or asset liquidity, we conduct robustness checks in Table A.6 by controlling for the percentage of each bond held by U.S. investment funds. While this mitigates the magnitude of the coefficients (ranging from 0.4% to 0.9%), 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. Standard errors are clustered by issuer. *, **, 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$_{t-1}$	0.036***	0.034***	0.006***	0.007***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Modified duration$_{t-1}$	0.032***	0.035***	0.084***	0.084***	0.088***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Life to maturity$_{t-1}$	0.034***	0.033***	−0.009*	−0.010**	−0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Size (log)$_{t-1}$	−0.006**	−0.009***	0.004***	0.003***	0.003***
	(0.002)	(0.002)	(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	12,979	12,979	12,979	12,979	12,979
R^2	0.312	0.308	0.914	0.916	0.934
Adjusted R^2	0.311	0.307	0.884	0.886	0.904

3.3 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 10), 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:

$$R_{n,t} = \beta_1 \mathcal{E}_n \text{LRISK}_{t-1} + \beta_2(\mathcal{E}_n \text{LRISK}_{t-1} \times RS_t) + \gamma \cdot \text{Controls}_{n,t-1} + \alpha_n + \lambda_t + \epsilon_{n,t} \tag{23}$$

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 10) 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)
$\mathcal{E}_n$LRISK$_{t-1}$	0.002***	0.001***	0.001	0.002***	0.001***	0.001
	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0004)	(0.001)
Redemption Shock (RS)	−0.024**			−0.023**		
	(0.010)			(0.009)		
$\mathcal{E}_n$LRISK$_{t-1}$ x RS	−0.011***	−0.011***	−0.012***	−0.010***	−0.011***	−0.012***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Fund Flows (%)				0.044***	0.011***	0.010***
				(0.009)	(0.002)	(0.002)
Fund Flows$_{t-1}$(%)	−0.004	0.0003	−0.001	−0.017**	−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	70,666	70,666	70,666	70,666	70,666	70,666
R^2	0.113	0.634	0.638	0.128	0.635	0.639
Adjusted R^2	0.113	0.633	0.634	0.128	0.634	0.635

3.4 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 the Corporate Bond Market Distress Index ($CMDI$), a comprehensive measure of U.S. market functioning (Boyarchenko et al., 2025).[11]

Following the specification proposed by Allen et al. (2012) and Brownlees and Engle (2017), we estimate predictive regressions for the future monthly change in this stress indicator (ΔCMDI_{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:

$$\Delta\text{CMDI}_{t+h} = \alpha + \sum_{k=0}^{2} \beta_k \Delta\text{LRISK}_{t-k} + \sum_{k=0}^{2} \phi_k \Delta\text{CMDI}_{t-k} + \delta \cdot \Delta\text{Macro}_t + \epsilon_{t+h} \tag{24}$$

The control variables ΔMacro_t include 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 reports the results for the Corporate Bond Market Distress index. We find that aggregate corporate LRISK contains significant predictive information for future deteriorations in market functioning. Increases in current and lagged LRISK exhibit positive and statistically significant coefficients across multiple short- to medium-term horizons, specifically from 1 to 6 months ahead (e.g., ΔLRISK_t at Lead 1, ΔLRISK_{t-2} at Lead 2, and ΔLRISK_{t-1} at Lead 3 and Lead 6). This indicates that a buildup in systemic liquidity risk in the fund sector anticipates broader corporate bond market distress up to two quarters in advance. Furthermore, the incremental explanatory

[11] 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.

power is meaningful: including LRISK as a predictive variable increases the adjusted R^2 by up to 2.0 percentage points (at Lead 2) over the baseline model, with positive contributions persisting throughout the first six months. Beyond Lead 6, the ΔAdj. R^2 becomes negative, confirming LRISK's role as an early warning signal for impending, rather than distant, market fragility.

Table 3: 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$_t$	0.059**	−0.037	−0.013	0.051*	−0.036	−0.003	0.037	0.004	0.002	0.002
	(0.026)	(0.029)	(0.020)	(0.027)	(0.024)	(0.033)	(0.039)	(0.024)	(0.025)	(0.025)
ΔLRISK$_{t-1}$	−0.011	−0.010	0.059**	−0.016	0.014	0.058**	0.006	−0.004	−0.007	−0.007
	(0.030)	(0.022)	(0.024)	(0.027)	(0.035)	(0.028)	(0.024)	(0.027)	(0.027)	(0.019)
ΔLRISK$_{t-2}$	−0.004	0.055*	−0.015	0.017	0.051*	0.005	0.005	0.002	−0.007	−0.011
	(0.023)	(0.029)	(0.026)	(0.035)	(0.028)	(0.026)	(0.023)	(0.025)	(0.022)	(0.021)
ΔCMDI$_t$	0.146**	−0.048	−0.042	−0.090	−0.182**	−0.016	0.032	−0.064	−0.014	−0.143***
	(0.071)	(0.116)	(0.063)	(0.084)	(0.075)	(0.070)	(0.080)	(0.083)	(0.071)	(0.055)
ΔCMDI$_{t-1}$	0.012	−0.042	−0.086	−0.150**	0.008	0.032	−0.070	−0.032	−0.107*	−0.081*
	(0.078)	(0.071)	(0.076)	(0.068)	(0.082)	(0.077)	(0.069)	(0.076)	(0.062)	(0.044)
ΔCMDI$_{t-2}$	−0.022	−0.146*	−0.153*	0.060	0.002	−0.071	−0.036	−0.146**	−0.059	0.081
	(0.068)	(0.084)	(0.089)	(0.096)	(0.074)	(0.075)	(0.049)	(0.059)	(0.050)	(0.056)
ΔTerm Spread$_t$	−0.006	−0.014	−0.001	0.006	−0.040**	0.016	0.001	−0.027	−0.021	−0.009
	(0.023)	(0.020)	(0.018)	(0.017)	(0.016)	(0.024)	(0.015)	(0.024)	(0.018)	(0.016)
ΔHousing Market$_t$	0.004	−0.074**	0.054	0.041	−0.020	−0.020	−0.022	0.001	0.076*	−0.062*
	(0.035)	(0.031)	(0.039)	(0.026)	(0.028)	(0.029)	(0.043)	(0.039)	(0.045)	(0.037)
ΔS&P500$_t$	−0.125	−0.107	−0.067	0.037	0.018	−0.184	−0.071	0.094	0.152	−0.077
	(0.144)	(0.129)	(0.121)	(0.140)	(0.103)	(0.117)	(0.135)	(0.113)	(0.183)	(0.081)
ΔVIX$_t$	0.002	0.0001	0.0004	−0.0002	−0.0002	−0.002	−0.0004	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	−0.003	−0.005*	−0.006*	−0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	158	157	156	155	154	153	152	151	150	149
R^2	0.241	0.095	0.094	0.079	0.095	0.056	0.028	0.039	0.066	0.054
Adj. R^2	0.189	0.033	0.031	0.016	0.031	-0.011	-0.040	-0.030	-0.001	-0.015
Δ Adj. R^2	0.017	0.020	0.016	0.007	0.019	0.007	-0.013	-0.021	-0.024	-0.024

4 Regulatory Implications

For regulatory purposes, the appeal of LRISK is not simply that it measures vulnerability, but that it does so in a way that speaks directly to mechanisms that both funds and regulators care about: redemption pressure, asset liquidation, and spillovers through common markets. This makes LRISK useful both for studying how funds prepare for liquidity stress and for assessing how liquidation decisions affect the system as a whole. Accordingly, we proceed in this final section in two steps. We first examine the relation between LRISK and the use of formal liquidity management tools. We then study how coordinated liquidation compares with decentralized fund-level sales.

4.1 LRISK and Fund Liquidity Management

Liquidity management 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[12]. We therefore focus on redemption in kind (RIK), 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

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

exposure to systemic liquidity risk are more likely to adopt these rights, we construct a panel of RIK 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, 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 10). 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:

$$RIK_{n,t} = \beta_1 \mathcal{E}_n LRISK_{t-1} + \gamma \cdot \text{Controls}_{n,t-1} + \alpha_c + \lambda_t + \epsilon_{n,t} \tag{25}$$

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 RIK 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 4 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 4: Exposure LRISK and the Probability of Using Redemption-in-Kind

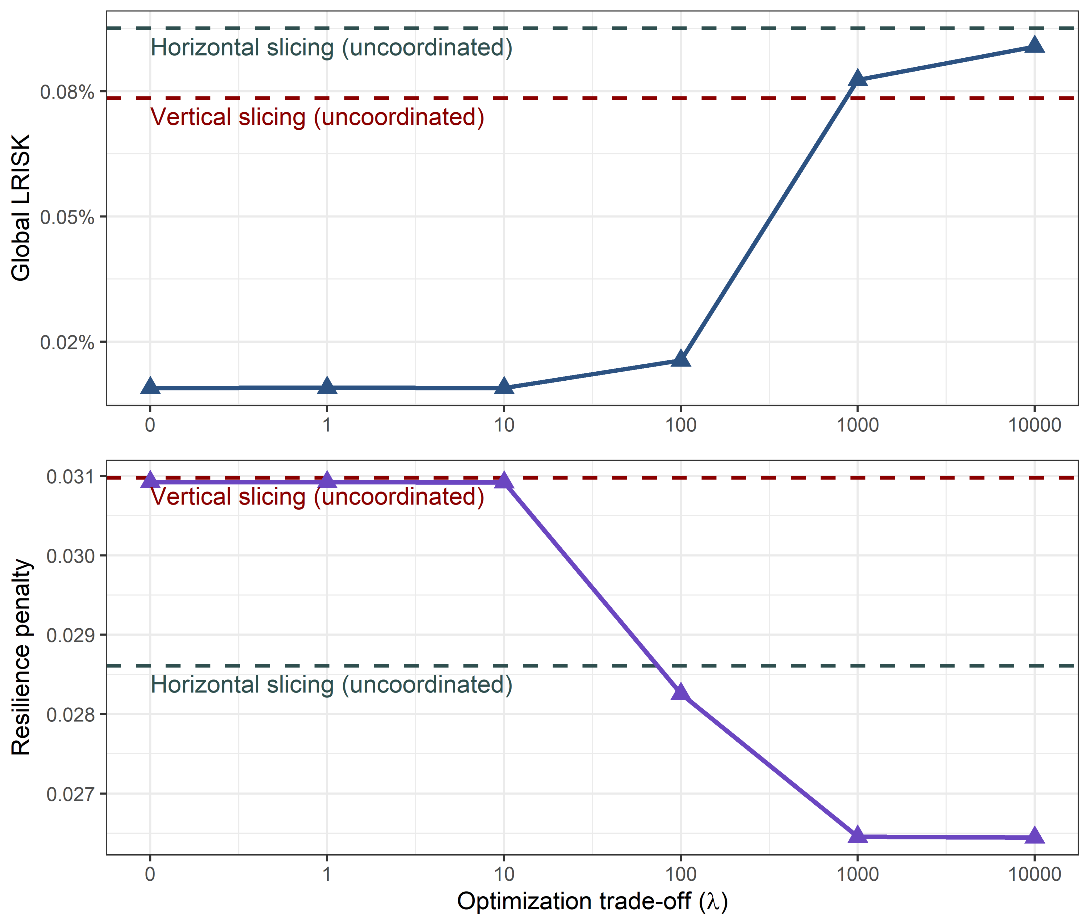
This table displays the relationship between a fund's specific Exposure-LRISK and the probability that the fund uses Redemption-in-kind. To isolate the specific information content of the proposed measure, the specifications control for fund group and time variables, as well as fund-level variables pertinent 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)
$\mathcal{E}_n\text{LRISK}_{t-1}$	0.022**	0.024**	0.027**	0.027**	0.034**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.016)
Corporate Bond Share$_{t-1}$(log)		−0.007	−0.006	−0.006	0.008
		(0.008)	(0.009)	(0.009)	(0.012)
TNA$_{t-1}$(log)			0.004	0.003	−0.010
			(0.006)	(0.007)	(0.008)
Return volatility$_{t-1}$(log)			−0.002	−0.002	−0.027**
			(0.011)	(0.011)	(0.012)
Fund age (log)			−0.003	0.002	−0.009
			(0.024)	(0.024)	(0.028)
Fund Group FEs	Yes	Yes	Yes	Yes	No
Time FEs	No	No	No	Yes	Yes
Observations	26,702	26,702	25,848	25,848	25,848
R^2	0.593	0.594	0.599	0.601	0.018
Adjusted R^2	0.591	0.591	0.596	0.597	0.016

4.2 The Value of Coordination

To evaluate the inefficiencies generated by decentralized liquidation decisions, we compute the coordinated liquidation strategy that minimizes the objective function defined in Equation 12. The planner's preference parameter λ allows regulators to strike a balance between reducing immediate systemic costs and preserving future resilience. Figure 2 illustrates this trade-off as of January 2020, using the full sample of portfolio holdings. The top panel reports the resulting aggregate LRISK, while the bottom panel reports the TNA-weighted resilience penalty. For reference, we include the outcomes of the two uncoordinated baseline strategies evaluated at the same date: horizontal slicing (dashed grey line) and vertical slicing (dashed red line).

Figure 2: The Coordination Trade-off



This figure plots the trade-off defined in the central planner's coordinated liquidation strategy (see Equation 12) as of January 2020 using the full sample of portfolio holdings. The top panel displays the aggregate LRISK, and the bottom panel shows the TNA-weighted resilience penalty across different values of the preference parameter λ. The dashed lines represent the uncoordinated vertical (red) and horizontal (grey) slicing benchmarks.

The uncoordinated benchmarks reveal a market failure driven by portfolio overlap and flow commonality. Under uncoordinated vertical slicing, funds sell their most liquid assets first. While this reduces immediate systemic costs compared to the horizontal slicing strategy, it depletes the funds' liquidity buffers, maximising the resilience penalty. Conversely, uncoordinated horizontal slicing preserves the funds' asset allocation and liquidity ratios, but forces the sale of illiquid assets, thereby increasing immediate systemic costs.

When the central planner strictly prioritizes the mitigation of systemic risk ($\lambda \leq 10$), there is a significant improvement in market stability compared to the uncoordinated baselines. Immediate systemic costs are reduced by 70-80% compared to the uncoordinated benchmarks. The optimizer implements a smart vertical slicing strategy, targeting liquid assets first while avoiding the concentration of sales on specific bonds by distributing the liquidation burden across the system. However, the bottom panel shows that this strategy requires the depletion of the funds' liquidity buffers, resulting in a high resilience penalty.

The optimizer achieves an optimal balance when λ increases to 100, as the central planner succeeds in reducing the resilience penalty below the uncoordinated benchmarks while keeping immediate systemic costs low. This balance is achieved by forcing funds with ample liquidity buffers to sell their liquid assets while enabling the most vulnerable funds to dispose of some illiquid assets with a low aggregate fund footprint. Within this optimal range, the central planner largely avoids the effects of fire sale spillovers on financial markets while using the shock to improve the distribution of liquidity buffers across the mutual fund universe.

Ultimately, this optimization exercise emphasizes the importance of system-wide coordination in mutual fund liquidity management. In a decentralized market, individually rational behavior can drive funds toward mutually destructive liquidation strategies. However, our findings show that central planners can strike an optimal balance between reducing immediate systemic costs and preserving future resilience. Although perfectly coordinated sales may be impractical, these results suggest that regulators have scope to develop and implement new macroprudential liquidity management tools to guide the mutual fund sector toward this optimal balance.

5 Conclusion

This paper introduces LRISK, a new forward-looking measure of systemic liquidity risk in mutual funds, and demonstrates its value for macroprudential oversight. LRISK captures the amplification mechanisms that make the mutual fund sector and financial markets vulnerable to fire sale spillovers, i.e., correlated redemption risk, portfolio similarity, and liquidity 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.

Finally, while current regulations primarily target individual fund resilience, our coordination analysis indicates that individually rational behavior during a shock can still drive funds toward mutually destructive liquidation strategies. As authorities look to design new macroprudential liquidity instruments and implement system-wide stress testing, our framework suggests that these tools must be calibrated to target flow commonality and portfolio similarity. By adopting a system-wide perspective, regulators can guide the mutual fund sector toward an equilibrium that successfully mitigates aggregate price pressure while preserving fund resilience.

Taken together, LRISK provides a scalable, data-driven framework for quantifying systemic vulnerabilities in near real time and offers a practical tool for policymakers seeking to assess and mitigate the fire sale risks posed by the rapidly expanding mutual fund sector.

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A Fund Sample Construction

We follow Jiang et al. (2021) by selecting corporate bond funds based on the objective codes provided by the CRSP.[13] 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 769 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:

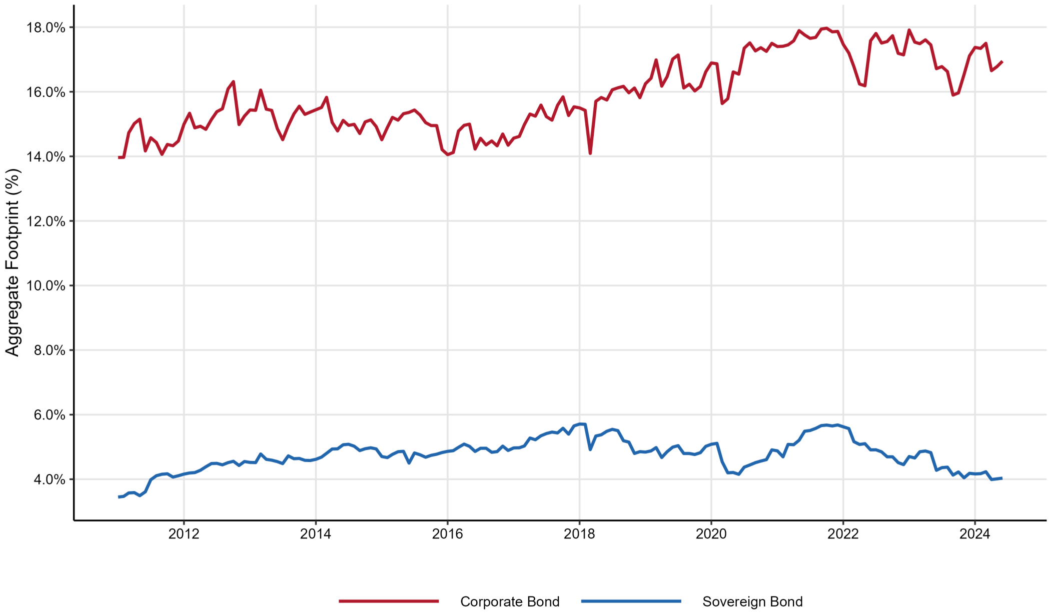
$$Flows_{n,t} = \frac{TNA_{n,t} - (TNA_{n,t-1} \cdot (1 + R_{n,t}))}{TNA_{n,t-1}} \tag{26}$$

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.

Figure A.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, from approximately 14% in 2011 to a peak of 18% at the end of 2020. This highlights that mutual funds have become increasingly critical marginal holders of corporate credit. Notably, the volatility observed around 2020 reflects the 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.

[13] 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".

Figure A.1: Fund Footprint



Note: The figure shows the aggregate monthly holdings of our sample of mutual funds relative to the total market capitalization of U.S. corporate and sovereign bonds. To compute the total market capitalization (the denominator), we rely on representative Bloomberg fixed-income indices. Specifically, the corporate bond universe is proxied by the Bloomberg US Corporate Bond Index and the Bloomberg US Corporate High Yield Bond Index. The sovereign bond universe is proxied by the Bloomberg US Treasury Index and the Bloomberg US Treasury Bills Index. We favor these indices because they impose strict size and liquidity inclusion rules, thereby serving as a proxy for the actual investable universe of securities actively traded by institutional investors.

B 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, P75, P95 denote the 5th, 25th, 75th and 95th percentiles, respectively.

Characteristics	Mean	SD	P5	P25	Median	P75	P95	N
Fund-level								
TNA (USD millions)	2135.526	6289.075	27.500	145.600	483.100	1583.400	8991.800	88709
Monthly return (%)	0.269	2.347	-2.353	-0.288	0.268	0.956	2.889	88348
Monthly flows (%)	0.920	77.083	-5.265	-1.154	-0.074	1.287	7.697	88337
Fund age (years)	17.200	12.116	2.351	7.778	15.167	24.600	37.495	88709
Open to investors	0.986	0.100	0.987	1.000	1.000	1.000	1.000	88709
Share of retail investors (%)	29.914	36.406	0.000	0.000	10.417	56.339	100.000	88709
Expense ratio	0.007	0.003	0.001	0.005	0.007	0.009	0.012	73150
Maximum front-end load (%)	0.004	0.012	0.000	0.000	0.000	0.000	0.040	88709
Maximum rear-end load (%)	0.000	0.002	0.000	0.000	0.000	0.000	0.000	88709
Quarterly turnover ratio	0.992	2.062	0.140	0.350	0.580	1.010	3.280	73261
Average portfolio maturity (years)	8.880	5.342	2.800	5.800	7.400	11.300	17.200	88673
Corporate bond holdings (%)	61.701	26.768	16.828	41.130	61.150	87.820	97.370	88709
Government bond holdings (%)	15.861	21.605	0.000	0.370	6.370	23.460	64.910	88709
Cash holdings (%)	3.568	8.112	0.000	0.090	1.420	3.710	12.540	88709
Exposure LRISK	0.184	0.241	0.007	0.026	0.065	0.270	0.712	88709
Bond-level								
Market value (USD millions)	3950.676	16712.243	80.113	355.842	617.677	1206.378	15815.497	4070967
V/A	0.001	0.003	0.000	0.000	0.000	0.001	0.006	4070967
Liquidity	0.868	0.138	0.661	0.744	0.927	0.974	0.996	4070967
Expected price pressure	0.086	0.289	0.000	0.002	0.012	0.044	0.431	4070967

C LRISK Calibration

C.1 LRISK Calibration: Fund Liquidation Strategies

The baseline LRISK measure assumes that, conditional on a systemic redemption shock, mutual funds employ a proportional liquidation strategy (horizontal slicing), thereby preserving their initial portfolio allocation $w_{n,j,t}$. To evaluate the empirical validity of this assumption against the alternative of liquidity-driven liquidation (vertical slicing), we estimate a series of regressions at the fund-bond level during the COVID-19 market turmoil.

To test this mechanism, we first need to isolate the active trading decisions of fund managers (the flow effect) from mechanical changes in portfolio weights driven by asset price fluctuations (the valuation effect). Therefore, we construct our dependent variable, $NetSold_{n,j,t}$, based on the change in the quantity of the asset held, holding prices constant at their pre-shock levels. Specifically, let $S_{n,j,t-1}$ and $S_{n,j,t}$ denote the number of shares (or par amount) of bond j held by fund n at the end of January 2020 and March 2020, respectively. We compute the dollar volume of the trade by multiplying the change in shares by the pre-shock asset price, $P_{j,t-1}$. We then normalize this active flow by the initial dollar value of the fund's position in that bond to determine the proportion of the position that was liquidated. Finally, we invert the sign such that a positive value strictly indicates a net sale. For positions that are completely liquidated by March, $S_{n,j,t}$ is set to zero, yielding a $NetSold$ value of 1.

We examine how $NetSold_{n,j,t}$ responds to aggregate fund outflows ($Outflow_{n,t}$) and the lagged liquidity of the underlying asset by estimating the following general specification:

$$NetSold_{n,j,t} = \alpha_j + \alpha_n + \beta_1(Outflow_{n,t} \times Liq_{j,t-1}) + \delta Controls_{n,j,t-1} + \epsilon_{n,j,t} \quad (27)$$

where α_j and α_n represent bond and fund fixed effects, respectively, which absorb unobserved heterogeneity at the asset and institution level. The regressions are value-weighted by the fund's pre-shock portfolio shares as of January 2020. We measure liquidity both in absolute terms ($Liquidity_{j,t-1}$) and as the relative liquidity rank of the bond within the fund's specific portfolio ($FundLiqRank_{n,j,t-1}$). Following Ma et al. (2022), the relative liquidity rank is defined as the value-weighted rank of bond j's liquidity within fund n's portfolio. We sort all bonds held by fund

n in ascending order of their lagged liquidity and compute the rank as the mid-point cumulative portfolio weight:

$$FundLiqRank_{n,j,t-1} = \frac{\sum_{k \in \Omega_n, Liq_k < Liq_j} w_{n,k,t-1} \ + \ 0.5 \cdot w_{n,j,t-1}}{\sum_{k \in \Omega_n} w_{n,k,t-1}} \tag{28}$$

where Ω_n is the set of all corporate bonds held by fund n. This specification transforms the absolute liquidity score into a continuous variable bounded between 0 (the least liquid bond in the fund's portfolio) and 1 (the most liquid bond).

Table A.2 presents the estimation results. In Column (1), we test the direct macro pass-through of outflows to asset sales, controlling for bond fixed effects to absorb asset-specific shocks. The coefficient on fund outflows is positive and statistically significant at the 1% level. This provides baseline evidence that a 1% redemption at the fund level translates, on average, into an 0.86% liquidation of the underlying bond holdings.

In Column (2), we investigate the unconditional presence of a pecking order. The positive and significant coefficient on lagged liquidity (0.227) suggests that funds exhibit a tendency to liquidate more liquid assets. However, to evaluate the mechanics of the LRISK framework, we need to determine whether this vertical slicing is amplified during a severe redemption shock at the fund level. Columns (3) and (4) test this effect by interacting the fund's outflow percentage with the bond's absolute liquidity and its relative intra-fund liquidity rank (Equation 28), respectively. In both specifications, the interaction terms are not statistically different from zero. This indicates that the sensitivity of fund sales to asset liquidity does not exhibit a statistically significant increase as outflows become more severe.

Overall, we do not find evidence that mutual funds increasingly rely on vertical slicing in the event of a large redemption shock. Consequently, the proportional liquidation assumption serves as a plausible baseline to compute the expected sales volume ($V^E_{j,t}$) in our aggregate LRISK measure.

Table A.2: Mutual Fund Liquidations Strategy

This table presents micro-level regressions examining mutual fund liquidation strategies. The dependent variable is the Net Sold (%) of individual assets by fund. Columns (1-4) evaluate the horizontal and vertical slicing strategies. Regressions are value-weighted by January 2020 portfolio shares. Standard errors are clustered at the fund level and reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.**

	Dependent variable:			
	Net Sold (%)			
	(1)	(2)	(3)	(4)
Outflow (%)	0.863***			
	(0.170)			
Asset liquidity		0.227***		
		(0.026)		
Outflow (%) × Asset Liquidity			0.350	
			(0.280)	
Outflow (%) × Fund Liq. Rank				0.008
				(0.124)
Fund liquidity	−0.748***			
	(0.186)			
Log(Fund TNA)	−0.009			
	(0.008)			
Portfolio share	0.014	0.463	0.544***	0.544***
	(0.169)	(0.383)	(0.126)	(0.126)
Log(Asset size)		0.032***		
		(0.004)		
Log(Modified duration)		−0.021***		
		(0.006)		
Log(Maturity)		−0.031***		
		(0.004)		
Bond FE	Yes	No	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Observations	207,425	149,598	207,425	207,425
R^2	0.586	0.455	0.770	0.770
Adjusted R^2	0.442	0.454	0.689	0.689

C.2 LRISK Calibration: Estimating γ

Table A.3: Flow-Driven Fire Sales and the Liquidity Spiral

This table presents cross-sectional regressions estimating the impact of mutual fund flow-driven sales on corporate bond liquidity. The dependent variable is the change in bond liquidity (ΔLiquidity) from end of January 2020 to end of March 2020. Columns (1-2) report OLS estimates using Actual Sales (V/A) and Projected Sales (horizontal slicing). Columns (3-4) report 2SLS regressions where Actual Sales are instrumented by Projected Sales. The coefficient on the fitted Actual Sales represents the liquidity spiral parameter (γ). All control variables are lagged (as of January 2020). Standard errors are clustered at the issuer level and reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.**

	Dependent variable:			
	Δ Liquidity (Feb-Mar 2020)			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Actual sales (V/A)	-0.926^{***}			
	(0.139)			
Projected sales		-5.123^{***}		
		(0.619)		
Actual sales (fitted)			-2.035^{***}	-1.866^{***}
			(0.226)	(0.234)
Liquidity	0.397^{***}	0.400^{***}	0.394^{***}	0.380^{***}
	(0.026)	(0.026)	(0.026)	(0.026)
Log(Duration)	0.008^{**}	0.008^{**}	0.002	0.008^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
Log(Maturity)	-0.032^{***}	-0.033^{***}	-0.030^{***}	-0.032^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Log(Asset size)	0.011^{***}	0.009^{***}	0.013^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Constant			-0.484^{***}	
			(0.031)	
Bond type FE	Yes	Yes	No	Yes
Seniority FE	Yes	Yes	No	Yes
First-Stage F-Stat	-	-	176.0	213.5
Observations	15,793	15,793	15,801	15,793
R^2	0.131	0.133	0.115	0.127
Adjusted R^2	0.130	0.132	0.114	0.126

C.3 LRISK Calibration: Estimating κ

Table A.4: LRISK Normalization: Price Pressure and Bond Returns

This table reports the cross-sectional regressions of corporate bond returns during the COVID-19 crash (February–March 2020) on price pressure measures. Column (1-2) estimate OLS regressions using the Actual Price Pressure and the Projected Price Pressure (horizontal slicing), respectively. Columns (3-4) report 2SLS regressions where Actual Price Pressure is instrumented by Projected Price Pressure. The coefficient on the fitted Actual Price Pressure represents the LRISK normalization multiplier (κ). Standard errors are clustered at the issuer level and reported in parentheses. *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.**

	Dependent variable:			
	Bond Return (Feb-Mar 2020)			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Actual price pressure	-2.276^{***}			
	(0.603)			
Projected price pressure		-22.087^{***}		
		(3.993)		
Actual price pressure (fitted)			-5.131^{***}	-4.647^{***}
			(0.886)	(0.898)
Liquidity	0.287^{***}	0.252^{***}	0.282^{***}	0.264^{***}
	(0.018)	(0.020)	(0.019)	(0.019)
Log(Duration)	-0.001	-0.002	0.003	-0.002
	(0.003)	(0.003)	(0.002)	(0.003)
Log(Maturity)	-0.018^{***}	-0.019^{***}	-0.021^{***}	-0.019^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Log(Asset size)	0.010^{***}	0.010^{***}	0.009^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Constant			-0.363^{***}	
			(0.025)	
Bond Type FE	Yes	Yes	No	Yes
Seniority FE	Yes	Yes	No	Yes
First-Stage F-Stat	-	-	106.5	126.8
Observations	15,773	15,773	15,775	15,773
R^2	0.198	0.201	0.162	0.194
Adjusted R^2	0.197	0.200	0.162	0.193

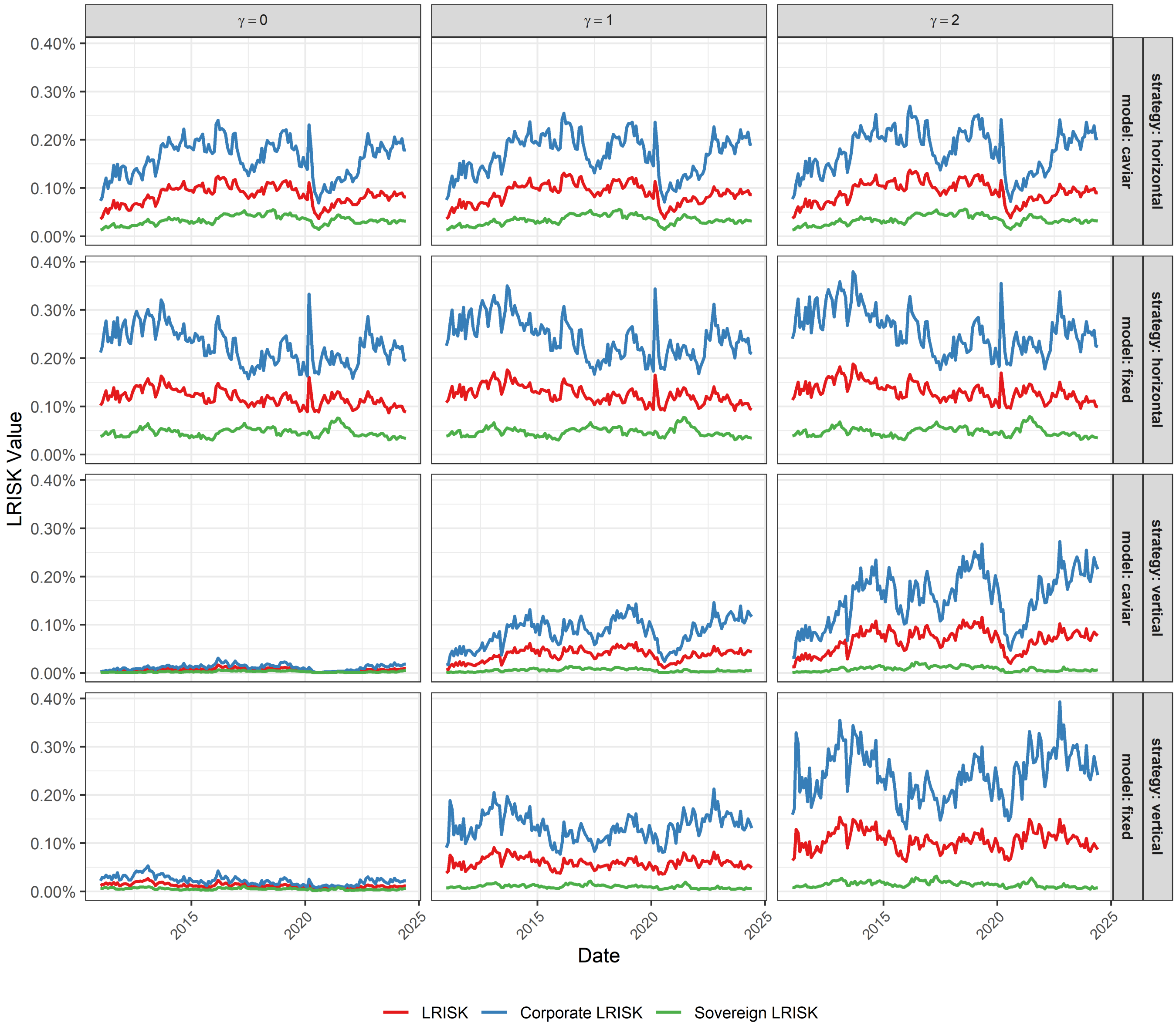
C.4 LRISK Calibration: Aggregate LRISK Sensitivity to γ

Table A.5: 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

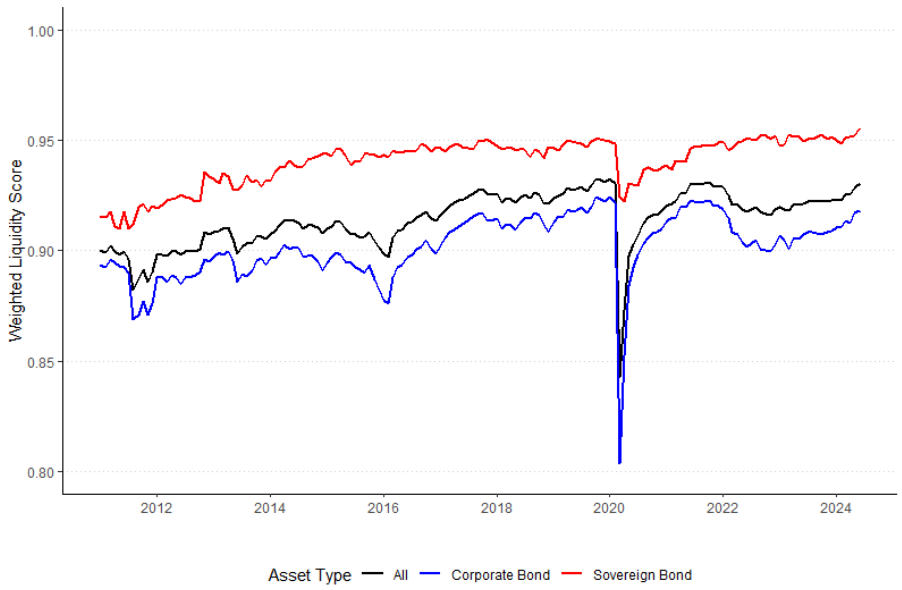
Figure A.2: Aggregate LRISK—Gamma Sensitivity



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 horizontal and vertical slicing, but with a different value for γ (ranging from 0 to 2). 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, especially in vertical slicing, the time variations and the identification of stress periods remain robust across parameter choices.

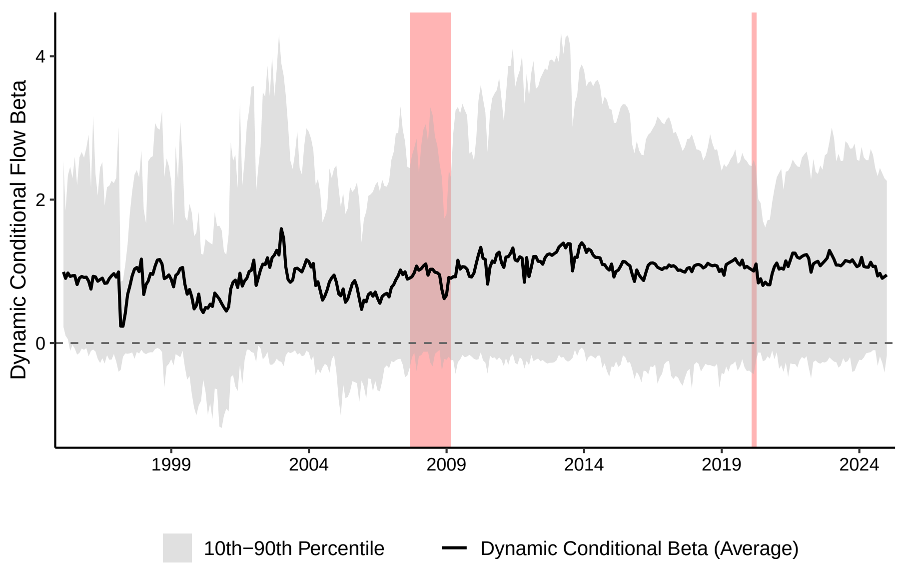
D Additional Figures

Figure A.3: Liquidity Score



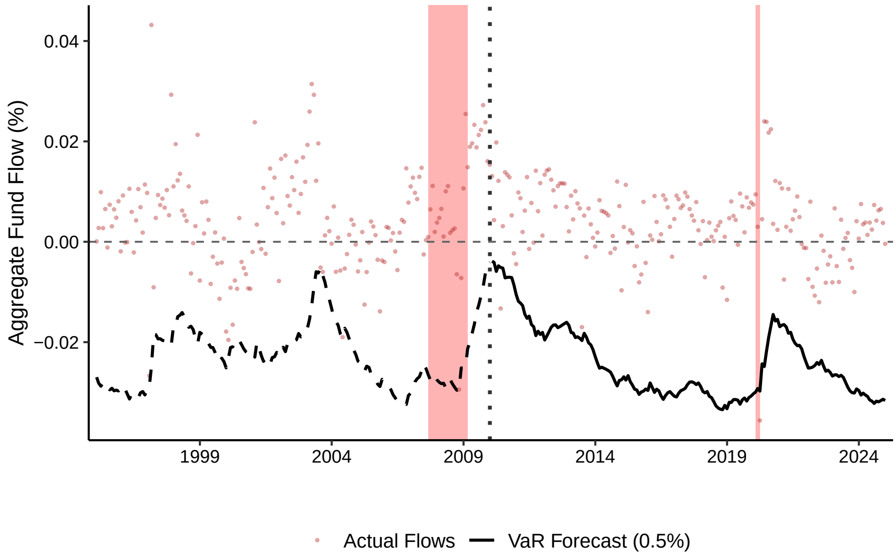
Note: *The figure displays the monthly mean of the liquidity score of assets held by our sample of mutual funds, weighted by the total holdings of funds in each asset type.*

Figure A.4: Dynamic Conditional Flow Beta



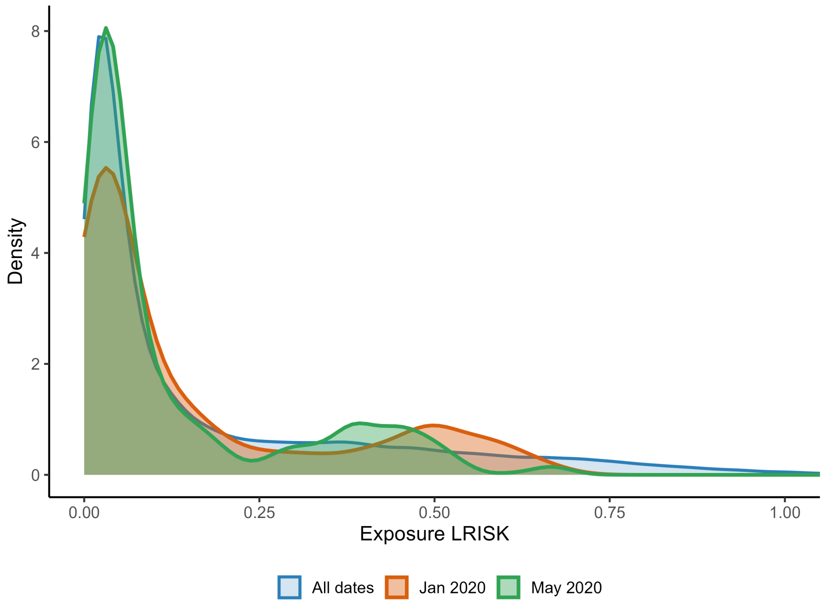
Note: *The figure illustrates the evolution of funds' dynamic conditional flow betas ($\beta_{n,t+1|t}$) from 1995 to 2024. The solid black line represents the cross-sectional average beta at each point in time. The grey shaded area represents the inter-percentile range (10th to 90th percentiles), highlighting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

Figure A.5: 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.

Figure A.6: Distribution of Exposure LRISK



Note: The figure shows the distribution of fund-level LRISK over time. This shows that the pre-COVID increase and subsequent decline reflect rising exposure among many, but not all, funds.

E Additional Robustness Tests

Table A.6: 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. Standard errors are clustered by issuer. *, **, 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$_{t-1}$	0.008***	0.006**	0.004**	0.005**	0.009***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Fund coverage$_{t-1}$	0.027***	0.025***	0.007***	0.007***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Asset liquidity$_{t-1}$	−0.340***	−0.369***	0.023	0.029*	0.030*
	(0.034)	(0.033)	(0.017)	(0.017)	(0.016)
Modified duration$_{t-1}$	0.033***	0.036***	0.085***	0.085***	0.088***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Life to maturity$_{t-1}$	0.027***	0.025***	−0.009*	−0.009**	−0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Size (log)$_{t-1}$	0.003	0.0002	0.005***	0.004***	0.005***
	(0.002)	(0.002)	(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	12,979	12,979	12,979	12,979	12,979
R^2	0.353	0.350	0.915	0.917	0.935
Adjusted R^2	0.353	0.348	0.885	0.888	0.906

F Imputation Strategies for Missing Market Data

F.1 Imputation Strategy for Missing Asset Liquidity

To address the (few) cases where an asset has no available bid-ask spreads we employ an imputation strategy that reflects the illiquidity premium associated with missing market data. This approach is mostly used for non-US corporate and non-US sovereign bonds without Datastream bid-ask data.

For each asset class, we first isolate the economically relevant core of the market, defined as the subset of securities comprising the top 90% of aggregate mutual fund holdings. We then calculate the 95th percentile of the observed bid-ask spreads by asset class within this core subset and use it to impute all missing spread values. This methodological choice ensures that the imputed illiquidity penalty is anchored to the actively tradable market rather than skewed by the noisy long tail of rarely held bonds, while still acknowledging that the absence of reported data is correlated with illiquidity.

F.2 Imputation Strategy for Missing 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 mitigate the influence of outliers and establish realistic estimation limits, we cap the observed MV based on asset type. Specifically, we set upper bounds at 50 billion for corporate bonds issuance and 5,000 billion for sovereign emissions. These thresholds serve to constrain all subsequent imputed values within economically plausible ranges. We also exclude observations where the aggregate value held by mutual funds exceeds the reported MV of the security. Then, 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.[14]

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

[14]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.

as:

$$\mathrm{MCR}_{\mathrm{class}} = \frac{\sum_{j \in \mathrm{class}} \mathrm{Holdings}_j}{\sum_{j \in \mathrm{class}} \mathrm{MV}_j} \tag{29}$$

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 ($\mathrm{MCR}_{\mathrm{class}}$):

$$\mathrm{MV}_{\mathrm{imputed},j} = \frac{\mathrm{Holdings}_j}{\mathrm{MCR}_{\mathrm{class}}} \tag{30}$$

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.