VULNERABILITY AND CONTAGION IN THE U.S. EQUITY MUTUAL FUNDS*

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Abstract

We study vulnerability and contagion risk across six major investment styles of the U.S. Domestic Equity Mutual Funds over the period 2003–2023. Using granular stock-level data, we extend the macroprudential stress-testing framework of Fricke and Fricke (2021) by incorporating stock betas, regime-dependent flow-performance sensitivities, and time-varying asset-specific price impacts. We therefore uncover cross-style heterogeneity that aggregate studies overlook. To capture system-wide spillovers, we implement a Ridge-VAR generalized connectedness framework suited to highly correlated equity styles. Although all styles respond to market shocks in the same direction, their sensitivities differ significantly. Growth and Growth Income funds consistently exhibit the highest vulnerability, particularly during the subprime crisis, whereas Small, Mid, and Micro Cap funds remain comparatively resilient. In the contagion network, Growth and Mid Cap funds consistently transmit shocks, while Micro Cap funds emerge primarily as shock absorbers. Overall connectedness remains high in both the subprime and COVID-19 crises, but the drivers of contagion shift over time. We advocate for a style-level regulatory framework and a counter-cyclical liquidity buffers to dampen fire-sale amplification.

Keywords: mutual fund vulnerability, financial stability, macroprudential stress test, financial contagion, systemic risk

JEL Classification: G10, G11, G23

Introduction

The structural transformation of the global financial system over the last two decades has been characterized by a decisive shift from bank-based intermediation toward market-based financing. At the center of this shift lies the mutual fund industry, which has experienced sustained expansion in both size and economic influence. In the U.S., the growth of this sector is particularly striking: by the end of 2022, approximately 7,500 U.S. mutual funds managed $22.1 trillion in assets, a marked increase from $13.05 trillion just a decade earlier. Within this universe, Domestic Equity Mutual Funds (DEMF) remain the dominant category, accounting for 46% of all mutual fund and Exchange-Traded Fund (ETF) assets. This accumulation of capital has enhanced the capacity of financial markets to allocate resources to the real economy, yet it has also concentrated risk within a sector that operates under a fundamentally different liquidity paradigm than the banking system. As mutual funds have become central nodes in the financial network, understanding their fragility and their potential to generate or propagate systemic risk has become a paramount concern for researchers and policymakers alike. Our paper aims to address these concerns by providing new evidence on how different styles respond to market shocks, how strongly they are interconnected, and how they propagate stress within the DEMF sector.

Traditionally, open-end mutual funds (henceforth mutual funds) with flexible end-of-day net asset value (NAV) pricing and no leverage were considered to be immune to bank-run-like crises. Unlike banks, funds make no guarantee that their customers' investments will be returned at face value. Instead, they manage assets on behalf of clients, with both risks and rewards borne by investors. In that view, it was believed that mutual funds would never experience runs and therefore would not be compelled to engage in fire sales of assets. However, mutual funds promise daily liquidity while engaging in illiquid assets. The stability of this liquidity transformation mechanism relies on the assumption that redemptions are frictionless and that the costs of liquidity provision are internalized by the redeeming investor. Yet, Zeng (2017) theoretically shows that the structural liquidity mismatch creates a structural "first-mover advantage" and render mutual funds inherently vulnerable to run-like behavior and fire-sale externalities. When investors redeem shares, funds must liquidate assets to meet outflows. Because liquidation typically occurs the day after redemptions are priced, the costs of selling are borne disproportionately by remaining investors. This creates strategic complementarities: investors anticipating redemptions by others have an incentive to redeem early, exacerbating the fund's overall fragility.[1] Chen et al. (2010) find that funds with illiquid assets induce stronger complementarities and thus exhibit stronger sensitivity to outflows than funds with liquid assets. However, this pattern is likely to disappear in funds where the shareholder base is composed mostly of large investors.

[1] Some of the potential risks associated with funds' liquidity mismatch can be illustrated by what happened during the summer of 2016, when several UK open-end funds invested in real estate experienced significant outflows and had to suspend any further redemptions. These suspensions resulted from the inability of affected funds to liquidate property assets at reasonable prices to meet large redemptions.

Beyond the idiosyncratic failure of individual funds, the distressed selling of assets can propagate shocks across the financial system through fire sales of common assets. Hau and Lai (2017) document that distressed funds in 2008 liquidated non-financial rather than financial stocks to meet redemptions in order to avoid realizing losses on underperforming stocks. By doing so, they triggered sharp price discounts on higher-quality non-financial stocks and transmitting shocks to the broader market. Similarly, Ma et al. (2022) report that during the COVID-19 crisis, distressed fixed-income mutual funds met redemptions by first selling their liquid assets, including Treasuries and high-quality corporate bonds. This liquidity transformation thus generated the most concentrated selling pressure in these markets. These findings align with Coval and Stafford (2007), who show that common ownership by institutional investors amplifies the downward pressure on stock prices during asset fire sales. Barucca et al. (2021) provide evidence that fire-sale externalities transmit distress through common asset holdings, linking mutual funds to one another and to other financial institutions such as banks and insurance companies. In the same vein, Adam and Klipper (2018) observe that fire sales by leveraged closed-end funds in the 2008 crisis caused temporary price drops in the stocks they sold, and those losses triggered outflows and further forced sales in open-end funds holding the same stocks. This shock propagation resulted from massive redemption demands combined with the inherent liquidity mismatch is described by Figure 1.

INSERT FIG. 1 HERE

The inherent bank-run-like risk of mutual funds provides therefore further impetus for financial regulators to assess their resilience in isolation as well as in interaction with each other within the industry as well as with other financial actors (Argyropoulos et al., 2024). Over the last decade, a burgeoning literature has emerged to evaluate the vulnerability of investment funds and their systemicness through macroprudential stress tests. Closest to our study is the work of Fricke and Fricke (2021) which adapts the stress-testing framework of Greenwood et al. (2015), originally developed for banks, to the mutual fund sector. Their framework quantifies the aggregate vulnerability of the mutual fund industry by considering the fire sales in presence of the flow-performance sensitivity. Using data on U.S. DEMF for the period 2003–2014, they find relatively small aggregate vulnerability compared to the banking sector, though it increases during periods of low market liquidity. Larger funds and illiquid funds are both more vulnerable and more systemic. Similarly, Lee (2020) conducts a similar stress test for the Luxembourg investment fund sector, incorporating a non-linear flow-performance relationship. He finds that while the sector is quite resilient over the period 2008–2019, its aggregate vulnerability increases over time. Fiedor et al. (2019) apply a standardized framework of macroprudential stress-test to seven categories of Irish investment funds. They observe that higher values of flow-performance sensitivity and price impact factor can result in significant contagion risk and that the fire-sale of assets by shocked funds creates higher second-round losses for other funds. A large body of this literature has focused on bond funds due to their perceived liquidity risks (see, for example, Arora et al., 2019; Baranova et al., 2017; Cetorelli et al., 2016).[2] Different frameworks have been developed but they

[2]More recently, a growing body of literature has emerged to investigate the interplay between banks and non-banks

all report a certain level of resilience of these funds. In parallel, Bouveret and Yu (2021) report that U.S. investment grade corporate bond funds, municipal bond funds and government bond funds are more likely to propagate distress compared to high yield, emerging market and loan funds. Bouveret et al. (2023) show that funds investing in less liquid assets (such as high-yield bond funds) or using complex strategies tend to transmit shocks more than funds investing in more liquid assets (such as government bond funds). Besides, contagion risk tends to increase during stress periods. While much of attention has been paid to bond funds, equity funds remain the largest segment of the U.S. asset management industry and a potentially important vector for systemic instability. Our study fills this gap by focusing on the DEMF sector.

Recognizing these potential systemic risks, a growing body of literature examines regulatory restrictions designed for the entire investment fund sector to contain outflows and thus reduce fire sales. These include macroprudential liquidity buffers (see, for example, Ahnert, 2016; Dekker et al., 2024; Di Iasio et al., 2022), redemption restrictions (see, for example, Agarwal et al., 2023; Molestina Vivar, 2025), swing pricing (see, for example, Capponi et al., 2020, 2023; Jin et al., 2022; Lewrick and Schanz, 2023; Ma et al., 2025).

However, treating the mutual fund sector as a monolithic entity overlooks their diversity and heterogeneity. In addition to their specific exposures to different sources of risks due to investment styles, recent literature suggests that fragility is not uniform but is also conditioned by the composition of the investor base. Contrary to the intuition that retail investors are the most prone to panic, Allaire et al. (2023) provide granular evidence from the COVID-19 turmoil showing that the "dash for cash" was largely driven by professional investors – specifically funds-of-funds and foreign institutions – who acted as the most elastic and run-prone agents. Funds with a higher share of household ownership were, in fact, more resilient. This finding aligns with Affinito and Santioni (2021), who document that professional investors, such as insurers, engaged in procyclical panic selling during the pandemic, exacerbating fire-sale dynamics. Furthermore, non-pecuniary motives can play a stabilizing role. Pástor and Vorsatz (2020) find that while active equity funds generally experienced heavy outflows during the COVID-19 crisis, those with high environmental, social, and governance (ESG) ratings were significantly more resilient, suggesting that sustainability-oriented investors are less sensitive to short-term performance dips. Sialm and Tham (2011) identify a reputational transmission channel where shocks to a management company trigger spillovers across its entire family of funds, regardless of individual fund performance. These studies collectively imply that vulnerability is a function of the clientele as much as the portfolio.

Yet, despite these insights, the existing macroprudential stress-testing literature has largely focused on

including mutual funds, hedge funds and insurers, via overlapping portfolios held by these financial institutions. Studies by Caccioli et al. (2015) Mirza et al. (2020), Aikman et al. (2019b), Farmer et al. (2020), Sydow et al. (2024), Chrétien et al. (2020), Calimani et al. (2022) highlight how the inclusion of non-banks significantly magnifies systemic risk. For an extensive survey of macroprudential stress tests, please refer to Aikman et al. (2023).

industry-level aggregates, often overlooking the granular vulnerability dynamics within the equity mutual fund sector. In particular, very little research examines how specific equity investment styles (e.g., Growth vs. Value, Large Cap vs. Small Cap) differ in their structural fragility and in their capacity to transmit shocks. Because these styles attract distinct investor clienteles and exhibit heterogeneous liquidity profiles, a "one-size-fits-all" assessment of mutual fund vulnerability is likely to be misleading. This paper addresses these omissions by providing the first comprehensive analysis of vulnerability and contagion risk across the six major styles of U.S. DEMF over the period 2003–2023.

In the first part of our study, we assess the vulnerability of different investment styles in isolation by extending the macroprudential stress-testing framework of Fricke and Fricke (2021) (FF). Vulnerability is measured as the percentage of aggregate equity (relatively to the initial value before the shock happens) that would be wiped out by fund's asset liquidation due to the shock. While the FF model focuses on aggregate sector vulnerability using fixed parameters, we introduce three granular specifications in order to capture cross-style heterogeneity and dress a more realistic assessment of style-specific vulnerability: (i) explicitly modeling the asset-specific sensitivity to the initial shock via stock betas; (ii) incorporating style-specific flow-performance sensitivity estimated via a two-regime model (distinguishing between tranquil and turbulent markets) to capture non-linear investor reactions, following Lee (2020); (iii) employing time-varying, asset-specific price impacts to gauge fire-sale effects. By integrating these components, we construct a dynamic measure of vulnerability that accounts for the interaction between the initial market shock, the behavioral reaction of the specific investor base, and the liquidity constraints of the underlying portfolio. Additionally, our empirical scope expands prior data used by FF from 2003–2014 to 2003–2023 thereby covering the post-subprime crisis, the COVID-19 turmoil, and the post-pandemic recovery. This extended horizon offers a comparative analysis of vulnerability across endogenous (2008) and exogenous (2020) shocks.

Our analysis provides new insights into the dynamics of DEMF style-level vulnerability. We find that aggregate vulnerability remains low during tranquil periods but rises sharply during the subprime crisis. Driven by outflows, vulnerability peaks in late 2008 for all styles before reversing abruptly as funds experience net inflows during the 2009 recovery. Both leverage and market stress can amplify fragility by roughly a factor of two. Since 2010, vulnerability measures remain very low for all styles. As a result, the temporal dynamics of vulnerability that we document differ from those reported by FF. These differences likely stem from our granular specification of stock betas and our non-linear flow-performance sensitivity, which capture more precisely the impact of initial shock. Consistent with its exogenous nature, the COVID-19 crisis did not generate significant vulnerability in any style.

Most importantly, while all styles respond in the same direction to market shocks, we document substantial heterogeneity in the magnitude of their responses. Counterintuitively, Growth and Growth Income funds are consistently the most vulnerable segments, particularly during the 2007-2009 crisis. This is despite having lower investor elasticity (flow-performance sensitivity) than their smaller-cap peers. In contrast, Small, Mid, and Micro Cap funds, despite higher investor elasticity and less liquid portfolios, prove surprisingly resilient. This pattern suggests that run dynamics are driven more by the strategic complementarities among sophisticated institutional investors, more prone to redeem procyclically (Affinito and Santioni, 2021; Allaire et al., 2023; Coval and Stafford, 2007; Greenwood and Thesmar, 2011; Pástor and Vorsatz, 2020) — who are more prevalent in Growth funds — than by simple performance-chasing. Furthermore, the high concentration of Growth funds in volatile, long-duration equities amplify their exposure during the subprime crisis.[3] While style-specific sensitivities persist through the COVID-19 shock, the crisis itself does not induce the same level of fragility, implying that vulnerability is determined by the interaction between a style's characteristics – both in terms of portfolio exposures and investor base – and the specific nature of the shock. These findings highlight the importance of adopting a style-level approach in macroprudential stress testing.

In the second part of our study, we investigate contagion dynamics across fund styles by analyzing their interconnectedness. Our contributions are twofold. First, we make a methodological advance by enhancing the spillover framework of Diebold and Yilmaz (2009, 2012, 2014) (DY) to obtain a robust measure of contagion in a highly correlated system.[4] While prior research highlights the role of common holdings and correlated investor behavior in propagating (see Adam and Klipper, 2018; Barucca et al., 2021; Coval and Stafford, 2007; Hau and Lai, 2017), quantifying these spillovers is challenging because the high correlation among equity fund styles. Although the standard DY framework is widely applied to study spillovers across asset classes (Bouveret et al., 2023; Bouveret and Yu, 2021), it is not directly suited to our context, where style returns of equity funds exhibit strong multicollinearity.[5] To overcome this limitation, we incorporate the Ridge-VAR estimator of Ballarin (2021, 2024), which regularizes the VAR coefficients and delivers stable, economically interpretable dynamics even under severe multicollinearity. We further employ the Generalized Forecast Error Variance Decomposition (GFEVD) to obtain ordering-invariant measures of interconnectedness. This enhanced framework allows us to map the directional connectedness of the system and identify which styles act as net transmitters of stress and which act as net receivers.

Second, we provide new empirical evidence on the contagion dynamics within the U.S. DEMF sector. We document not only a heightened interconnectedness among styles but also a notable shift in the contagion dynamics. Despite persistently high level of interconnectedness, the network structure exhibits remarkable balance but the systemic roles of individual styles shift over time. We identify

[3] Growth equities offer high expected long-run earnings growth which are inherently more volatile and more vulnerable to market stress. Such stocks tend to experience sharper devaluation during bear markets, making Growth-oriented funds more exposed to severe selloffs.

[4] Additionally, several methods have been developed to capture spillover effects in financial networks, including correlation analysis (Forbes and Rigobon, 2002), Granger pairwise causality and VECM (Gentile and Giordano, 2013), the GARCH factor model (Dungey and Martin, 2007), VAR-EGARCH (In et al., 2001), CoVaR (Tobias and Brunnermeier, 2016).

[5] The DY approach has been widely adopted in studies assessing volatility spillovers across different financial markets. For instance, Greenwood-Nimmo et al. (2016) analyze spillover effects in Forex markets, while Fernández-Rodríguez et al. (2016) apply the approach to the EMU sovereign bond market.

Growth and Mid Cap funds as persistent net transmitters of stress, driven by their structural exposure to volatile long-duration assets and less efficient market segments. In contrast, Micro Cap funds consistently function as net receivers, systematically absorbing spillovers due to their thin liquidity and limited influence on aggregate market dynamics. Additionally, the system experiences a notable reordering post-2010: Large Cap funds shift from transmitters to receivers as passive investing grows and investors fly to quality. Growth Income funds, significant receivers become significant new sources of contagion in the low-rate environment. These findings suggest that while overall systemic risk remains substantial, its specific drivers evolve dynamically with changes in market structure, investor behavior and the nature of underlying shocks.

We make several contributions to the ongoing debate regarding the design of an effective regulatory framework for investment funds. Our results challenge "one-size-fits-all" models, advocating instead for style-level differentiation in both vulnerability and systemic importance. Specifically, we argue that persistent shock transmitters, such as Growth and Mid Cap funds, require stronger ex-ante liquidity management tools, targeted swing pricing, while structurally distinct receiver styles need supervision focused on operational resilience and investor protection. Furthermore, the evolving structure of contagion supports the integration of network-based connectedness indicators into systemic monitoring and the implementation of counter-cyclical liquidity buffers to dampen fire-sale amplification.

The remainder of this paper is organized as follows. Section 1 describes the granular portfolio- and security-level data used in our study. Section 2 outlines the extended macroprudential stress testing framework and presents the empirical results on style-level vulnerabilities. Section 3 details the Ridge-VAR connectedness methodology and analyzes the contagion dynamics. Finally, Section 4 concludes and discusses the policy implications derived from our results.

1 Data

Data on mutual funds are retrieved from the Survivor-Bias-Free US mutual fund database of the Center for Research in Security Prices (CRSP MFDB henceforth). Due to data availability of funds' monthly portfolio compositions that only begin in 2002, the study covers the period 1/2003 - 12/2023. In order to have a focus on the U.S. equity market, we restrict our analysis to 11,032 unique domestic equity open-end mutual funds (DEMF henceforth) classified into six investment styles: Large Cap, Mid Cap, Small Cap, Micro Cap, Growth and Growth Income.[6] For funds having multiple share classes, we

[6]Funds are selected on the basis of their objective codes. We include funds with the following Strategic Insight Objectives (SI Code): GMC, SCG, AGG, GRO, GRI, ING. If this information is missing, we base our selection on funds' Lipper Objective Codes: SP, MC, SG, MR, CA, G, GI, EI. More precisely, the classification of the six styles proceeds as follows: Large Cap with Lipper Code = SP; Mid Cap with either Lipper Code = MC or SI Code = GMC; Small Cap with either Lipper Code = SG or SI Code = SCG; Micro Cap with Lipper Code = MR; Growth with Lipper Code = CA, G or SI Code = AGG, GRO; Growth Income with Lipper Code = GI or SI Code = GRI, ING.

aggregate all the observations pertaining to different classes into one fund observation, since they have the same holdings, the same managers.

INSERT TAB. 1 HERE

INSERT TAB. 2 HERE

INSERT FIG. 2 HERE

Table 1 provides at each December a breakdown of the number of funds across different investment styles along with their relative weights within the sector as a percentage of the total asset managed. Table 2 summarizes key statistics for each style. Figure 2 plots the dynamics of their portfolio holdings in stocks, bonds and cash over time.

Overall, we observe a robust and sustained growth, both in the number of funds and the Total Net Assets (TNA). Aggregate assets under management more than quintupled from $2,462 billion in 2003 to $14,552 billion in 2023, accompanied by an increase in the number of (unique) funds, from 2,335 in 2003 to 3,147. Growth and Growth Income consistently dominated, jointly managing nearly two-thirds of sector assets, well ahead of the other styles. Growth Income, the fastest-growing style with an average flow rate of 12.1%, registered substantial increases, in both TNA and market share, despite a significant decrease in the number of funds, especially during 2022 and 2023. Growth funds display a similar dynamics but to a lesser extent, exhibiting a flow rate of 9.7% but accompanied by a reduced number of funds in 2022 and 2023. The Large Cap segment experiences the highest flow rate over the period (16.7%), nearly doubling its market share from 11% in 2003 to 20% in 2023. By contrast, Micro Cap, the smallest segment, suffers a steady decline in market share, as reflected by a sharply negative flow rate (-32%), representing a mere 0.09% of sector assets by end-2023. Small Cap observes a relative loss of interest from investors, characterized by a constantly modest growth in TNA but a diminishing market share, managing 7% of sector assets by 2023. Meanwhile, Mid Cap maintains a stable market share with a slightly positive flow rate.

As shown in Table 2, Large Cap funds are characterized by a small number of seasoned funds (with an average age of 13.2 years, compared to 9.3 years for Growth Income), significantly larger sizes ($5,2 billions of assets compared to $161 millions for Micro Cap on average). Large Cap funds also exhibit the lowest expense ratio (0.6% on average, compared to the highest level of 1.6% for Micro Cap), the lowest turnover ratio (11.6% on average, against the highest turnover of 81.5% for Mid Cap), and the highest Sharpe ratio (0.17 on average compared to the smallest value of 0.11 for Micro Cap). In terms of asset allocation, funds generally invest over 90% of their portfolio value in common stocks, less than 1% in bonds and around 3% in cash.

Data on individual stocks used to investigate the portfolio composition of mutual funds are extracted from the CRSP US Stock database. Finally, the monthly number of unique stocks used to compute the price impact ranges from 6,529 in October 2009 to 9,652 in October 2022, with an average of 7,416 over the whole period (see Figure 3).

INSERT FIG. 3 HERE

2 Vulnerability analysis

In the section, we assess the vulnerability of different investment styles in isolation by extending the macroprudential stress-testing framework of Fricke and Fricke (2021) (FF). FF adapt the framework of Greenwood et al. (2015), originally developed for banks, to the mutual fund sector by modeling fire sales of assets triggered by investor redemptions in the presence of the flow-performance sensitivity. In this framework, vulnerability is measured as the percentage of aggregate equity (relatively to the initial value before the shock happens) that would be wiped out by fund's asset liquidation due to the shock. While the FF model focuses on aggregate sector vulnerability using fixed parameters, we introduce three granular specifications in order to capture cross-style heterogeneity and dress a more realistic assessment of style-specific vulnerability: (i) explicitly modeling the asset-specific sensitivity to the initial shock via stock betas; (ii) incorporating style-specific flow-performance sensitivity estimated via a two-regime model (distinguishing between tranquil and turbulent markets) to capture non-linear investor reactions, following Lee (2020); (iii) employing time-varying, asset-specific price impacts to gauge fire-sale effects. By integrating these components, we construct a dynamic measure of vulnerability that accounts for the interaction between the initial market shock, the behavioral reaction of the specific investor base, and the liquidity constraints of the underlying portfolio.

2.1 Fricke and Fricke (2021)'s framework

We consider N asset managers. Each manager i holds a portfolio composed of K assets. Let $W_{(N\times K)}$ denote the vector of asset weights in each portfolio, where each element $0 \leq w_{i,k} \leq 1$ is the share of asset k in portfolio i, and $\sum_{k=1}^{K} w_{i,k} = 1$ by construction. Suppose that the manager's objective is to maintain this targeted portfolio composition despite the shock.

The total asset of each portfolio, A_i, is financed with a mix of equity, E_i, and debt, D_i so that $A_i = E_i + D_i$. The leverage ratio of portfolio i is denoted by B_i with $B_i = D_i/E_i$. $F_{(K\times 1)}$ denotes the vector of asset-specific returns $F = (f_1, ..., f_k, ..., f_K)'$ where f_k is the return on asset k.

In the following, we describe the timeline of the model with a shock that happens at time 0. Time -1 refers to the pre-shock period while 1 refers to the post-shock.

Initial shock at time 0

When the shock happens, the return on each portfolio R_0 is:

$$R_0 = WF_0 \tag{1}$$

The pre-shock total assets of each portfolio A_{-1} is consequently updated to A_0:

$$A_0 = A_{-1}\Big(1 + R_0\Big) \tag{2}$$

which leads to a change in the equity value of the portfolio:

$$E_0 = E_{-1} + A_{-1}R_0 \tag{3}$$

while the debt value remains unchanged:

$$D_0 = D_{-1} \tag{4}$$

Investors' reactions at time 1 in response to the shock

It has been established in the literature that investors react positively to portfolio past performance. This implies that a positive (negative) shock causes a positive (negative) net inflow in equity and debt financing. Thus, the net inflow is assumed to be a positive linear function of the portfolio's last return and the sensitivity of investors' reactions, γ^E (for equity) and γ^D (for debt) as follows:

$$\frac{\Delta E_1}{E_0} = \gamma^E R_0 \tag{5}$$

$$\frac{\Delta D_1}{D_0} = \gamma^D R_0 \tag{6}$$

with ΔE_1 and ΔD_1 the dollar net inflows in equity and debt respectively. Due to investors' reactions, the equity and debt values of the portfolio become:

$$E_1 = E_0 + \Delta E_1 = E_0 + \gamma^E E_0 R_0 = E_0\Big(1 + \gamma^E R_0\Big) \tag{7}$$

$$D_1 = D_0 + \Delta D_1 = D_0 + \gamma^D D_0 R_0 = D_0\Big(1 + \gamma^D R_0\Big) \tag{8}$$

The updated total assets of the portfolio is:

$$\begin{aligned}
A_1 &= A_0 + \Delta E_1 + \Delta D_1 && (9)\\
&= A_{-1}\Big(1 + R_0\Big) + \gamma^E E_0 R_0 + \gamma^D D_0 R_0 && (10)\\
&= A_{-1}\Big(1 + R_0\Big) + \gamma^E\Big(E_{-1} + A_{-1}R_0\Big)R_0 + \gamma^D B E_{-1} R_0 && (11)\\
&= A_{-1}\Big(1 + R_0\Big) + \gamma^E\Big(\frac{E_{-1}}{A_{-1}} + R_0\Big)R_0 A_{-1} + \gamma^D B\frac{E_{-1}}{A_{-1}} R_0 A_{-1} && (12)\\
&= A_{-1}\Big(1 + R_0\Big) + \gamma^E\Big(\frac{1}{1+B} + R_0\Big)R_0 A_{-1} + \gamma^D B\frac{1}{1+B} R_0 A_{-1} && (13)\\
&= A_{-1}\Big(1 + R_0\Big(1 + \gamma^E\Big(\frac{1}{1+B} + R_0\Big) + \gamma^D \frac{B}{1+B}\Big)\Big) && (14)
\end{aligned}$$

with $E_{-1}/A_{-1} = 1/\Big(1+B\Big)$. Hence, the adjusted return (before asset liquidation) on the portfolio can be computed as follows:

$$R_1 = \frac{A_1 - A_{-1}}{A_{-1}} \tag{15}$$

$$= R_0\Big(1+\gamma^E\Big(\frac{1}{1+B}+R_0\Big)+\gamma^D\frac{B}{1+B}\Big) \tag{16}$$

It is clear that the more the portfolio is leveraged (higher B), the smaller the spread between R_1 and R_0, the weaker the impact of investors' reactions (γ^D, γ^E) on the portfolio return and thus on the portfolio total value since the equity part is relatively small.

In the case of no withdrawal of debt ($\gamma^D = 0$), the return is simply calculated as:

$$R_1 = R_0\Big(1+\gamma^E\Big(\frac{1}{1+B}+R_0\Big)\Big) \tag{17}$$

In the case of zero leverage ($B = 0$), equation (17) becomes:

$$R_1 = R_0\Big(1+\gamma^E(1+R_0)\Big) \tag{18}$$

Asset liquidation with a fixed leverage ratio and fixed portfolio weights

In line with Greenwood et al. (2015) and supported by empirical evidence about common practices used by mutual funds in liquidity management, asset managers are assumed to carry out asset liquidations while maintaining fixed leverage ratio B and fixed asset weights of their portfolios. This approach ensures that their initial investment strategy remains intact.

In order to deal with negative (positive) net inflows due to investors' reactions $\Delta E_1 + \Delta D_1$, portfolio managers need to liquidate (buy) a pro-rata percentage of assets while maintaining unchanged portfolio weights (W fixed). Since the flow-performance sensitivity of equity might be different from that of debt, i.e. $\gamma^D \neq \gamma^E$, there will be an additional adjustment of portfolio assets if the manager is committed to a fixed leverage ratio B. Let D_1^a denote the new value of debt with $D_1^a = E_1 B$, then the additional change in portfolio debt is:

$$\Delta D_1^a = D_1^a - D_1 = E_1 B - D_1 = A_{-1}B\Big(R_1 - \gamma^D R_0\Big) \tag{19}$$

In that case, the total net inflows of portfolio, denoted Φ, has three components: net inflow of equity

ΔE_1, net inflow of debt ΔD_1 and the additional change in portfolio debt D_1^a.

$$\begin{aligned}
\Phi &= \Delta E_1 + \Delta D_1 + \Delta D_1^a && (20)\\
&= \gamma^E E_0 R_0 + \gamma^D D_0 R_0 + A_{-1} B\Big(R_1 - \gamma^D R_0\Big) && (21)\\
&= \gamma^E R_0\Big(E_{-1} + A_{-1}R_0\Big) + \gamma^D D_0 R_0 + A_{-1} B\Big(R_1 - \gamma^D R_0\Big) && (22)\\
&= A_{-1}\Big[R_0\Big(\gamma^E\Big(\frac{E_{-1}}{A_{-1}} + R_0\Big) + \gamma^D\Big(\frac{D_0}{A_{-1}}\Big)\Big) + B\Big(R_1 - \gamma^D R_0\Big)\Big] && (23)\\
&= A_{-1}\Big[R_0\Big(\gamma^E\Big(\frac{1}{1+B} + R_0\Big) + \gamma^D\Big(\frac{B}{1+B}\Big)\Big) + B\Big(R_1 - \gamma^D R_0\Big)\Big] && (24)
\end{aligned}$$

since $\frac{1}{1+B} = \frac{1}{1+\frac{D_{-1}}{E_{-1}}} = \frac{E_{-1}}{E_{-1}+D_{-1}} = \frac{E_{-1}}{A_{-1}}$ and $\frac{B}{1+B} = \frac{\frac{D_{-1}}{E_{-1}}}{1+\frac{D_{-1}}{E_{-1}}} = \frac{D_{-1}}{E_{-1}+D_{-1}} = \frac{D_{-1}}{A_{-1}}$

If Φ is negative (positive) then there is an outflow (inflow). Hence Φ represents the whole amount to be liquidated (invested) to meet the outflow (inflow).[7]

Note that for unlevered funds having $B = 0$, Φ is simply calculated as follows:

$$\Phi = A_{-1} R_0 \gamma^E \Big(1 + R_0\Big) \tag{25}$$

In this case, Φ is always negative when R_0 is negative and γ^E is positive.

When there is no withdrawal of debt ($\gamma^D = 0$), equation (24) is reduced to:

$$\Phi = A_{-1}\Big[R_0 \gamma^E\Big(\frac{1}{1+B} + R_0\Big) + B R_1\Big] \tag{26}$$

Thus, the net asset purchases undertaken for all assets are denoted by ϕ computed as follows:

$$\phi = W' \Phi \tag{27}$$

Impacts of fire sales

Assume that fire sales generate a linear price impact measured by the matrix L composed of asset-specific price impact ratios, expressed in units of returns per dollar of net sales. Then the vector of asset-specific returns F is:

$$F_2 = L\phi = LW'\Phi \tag{28}$$

which gives a final return of:

$$R_2 = WF_2 = WLW'\Phi \tag{29}$$

[7] The equation (24) is different from the equivalent formula in Fricke and Fricke (2021) in the existence of R_0 which is next to A_{-1}. It is likely that the authors omitted R_0 in their equation.

Measuring vulnerability exposures

Suppose there is a negative shock on the market that affects all assets. Then the aggregate vulnerability (AV) on all funds' portfolios measures the percentage of aggregate equity (relatively to the initial asset value before the shock happens) that would be wiped out by institutions' asset liquidation due to the shock. AV is calculated as follows:

$$AV = \frac{1'_N A_{-1} R_2}{E_{-1}} = \frac{1'_N A_{-1} W L W' \Phi}{E_{-1}} \tag{30}$$

The corresponding contribution of a fund i to this aggregate vulnerability is:

$$AV_i = \frac{1'_N A_{-1} R_2}{E_{-1}} = \frac{1'_N A_{-1} W L W' \delta_i \delta_i' \Phi}{E_{-1}} \tag{31}$$

where δ_i is a $(N \times 1)$ vector with all zeros except for the ith element, which is equal to one, and $\sum_{i=1}^{N} AV_i = 1$.

2.2 Parameter calibration

The sub-sections below describe the empirical strategy used to quantify the aggregate vulnerability AV computed following equation (30) with Φ described by equation (24).

Impact of initial shock on asset returns

Unlike FF, we conjecture that the impact of a market shock on a given asset is proportional to the asset's degree of exposure to the market measured by its beta.[8] To do so, we first estimate the beta for each asset k as follows:

$$F_{k,t} = \alpha_k + \beta_k \; F_{\text{market},t} + u_{k,t} \tag{32}$$

where $F_{k,t}$ represents the asset k's return at time t, $F_{\text{market},t}$ denotes the market's return at time t, represented here by the S&P 500 index; $u_{k,t} \sim N(0, \sigma_k^2)$; α_k stands for the asset's return that is independent of the market; β_k measures the asset's sensitivity to market movements.

Table 3 provides the distribution statistics for the 23,534 unique beta values obtained from the regression (32) using monthly returns of stocks and the market. The average beta value is around 1 with a very large dispersion because of the presence of many extreme values.[9] To tackle the problem of outliers, we follow previous studies in the literature and set the maximum value of betas to 3 and the minimum value to 0.

INSERT TAB. 3 HERE

[8]We thank Jean-Laurent Viviani for this suggestion.

[9]We also recalculated beta excluding the year 2008 and obtained similar values.

The return of fund i when the negative shock occurs, denoted $R_{0,i}$, is then computed as follows:

$$R_{0,i} = W_i \times F_{0,i} = W_i \times (F_{0,i}^{obs} + \beta_i \times \text{Shock}) \tag{33}$$

where $Shock = -5\%$ for a negative shock of 5%. In this paper, we study two levels of negative shocks: -5% in the baseline scenario and -10% in one alternative scenario.

Fund debts

Due to a lack of information on funds' leverage in the CRSP MFDB database, we follow the approach of FF by considering three values of B: 0, 0.33 and 0.5. The first value corresponds to an absence of leverage, which is commonly observed in empirical studies (Almazan et al., 2004; Boguth and Simutin, 2018). The two latter values refer to an intermediate and maximum level of leverage allowed by the regulatory framework.[10]

In these two scenarios, we assume that there is no withdrawal of debt, meaning that $\gamma^D = 0$.

Flow-performance sensitivity of funds

This subsection describes the methodology that we adopt to gauge, for each style, the flow-performance sensitivity (FPS), denoted by γ^E within the theoretical framework.

We compute the monthly net inflow of fund i in month t, denoted by $Fl_{i,t}$, using the following equation:

$$Fl_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{34}$$

where $TNA_{i,t}$ and $TNA_{i,t-1}$ represent the total net assets managed by the fund i in month t and $t-1$ respectively and $R_{i,t}$ is the fund's return for month t, net of total expenses (including annual fees and other associated costs).

A large body of literature has identified a positive and convex relationship between mutual fund flows and past performance. Specifically, investors tend to chase past performance by subscribing to high-performing funds, while underperforming funds do not experience a proportional withdrawal (see, for example, Chevalier and Ellison, 1997; Del Guercio and Tkac, 2002; Fant and O'Neal, 2000; Goldstein et al., 2017; Huang et al., 2007; Ippolito, 1992; Sirri and Tufano, 1998).

Previous research has suggested several factors that influence the flow-performance relationship, including clientele sophistication, with retail investors being more reactive than institutional investors (Jiang and Yuksel, 2017), investor learning from fund past performance (Huang et al., 2022), participation costs (Huang et al., 2007), market conditions (Fant and O'Neal, 2000; Franzoni and Schmalz, 2017; Jun et al., 2014), and portfolio liquidity (Chen et al., 2010; Covachev and Yadav, 2024).

[10] $B = 0.33$ and $B = 0.5$ refers to the case where debts represent respectively one-third and a half of the equity values.

Ferreira et al. (2012) report different levels of FPS across countries due to the maturity of financial markets, which aligns with the observed link between FPS and investor sophistication as well as participation costs. Grillet-Aubert and Sow (2009) notice that the flow-past performance is significant only at the aggregate level and very weak at the individual level. While these studies differ in many ways, most studies employ a pooled cross-sectional regression of fund flows on their past returns, overlooking the heterogeneity in investor sensitivity for each investment style that in turn depends on market conditions. Spiegel and Zhang (2013) show that in the presence of strong heterogeneity across time and funds, this empirical specification can yield false convexity estimates. In addition, Franzoni and Schmalz (2017) observe that in the U.S. DEMF sector, FPS is significantly higher during moderate volatility state (in calm markets) compared to periods of high-volatility state (in market turmoils).

To address the asymmetry in investor reactions across different market conditions and investment styles, we follow Lee (2020) and estimate a two-regime Markov-Switching Intercept Autoregressive Heteroscedasticity model for each fund. The model is specified as follows:

$$Fl_{i,t} = \mu_{s_t} + \sum_{q=1}^{k} \gamma_{i,q,s_t} R_{i,t-q} + \sum_{q=1}^{k} \beta_{i,q,s_t} Fl_{i,t-q} + \varepsilon_{i,t} \tag{35}$$

where $Fl_{i,t}$ denotes the percentage of net inflows into fund i at time t. $R_{i,t-q}$ represents the return on fund i at time $t-q$ (with $q > 0$). s refers to the regime with $s_t \in \{1;2\}$. $\varepsilon_{i,t}$ are normally distributed with $\varepsilon_{i,t} \sim N(0, \sigma^2_{i,s_t})$. Note that μ, γ, β and σ^2 are all regime-dependent. Following the standard in the literature (see, for example, Franzoni and Schmalz, 2017; Spiegel and Zhang, 2013), we measure fund past performance by one lag of monthly return. Other lagged returns and lagged flows are also included in the explanatory variables to account for flow persistence and investor sensitivity to fund returns over longer horizons. Under this specification, FPS is gauged by the coefficient $\gamma_{i,1,s}$ associated with the one lagged return R_{t-1}.

We estimate the model using the expectation-maximisation (EM) algorithm. To select the optimal number of lags and regimes, we apply the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) respectively. Additionally, we compute the Regime Classification Measure (RCM) to select the optimal number of regimes. Based on these criteria, we estimate a two-regime Markow switching model with three lags for each fund having at least 100 monthly observations. For 90% of these funds, the p-value associated with the probability of switching between two regimes is below 0.1, suggesting the strong discriminatory power of the model and the existence of two distinct regimes. In total, this exercise is run on 9,075 individual funds belonging to the six predefined styles.[11] By taking the median of all the estimated $\gamma_{i,1,s}$ that are statistically significant, we obtain, for each style, the γ^E corresponding to the two regimes as reported in Tab 4.[12] Regime 1 refers to a state with low residual variance (i.e., normal market conditions) while regime 2 corresponds to a high-variance state

[11] We excluded funds that changed styles at least once during the study period.

[12] Due to the highly asymmetric distribution of $\gamma_{1,s}$ across the six styles, the median is used instead of the mean.

(i.e., turbulent market conditions).

INSERT TAB. 4 HERE

On average, γ_1 is 0.052 under regime 1, and nearly doubles to 0.103 under regime 2.[13] This result indicates that investor reactions to past performance are nearly two times stronger during turbulent phases than during normal ones. These estimates are qualitatively consistent with those reported in prior studies (see, for example, Capota and Darpeix, 2023; Ferreira et al., 2012; Huang et al., 2007) but are substantially lower than the value of 0.2748 adopted by FF as well as those documented in Chen et al. (2010), Bellando et al. (2021) and Franzoni and Schmalz (2017).[14] The regime-dependent differences are particularly pronounced for Growth, Mid Cap, Small Cap and Micro Cap funds, whose flow-performance sensitivity double or triple during market turmoils. In contrast, Growth Income funds exhibit slightly lower sensitivity under high-volatility conditions. In the meantime, Large Cap funds not only record the lowest FPS values across both regimes but also experience a decrease in sensitivity during turbulent periods.

These cross-style patterns can be partially explained by the clientele composition of each style documented in the existing literature (see, for example, Bams et al., 2017; Barber et al., 2016; Salganik-Shoshan, 2016). Large Cap funds are predominantly composed of institutional and highly sophisticated investors who rely on risk-adjusted evaluation metrics and seek stability and long-term performance. Growth and Growth Income attract a mix of retail and institutional investors, resulting in moderate overall sophistication and thus moderate overall sensitivity. In contrast, Mid Cap and Small Cap funds are more retail-oriented, with lower average sophistication, and a stronger propensity for return-chasing behavior. Finally, Micro Cap funds' investor base is overwhelmingly retail clients, representing the least sophisticated segment which is characterized by strong and rapid responsiveness to recent returns rather than to long-term risk-adjusted measures.

Price impact

In line with prior research, we gauge the price impact of each stock (denoted as L in equation (28)) by using the Amihud (2002) liquidity ratio calculated from daily stock data. The Amihud ratio for a given stock k on day d is computed as follows:

$$\text{Amihud}_{k,d} = \frac{|R_{k,d}|}{V_{k,d}} \tag{36}$$

where $|R_{k,d}|$ represents the absolute value of the stock's daily return on day d, and $V_{k,d}$ denotes the total dollar daily trading volume of the stock on the same day. This ratio indicates the absolute percentage

[13]For instance, an FPS of 0.094 implies that a -5% return would lead to net outflows of approximately $-5\% \times 0.094 = -0.47\%$.

[14]FF used pooled cross-sectional regressions of fund flows on past returns and tested several specifications. Their estimated FPS values ranged from 0.0508 to 0.2748, with the latter retained due to the highest adjusted R^2.

price change per dollar of trading volume, thereby serving as a general proxy for price impact. A higher Amihud ratio reflects increased illiquidity.

To compute the price impact for each stock k at month t, we take the monthly average of daily Amihud ratios obtained in the previous step.

$$\text{PriceImpact}_{k,t} = \frac{1}{D_{k,t}} \sum_{d=1}^{D} \text{Amihud}_{k,d} \tag{37}$$

where $D_{k,t}$ is the number of daily Amihud ratios for stock k in month t.

Figure 3 depicts the monthly number of stocks and the monthly cross-sectional equal-weighted average of price impact over time, with the price impact figure displayed in semi-logarithmic scale.[15] The number of stocks varies between 6,529 and 9,652 over the period. The overall average price impact during the whole period is 2.6 $\times 10^{-5}$, obtained from the monthly average of all stocks.[16] This estimate is higher than the equal-weighted mean price impact of 4.8 $\times 10^{-6}$ reported by FF over the 2003 - 2014 period. The figure reveals a pronounced upward trend in stock illiquidity during the last two decades. Notable spikes are observed around periods of severe crises such as in February 2009 (subsequent to the global financial crisis), March 2020 (at the beginning of the COVID-19 lockdown). We also notice a persistently high level of illiquidity from June 2022 through December 2023.

INSERT FIG. 3 HERE

Whereas FF assume a constant and common price impact ratio of 4.8×10^{-6}, for all asset types, we incorporate time-varying and asset-specific price impact measures with higher average values.[17]

[15] The value-weighted Amihud ratios provide, by construction, lower values than equal-weighted ones, since large-cap stocks tend to be more liquid than small stocks. To maintain a conservative approach, we therefore adopt the higher illiquidity estimates derived from the equal-weighted average.

[16] In the prior draft, due to data availability, we computed the monthly cross-sectional equal-weighted average of stocks' Amihud ratio using monthly data over the period 2003-2018. The resulting mean Amihud ratio is 5.6 $\times 10^{-5}$, which exceeds the value of 2.6 $\times 10^{-5}$, derived from the monthly average of all stocks calculated using daily data. As documented in the extant literature on stock illiquidity measurement, the Amihud measure constructed from daily data provides a more accurate representation, whereas aggregation at the monthly frequency yields higher average Amihud ratios. This discrepancy arises from statistical and methodological factors inherent to the aggregation of returns and trading volumes at lower frequencies (see, e.g., Lee et al. (2024) and Amihud (2002)).

[17] We also replace the time-varying, asset-specific Amihud ratios with their time-averaged equivalents. This adjustment smooths the impact of significant events, particularly diluting the effects of the subprime crisis and the COVID-19, which are now spread across the entire period. As a result, the price impact during these events is attenuated, while periods preceding and following them experience relatively larger effects. Overall, the qualitative pattern of AVs remains consistent across all styles, with the highest peak occurring around the subprime crisis. A second, substantially smaller peak appears in the aftermath of the COVID-19 for all styles. Outside these crisis periods, AVs remain economically insignificant. These results are available upon request.

2.3 Results

We study a negative shock of 5% which represents the standard magnitude typically used in stress tests for banking systems.[18] The shock affects all stocks proportionally to their market sensitivity, as measured by their individual beta. For each month, we follow equation (30) to compute the aggregate vulnerability (AV) for each style by considering style-specific FPS under two regimes, time-varying and asset-specific price impact, and three levels of leverage: no leverage ($B = 0$), medium leverage ($B = 0.33$) and the max authorized leverage ($B = 0.5$).

Figure 4 illustrates the aggregate vulnerabilities for all styles under varying market regimes and leverage levels. A positive (negative) AV indicates the percentage of assets lost (newly allocated) due to the shock. We observe a similar and consistent AV pattern for all styles, regardless of leverage and market sentiment. In general, AVs remain initially close to zero with minor fluctuations but they progressively increase in late 2007, peaking at the end of 2008 (outflows), before sharply reversing to negative values (inflows) during 2009. The subprime crisis combined with heightened market volatility (regime 2) leads to the highest vulnerability, particularly for Growth funds. Since 2010, AVs remain consistently low for all styles. The fact that all styles respond directionally to shocks in unison, differing only in magnitude, highlights the systemic nature of the DEMF sector.

Compared to FF, we observe distinct temporal dynamics of AVs. FF report only positive AVs (outflows) with a peak in late 2008 under time-varying and asset-specific price impact. Under constant, asset-specific price impact and homogeneous price impact, their AVs steadily increase over time. In contrast, our results capture a broader range of responses. These differences likely stem from our granular specification of stock betas and non-linear flow-performance sensitivity, which better capture shock impact.[19] Furthermore, we find no significant vulnerability during the COVID-19 crisis, consistent with the exogenous and transitory nature of the shock.[20] The pandemic triggered a short-lived liquidity panic that primarily affected bond and money market funds rather than equity funds.[21] As noted

[18] We also study the impact of a more severe negative shock of 10% on the aggregate vulnerability across all styles. Given the linearity inherent in the model, a larger shock naturally results in higher AVs which follow the same general patterns as those observed under the baseline scenario. These results remain qualitatively consistent across varying leverage levels and market conditions. They are available upon request.

[19] In their analysis, FF use a fixed flow-performance sensitivity estimated from a pooled OLS and do not take into account stock betas.

[20] Pástor and Vorsatz (2020) define the COVID-19 crisis period as the ten-week between February 20 and April 30, 2020. In the equity market, the S&P500 index experienced a loss of 34% of its value in the five week period between February 19 and March 23, 2020 before bouncing back by over 30% by the end of April.

[21] At the peak of the COVID-19 crisis (March 2020), U.S. equity mutual funds had outflows of about $14 billion in the single week of March 4 (about 0.12% of their assets as of the end of January) while bond funds saw outflows of $24 billion that same week (about 0.50% of their assets as of the end of January). In the meantime, domestic equity ETFs registered a strong net inflow of $31 billion in March 2020. For more details, see ICI reports available at https://www.ici.org/system/files/private/2021-04/20_rpt_covid2.pdf and https://www.ici.org/viewpoints/20_view_mf_flows_covid.

by Affinito and Santioni (2021), funds managed this largely through portfolio rebalancing — selling COVID-affected assets to meet redemptions — before central bank interventions rapidly contained the liquidity episode.

INSERT FIG. 4 HERE

As expected, leverage considerably magnifies AVs, indicating that funds are more vulnerable as debts grow. In 2008, under regime 1 (normal markets), the maximum AV reaches approximately 0.5% without leverage (see Fig. 4a) but shifts to a sudden level of 5% with moderate leverage ($B = 0.33$) (see Fig. 4c) and further to 8% under max leverage ($B = 0.5$) (see Fig. 4e). Market disruptions exacerbate style vulnerability. Under regime 2 (turbulent markets), AVs are substantially higher compared to regime 1 (normal markets). This result suggests that in periods of stress, the percentage of equity wiped out by fund liquidations is greater, consistent with generally stronger flow-performance sensitivity (higher FPS) observed in stress periods. Without leverage, AVs in regime 2 can be twice as large as those in regime 1. With leverage, the increase in vulnerability between regimes is less pronounced. This pattern suggests a threshold effect: leveraged funds become highly vulnerable to shocks, and even calm market conditions can precipitate substantial losses and outflows due to liquidity constraints (e.g. margin calls).[22]

A closer look at the AV dynamics for each style, as depicted in Figures 5, 6 and 7, reveals substantial heterogeneity in vulnerability across styles, particularly during 2008-2010. Growth consistently exhibits the highest vulnerability, followed by Growth Income. Under zero leverage (Fig. 5a), the AV for Growth peaks in late 2008 at 0.46% in regime 1, and rises to 0.54% in regime 2. Under moderate leverage (Fig. 6a), Growth's AV reaches 4.6% in regime 1 with a slight increase in regime 2. Under the most adverse conditions – maximum leverage combined with regime 2 (Fig. 7a) – Growth's AV reaches 8%. Growth Income shows lower vulnerability, with maximum AV values ranging from 0.1% (zero leverage, regime 1; Fig. 5b) to 3% (maximum leverage, regime 2; Fig. 7b). Large Cap displays AV dynamics broadly similar to those of Growth and Growth Income, though with slightly lower vulnerability compared to Growth Income's. Thus, flows from Growth, Growth Income and Large Cap funds appear relatively less sensitive to performance in normal times but exhibit the highest vulnerability during crisis periods. By contrast, Mid Cap, Small Cap and Micro Cap funds, which all show the strongest flow-performance sensitivity, particularly in turbulent markets, reveal comparatively resilient, even under high leverage and severe market stress. Excluding the 2003-2010 period, we continue to observe relatively higher level of vulnerability for Growth and Growth Income while Large Cap turns out to be generally resilient over time. Mid Cap, Small Cap and Micro Cap remain resilient across configurations.

INSERT FIG. 5 HERE

[22] The collapse of Archegos Capital Management in March 2021 provides a compelling example of how excessive leverage can cause fund failure even in relatively stable markets. For more details, see "Leverage and derivatives: the case of Archegos", ESMA TRV Risk Analysis, May 2022.

INSERT FIG. 6 HERE

INSERT FIG. 7 HERE

The persistently high level of AVs observed for Growth and Growth Income funds, compared to those of other styles, can be attributed to several factors related both to fund style characteristics and investor base. First, Growth and Growth Income funds typically concentrate on stocks with high expected long-run earnings growth, which are inherently more volatile and more vulnerable to market stress. Such stocks tend to experience sharper devaluation during bear markets, making Growth-oriented funds more exposed to severe selloffs. During the subprime crisis, the need to meet large redemption requests forced these funds to liquidate positions into a falling market[23], amplifying losses and vulnerability because of fire-sale externalities. These effects are further exacerbated by the prevalence of momentum trading among mutual funds, which reinforced market pressure on growth stocks (see, for example, Frijns et al., 2016).

Second, compared with other styles, Growth and Growth Income funds are likely to attract a larger share of institutional and financially sophisticated investors. Although these investors display relatively moderate sensitivity to fund recent returns (i.e., lower FPS), they tend to respond more quickly to market-wide shocks. By contrast, Mid Cap, Small Cap and Micro Cap funds have more retail-oriented clienteles characterized by lower investor sophistication. While retail investors react more aggressively to recent returns, they appear less reactive to market-wide shocks. These patterns support the evidence on shock-driven investor behavior across sophistication levels. For example, Ben-David et al. (2012) document that during the subprime crisis, hedge fund investors – who are generally more sophisticated than mutual fund investors – redeemed at substantially larger scale. Similarly, Allaire et al. (2023) show that the "dash for cash" during the March 2020 turmoil was not driven by households, but by the fund sector itself: funds-of-funds and foreign investors were the most run-prone, whereas funds with a high share of household (retail) ownership experienced significantly lower outflows. This aligns with Affinito and Santioni (2021), who find that professional investors (like insurers and funds themselves) acted procyclically during the turmoil, engaging in panic selling and failing to play a stabilize markets. These results are corroborated by Pástor and Vorsatz (2020) who also find that U.S. DEMF funds with more institutional investors suffered larger outflows than retail-oriented funds during the COVID-19 crisis. Greenwood and Thesmar (2011) observe that stocks widely held by institutional investors are more susceptible to non-fundamental demand shifts. However, they do not find statistically significant evidence of fire sales in equity markets during the COVID-19.[24] This finding thus suggests that vulnerability dynamics are driven more by the strategic complementarities among sophisticated institutional investors than by simple performance-chasing behavior. It also contrasts to Fiedor et al. (2019), who

[23]Hau and Lai (2017) document that in the early stage of the subprime crisis, equity funds were most affected by large value losses of bank stocks. In order to meet large redemptions, distressed funds were likely to liquidate best-performing non-financial stocks to avoid loss realization associated to financials.

[24]In the same vein, Coval and Stafford (2007) show that common ownership by institutional investors amplifies the downward pressure on stock prices during asset fire sales.

observe that higher values of flow-performance sensitivity can result in higher vulnerability.

3 Contagion analysis

Our findings in the previous section show that the U.S. DEMF display substantially heterogeneous vulnerability in response to shocks, depending on their styles. Some styles are much more vulnerable than others. In this section, we explore how these styles can impact each other and thus transmit shocks within the U.S. DEMF. To this end, we perform a contagion analysis between fund styles by enhancing the spillover approach developed by Diebold and Yilmaz (2009, 2012, 2014) (DY).[25] While the standard DY framework is widely used for asset class spillovers (Bouveret et al., 2023; Bouveret and Yu, 2021), it faces limitations when applied to highly correlated equity fund styles.[26] We address this by implementing a Ridge-VAR estimation strategy, as proposed by Ballarin (2021, 2024), to stabilize parameter estimates in the presence of strong cross-style correlations. Furthermore, we employ Generalized Forecast Error Variance Decomposition (GFEVD) to ensure that our interconnectedness measures are invariant to the ordering of variables. This framework allows us to map the directional connectedness of the network, identifying which styles act as net transmitters of stress and which act as net receivers.

3.1 Data

This section employs daily data of fund returns and TNA to more accurately capture the transmission of shocks between fund styles. Daily data allows for a finer resolution in analyzing short-term dynamics and provides a more immediate reflection of market events and investor reactions. We then construct six style series: Growth, Growth Income, Large Cap, Mid Cap, Small Cap and Micro Cap. The daily return of each index is the TNA-weighted value of the return of all funds forming the index on that day. This aggregation enables us to assess the overall contagion effects across different fund styles while accounting for the relative size and influence of each fund in the market.

As expected, the six return series exhibit substantial correlations (Tab. 5). Pairwise Granger causality tests (Tab. 6) also indicate statistically significant causal links among nearly all mutual fund styles. However, these results should be interpreted with caution in light of the very high correlations across the series. In such settings, Granger causality may primarily capture shared information, market-wide factors, or common trends, rather than distinct causal influence of one style over another. Consequently,

[25] Several methods have been developed to capture spillover effects in financial networks, including correlation analysis (Forbes and Rigobon, 2002), Granger pairwise causality and VECM (Gentile and Giordano, 2013), the GARCH factor model (Dungey and Martin, 2007), VAR-EGARCH (In et al., 2001), CoVaR (Tobias and Brunnermeier, 2016).

[26] The DY approach has been widely adopted in studies assessing volatility spillovers across different financial markets. For instance, Greenwood-Nimmo et al. (2016) analyze spillover effects in Forex markets, while Fernández-Rodríguez et al. (2016) apply the approach to the EMU sovereign bond market.

although the test statistically confirms interconnectedness, it may overstate the strength or specificity of true causal linkages among fund styles. To avoid misinterpreting spurious causality in such a tightly integrated system, it is crucial to complement these tests with connectedness measures and regularization techniques that explicitly address multicollinearity.

INSERT TAB. 5 HERE

INSERT TAB. 6 HERE

3.2 Spillover approach - Methodology

Diebold and Yilmaz (2009, 2012, 2014) develop a multivariate time-series approach to measure the interdependence between financial assets and between financial institutions. The approach builds upon the Vector Autoregression (VAR) framework and the variance decomposition procedure.

Following this approach, we first estimate a K variable VAR(p) model in the form:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t \tag{38}$$

where y is a $(K \times 1)$ vector of variables at date t, c is a $(K \times 1)$ vector of constants, and u is a $(K \times 1)$ vector of error terms at date t; A_i is a $(K \times K)$-dimensional matrix of dynamic coefficients. The error term u_t represents the unexplained variability in the variables y at time t. In our case, y_t are the daily return series of fund styles, $K = 6$ representing the six styles, p corresponds to the number of optimal lags for our VAR estimates.

Prior to this estimation, the stationarity of all variables is verified via an augmented Dickey-Fuller (ADF) test. The results show that all series are stationary and suitable for further analysis (Tab. 7). We then perform several VAR lag selection tests including AIC, BIC, FPE, HQIC to determine the optimal number of lags for the model (Tab. 8). Based on the AIC criteria, a lag of 4 is chosen.

INSERT TAB. 7 HERE

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INSERT TAB. 9 HERE

Due to multicollinearity problem caused by the high degree of correlation among the six return series (Tab. 9), we can not implement the DY approach to estimate the model. We therefore estimate our VAR(6) system using the Ridge approach, following Ballarin (2021, 2024). To tackle the multicollinearity, the Ridge approach adds a penalty term λ to the objective function to shrink the coefficients A_i towards zero as follows:

$$\min_{A_1, A_2, \ldots, A_p} \sum_{t=1}^{T} \left(y_t - c - \sum_{i=1}^{p} A_i y_{t-i} \right)^2 + \lambda \sum_{i=1}^{p} \|A_i\|_F^2 \tag{39}$$

where the first term $\sum_{t=1}^{T} \left(y_t - c - \sum_{i=1}^{p} A_i y_{t-i}\right)^2$ is the sum of squared residuals from fitting the VAR model; The second term introduces a penalty on the magnitude of the coefficients. $\|A_i\|_F^2$ corresponds to the sum of squared elements in the coefficient matrix A_i, so the penalty applies to all lagged effects in the system. This penalization shrinks the estimated coefficients towards zero without setting them exactly equal to zero, which helps stabilize the estimation when the regressors are highly correlated. It also reduces the variance of the estimators, which is crucial because multicollinearity inflates the variance of OLS-VAR estimates, leading to unstable and unreliable reference. All Ridge regressions are estimated without an intercept. This specification is justified by the properties of our data: daily mutual fund returns are strongly stationary and fluctuate around a mean that is essentially zero (see Tab. 7). Including a constant term would therefore not improve model fit and would only capture noise around the zero mean.

For each equation of the system, the penalty parameter λ is selected using a time-series cross-validation procedure with rolling folds and a buffer zone to avoid information leakage. More precisely, we consider a grid of 100 candidate values for λ, logarithmically spaced between 10^{-2} and 10^{6}. The sample is then divided into five sequential folds. For fold f, the model is estimated on an expanding training window and evaluated on a later validation block. To ensure that the validation set does not mechanically benefit from short-term serial correlation, a buffer of $m = 20$ periods is introduced between the end of the training sample and the beginning of the validation window. This gap prevents information from the future from leaking into the estimation of the model, which is a crucial requirement when dealing with financial time series. For each candidate value of λ, we compute the mean squared prediction error over all folds. The value that minimizes this out-of-sample loss is selected as the optimal penalty for equation i. This procedure yields an equation-specific regularization level, which is particularly useful in our context since some return series are more collinear or noisier than others. As a result, the Ridge estimator is allowed to apply stronger shrinkage where needed, while preserving flexibility in the remaining equations.

Once the Ridge VAR model is estimated, we apply a Generalized Forecast Error Decomposition (GFEVD), following the order-invariant approach of Pesaran and Shin (1998). Using the estimated VAR coefficients, we obtain the moving-average representation recursively:

$$y_{t+h} = \Phi_h u_t, \tag{40}$$

where each matrix Φ_h captures the propagation path of shocks h periods ahead. To illustrate, ϕ_0 quantifies how much each style reacts immediately to a shock; ϕ_1 specifies how much each style reacts one day later, through lagged effects while ϕ_2 tells how the impact continues two days later, and so on. By stacking these dynamic effects, the model quantifies a complete shock-transmission path.

With these impulse response matrices, the GFEVD is computed over a horizon of $H = 50$ days:

$$\theta_{i,j,H}^{g} = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} \left(e_i' \Phi_k \Sigma_u e_j\right)^2}{\sum_{l=1}^{K} \sigma_{ll}^{-1} \sum_{k=0}^{H-1} \left(e_i' \Phi_k \Sigma_u e_l\right)^2}. \tag{41}$$

where $\theta^g_{i,j,H}$ is the generalized variance decomposition for horizon H, measuring the proportion of the forecast error variance of variable i that is attributable to shocks in variable j. The term $e_i' \Phi_k \Sigma_u e_j$ isolates the dynamic impact of a shock to style j on style i after k periods, accounting for contemporaneous correlations through Σ_u. Equation 40 shows how a shock hitting one style today affects all styles in the following days. The matrix Φ_h tells us the strength and direction of this transmission at each horizon h. These dynamic effects are needed to compute how much each style contributes to the future uncertainty of the others, which is the basis of the connectedness framework.

Importantly, the GFEVD is order-invariant: it does not depend on the ordering of the variables, unlike the Cholesky decomposition used in traditional spillover analysis. In our implementation, each row of the GFEVD matrix is normalized so that it sums to one. This step ensures that, for each style i, the contributions from all styles j exhaustively decompose the forecast error variance of i. The normalized GFEVD matrix therefore provides a consistent basis for measuring the relative importance of each transmission channel.

Building on the GFEVD framework, Diebold and Yilmaz (2012) propose constructing a connectedness matrix where $\theta^g_{i,j,H}$ represents the percentage of Forecast Error Decomposition (FEVD) for variable i explained by shocks to variable j. The connectedness matrix can be written as:

$$C = \begin{pmatrix} \theta^g_{1,1,H} & \theta^g_{1,2,H} & \cdots & \theta^g_{1,K,H} \\ \theta^g_{2,1,H} & \theta^g_{2,2,H} & \cdots & \theta^g_{2,K,H} \\ \vdots & \vdots & \ddots & \vdots \\ \theta^g_{K,1,H} & \theta^g_{K,2,H} & \cdots & \theta^g_{K,K,H} \end{pmatrix}$$

The diagonal elements $\theta^g_{i,i,H}$ show the proportion of forecast error variance for the variable i explained by its own shocks (self-contribution). The off-diagonal elements $\theta^g_{i,j,H}$ (where $i \neq j$) indicate the spillover effects, measure how much of variable i's forecast error variance is due to shocks from variable j.

In addition, Diebold and Yilmaz (2014) establish four supplementary measures that demonstrate the relative importance of each variable, i.e. each fund style in our framework, within the system:

- Inward Connectedness ('From others'): a measure of the shocks transmitted from the system to fund style i. It is calculated by summing the contributions of shocks from all other styles j to style i. The value is normalized between 0 and 1.

$$CHI_i = \sum_{j=1}^{K} \theta^H_{ji}, \quad j \neq i \tag{42}$$

- Outward Connectedness ('To others'): a measure of the shocks that style i transmits to the system. It is computed by summing the contributions of style i to the forecast error variance of all other styles j. This value is not constrained by 1.

$$CHO_i = \sum_{j=1}^{K} \theta_{ij}^{H}, \quad j \neq i \tag{43}$$

- Net Directional Connectedness (NDC): the difference between the outward and inward connectedness of each style. It indicates whether a style is a net transmitter or a net receiver of shocks. If the NDC of a style i is positive (negative), style i is considered as a net transmitter (receiver) of shocks.

$$NDC_i = CHO_i - CHI_i \tag{44}$$

- Total Connectedness Index (TCI): a measure of the overall connectedness in the system, representing the percentage of forecast error variance in the system that is due to shocks transmitted between styles (rather than within each style itself). A higher TCI indicates more interconnectedness, meaning the styles are strongly influenced by each other.

$$\text{TCI} = \frac{\sum_{i=1}^{K} \sum_{j=1, j\neq i}^{K} \theta_{ij}^{H}}{K} \tag{45}$$

where θ_{ij}^{H} represents the contribution of variable j to the forecast error variance of variable i over the horizon H; The numerator sums the off-diagonal contributions of the connectedness matrix C, indicating shocks transmitted between variables. In this study, $K = 6$ corresponds to the total number of fund styles (variables) in the system.

These connectedness measures provide valuable insights into the dynamics of the system, showing which styles are most influential and which are most affected by the interconnections within the system.

We then estimate the Ridge-VAR model over two distinct subperiods – 2003–2009 and 2010–2023 – to study connectedness among fund styles under shocks of different natures: an endogenous (financial) shock (subprime crisis, 2003-2009) and an exogenous (health) shock (COVID-19 crisis, 2010-2023). This choice reflects major regime changes documented in the literature: a pre-subprime crisis period with traditional risk-return dynamics, and a post-subprime crisis shaped by exceptionally low interest rates, massive flows into passive investment, factor crowding, and global macro shocks. Splitting the sample enables us to capture these structural differences more precisely than a single-sample analysis.

3.3 Results

Table 10 reports the optimal Ridge penalties (λ) associated to each style for the two subperiods. λ exhibit notable differences between the two subperiods, reflecting changes in the underlying correlation structure of the equity style returns. During 2003–2009, their values are generally moderate, suggesting limited multicollinearity and a more diversified information content across styles. In contrast, the

2010–2023 estimates show several λ's reaching the upper bound, indicating much stronger collinearity and a heavier reliance on regularization in the post-crisis environment. This shift is consistent with the increased integration of U.S. equity markets and the growing dominance of common risk factors in the more recent period. Overall, the evolution of the λ-pattern highlights a structural increase in return co-movements across styles, especially after the subprime crisis.

INSERT TAB. 10 HERE

Table 11 presents various connectedness measures among the six fund styles for the two subperiods 2003-2009 (Panel A) and 2010-2023 (Panel B). The off-diagonal values correspond to pairwise directional connectedness ($\theta_{i,j,H}$), which captures the percentage of the forecast error variance of style $i$attributable to shocks originating from style j. The column sums, labeled CHO (To), represent the total shock spillovers transmitted by each style to the system. Similarly, the row sums in the CHI (From) column indicate the total spillovers received by each style from the system. The Net Directional Connectedness (NDC), displayed in the rightmost column, measures the difference between each style's transmitted (CHO) and received (CHI) spillovers. The bold values at the bottom-right corner represents the Total Connectedness Index (TCI), which summarizes the overall intensity of spillovers within the system.

INSERT TAB. 11 HERE

Both subperiods exhibit exceptionally high Total Connectedness Index (TCI) values—approximately 81% during 2003–2009 and 82% during 2010–2023—implying that directional spillovers account for more than four-fifths of all forecast error variation in the system. This indicates that U.S. DEMF operate as a tightly integrated network in which shocks to any single investment style quickly propagate to all others. Importantly, neither the subprime crisis nor the COVID-19 turmoil fundamentally alter the aggregate level of spillover intensity: the system is persistently highly interconnected. This result is unsurprising given that all six styles ultimately draw from the same U.S. equity universe and thus share exposure to common macroeconomic forces, monetary policy, and aggregate investor sentiment. The finding aligns with Nguyen and Karamé (2022), who document increasingly convergent exposure of these styles to macro risk factors over the same period. Consistent with this high correlation structure, we also find that the connectedness structure itself relatively balanced: TO and FROM spillover values cluster within similar ranges across periods, with no style emerging as a dominant systemic driver. The system is thus characterized by symmetry, with styles operating as either mild net transmitters (NDC > 0) or mild net receivers (NDC < 0), rather than extreme outliers.

While aggregate connectedness of the sector remains stable, the roles played by individual styles in transmitting and receiving shocks evolve significantly between the two subperiods. In the first subperiod, the principal net transmitters are Growth (NDC = 2.82), Mid Cap (2.43) and Large Cap (1.5), whereas Growth Income (NDC = -3.53), Micro Cap (-2.94) and Small cap (-0.28) absorb slightly more shocks than they transmit. In the second subperiod, the network structure remains balanced in magnitude, the roles of individual styles shift. Mid Cap emerges as the strongest transmitter (NDC = 2.52), followed by Growth Income (1.89) and Growth (1.50). Large Cap, by contrast, moves from being a mild transmitter in subperiod 1 to a mild receiver in subperiod 2 (-0.82). Small Cap plays a neutral position while Micro Cap remains consistent net receivers in both subperiods, absorbing shocks without displaying large imbalances. Thus, the key structural change is not an increase in asymmetry, but rather a reallocation of systemic influence across investment styles.

The persistent role of Growth and Mid Cap as net transmitters across crises is a central result that can be attributed to several factors. For Growth funds, the portfolio is heavily tilted toward long-duration equities, whose valuations are particularly sensitive to discount-rate shocks and tend to experience the promptest and sharpest corrections during market stress. Their vulnerability in the subprime crisis is further amplified by nontrivial exposures to financial stocks, which are at the center of the turmoil. In addition, Growth funds represent the largest segment of the equity mutual fund universe for most of the sample period; their size alone means that shocks affecting Growth can exert outsized pressure on the broader market and thereby propagate to other styles. Mid Cap funds, in contrast, invest predominantly in U.S.-focused, mid-sized firms that are more sensitive to domestic economic fluctuations. These equities are relatively liquid but less efficiently priced, attracting more active and performance-sensitive investors who tend to adjust portfolios more aggressively during periods of heightened uncertainty. This combination of macro sensitivity, investor composition, and trading intensity makes Mid Cap a recurring transmitter.

In contrast, Micro Cap remains a persistent net receiver of shocks in both periods (NDC = -2.94 and -5.24), indicating that it systematically absorbs shocks emanating from other styles rather than originating them. This behavior is consistent with the structural characteristics of the Micro Cap segment: thin liquidity, high idiosyncratic volatility, and limited influence on aggregate market movements. All these characteristics constraint Micro Cap's capacity to generate system-wide shocks. Unlike Micro Cap, Small Cap displays NDC values close to zero in both subperiods, suggesting its neutral position within the network. Small Cap neither consistently transmits nor absorbs shocks to a meaningful extent, reflecting its intermediate role between micro-cap stocks dominated by idiosyncratic factors and larger, more systemically influential style categories. Overall, these patterns indicate that the lower capitalization segment of the market play a little role in driving system-wide dynamics.

Finally, another notable evolution in the connectedness structure concerns the changing roles of Large Cap and Growth Income, whose positions shift in opposite directions across the two subperiods. In the first superiod, Large Cap acts as a mild net transmitter, consistent with its traditional role as a broad market benchmark capable of influencing other style segments. This influence is reinforced by the fact that, in 2007, more than 20% of Large Cap holdings are financial, placing the segment at the epicenter of the subprime crisis. In the second subperiod, however, Large Cap becomes a net receiver. Post-2010 shocks — driven by monetary policy, macroeconomic uncertainty, and the COVID-19 lockdown

— are largely exogenous to the large-cap universe, making its dynamics more reactive than causal. The growing concentration in technology mega-caps, combined with the flight-to-quality and the rise of passive investing, further enhances this receptor role: Large Cap increasingly absorbs system-wide shocks but originates fewer.

In contrast, Growth Income shifts from a significant receiver in the first period to a mild net transmitter in the second. This reflects the rising macro sensitivity of dividend- and income-oriented equities in the a low-rate environment. As yield-search behavior intensifies post-2010, Growth Income portfolios, become more responsive to macroeconomic news, elevating their systemic relevance. This transition highlights a reallocation of systemic importance away from traditional market leaders toward styles more tightly linked to interest-rate expectations and defensive investment strategies.

4 Concluding remarks and policy implications

In this paper, we contribute to the debate about the systemicness of investment funds by examining vulnerability and contagion risk across the six most popular styles of U.S. DEMF over the period 2003-2023. To assess the resilience of these styles to shocks, we extend the macroprudential stress-testing framework of Fricke and Fricke (2021) (FF) by exploiting granular portfolio- and security-level data. While the FF model focuses on aggregate sector vulnerability using fixed parameters, we introduce three granular specifications in order to capture cross-style heterogeneity and dress a more realistic assessment of style-specific vulnerability: (i) explicitly modeling the asset-specific sensitivity to the initial shock via stock betas; (ii) incorporating style-specific flow-performance sensitivity (FPS) estimated via a two-regime model (distinguishing between tranquil and turbulent markets) to capture non-linear investor reactions, following Lee (2020); (iii) employing time-varying, asset-specific price impacts to gauge fire-sale effects. By integrating these components, we construct a dynamic measure of vulnerability that accounts for the interaction between the initial market shock, the behavioral reaction of the specific investor base, and the liquidity constraints of the underlying portfolio. Additionally, our empirical scope expands prior data used by FF from 2003–2014 to 2003–2023 thereby covering the post-subprime crisis, the COVID-19 turmoil, and the post-pandemic recovery. This extended horizon offers a comparative analysis of vulnerability across endogenous (2008) and exogenous (2020) shock regimes.

We find that while all styles respond directionally to shocks in unison, they display substantial heterogeneity in the magnitude of their responses, depending on the nature of shocks. As expected, vulnerability increases systematically with leverage and the level of market stress. During turbulent periods, vulnerability becomes significantly higher than during tranquil times and can not be neglected. Specifically, Growth and Growth Income funds consistently exhibit the highest vulnerability, particularly during the 2007–2009 subprime crisis. In contrast, Mid, Small, and Micro Cap funds remain comparatively resilient. This asymmetry can be explained by differences in investor clientele, liquidity structures, and exposure to the underlying shock. The COVID-19 episode introduced a regime shift: although equity funds as a whole were far less vulnerable in 2020 than in 2008, the style-specific sensitivities persisted, highlighting that vulnerability is largely driven by the interaction between style-specific characteristics and the nature of the shock. These results thus highlight the importance of style-level analysis in macroprudential stress testing.

We further investigate how these styles interact and propagate contagion within the U.S. DEMF sector. We implement a Ridge-VAR connectedness framework by enhancing the spillover approach of Diebold and Yilmaz (2009, 2012, 2014) to address strong cross-style correlations. Our results reveal that the U.S. DEMF sector is highly interconnected, with spillovers consistently accounting for more than 80% of the variation across styles. While this strong integration persists across both the subprime and COVID-19 crises, the identities of systemic transmitters and receivers shift over time. Growth and Mid Cap funds repeatedly emerge as key transmitters of stress, whereas Micro Cap funds consistently absorb spills due to their thin liquidity and limited market influence. Post-2010, the network undergoes a reordering: Large Cap funds shift from mild transmitters to net receivers amid rising passive investing and flight-to-quality flows, while Growth Income funds move from absorbing shocks to originating them in a prolonged low-rate environment. These patterns show that systemic risk is not only high but also evolve dynamically with changes in the nature of shocks, market structure and investor behavior.

Policy discussion From a regulatory perspective, our findings provide several contributions to the SEC's ongoing discussion on fund stress testing, liquidity risk management and systemic monitoring.

First, the pronounced cross-style heterogeneity uncovered by our extended stress-testing framework — specifically the regime-dependent flow reactions and time-varying price impacts — suggests that uniform liquidity standards may be insufficient. The consistent identification of Growth, Growth Income, and Mid Cap funds as shock transmitters justifies stronger ex-ante liquidity risk management tools for these specific categories. This could include more conservative liquidity bucketing, or targeted swing pricing thresholds calibrated to their empirically higher fragility and systemicness. Conversely, structurally less systemic styles like Micro Cap, which function primarily as shock absorbers, calls for a supervisory focus centered on investor protection rather than systemic spillovers.

Second, the structural shift in systemic roles – specifically the transition of Large Cap funds from net transmitters to net receivers and the emergence of Growth Income and Mid Cap as transmission hubs in the post-2010 environment – demonstrates that size-based supervisory metrics are insufficient. Integrating network-based connectedness indicators into systemic risk monitoring, while taking into account for distinct natures of market shocks, would allow regulators to reorient scrutiny toward the actual engines of contagion rather than relying on traditional large-cap proxies.

Finally, the persistently high connectedness of the DEMF sector supports the case for counter-cyclical liquidity buffers and enhanced portfolio disclosure to mitigate fire-sale spillovers during periods of widespread stress (see, for example, Ahnert, 2016)[27]. Taken together, these findings argue for a granular, style-sensitive supervisory framework that aligns with the SEC's dual mandate of safeguarding market stability and protecting investors.

However, as emphasized by Ahnert (2016) and Aikman et al. (2019a), the effectiveness of macroprudential regulation ultimately depends on institutional design. It requires not only a combination of well-calibrated instruments but also a regulator willing to tighten conditions preemptively, and a governance structure capable of sustaining such actions even when they are unpopular.

Further research Despite these contributions, several avenues for future research remain open. A first direction would be to examine the evolution of contagion dynamics granuarly over time and to identify the precise channels through which shocks propagate within the U.S. DEMF sector. It would also be valuable to investigate whether the level and structure of connectedness exhibit nonlinearities by estimating a Threshold VAR model in the spirit of Candelon et al. (2021), with regimes driven by market uncertainty. Furthermore, disentangling the effects of investor-driven flows from those arising from shared exposure to common risk factors would yield deeper insight into the mechanisms underlying contagion.

[27] Ahnert (2016) show that intermediaries hold insufficient liquidity from a social perspective because they do not internalize rollover risk and fire-sale externalities. Besides, they tend to free-ride on the liquidity of the others. Hence, it is indispensable to impose a minimum regulatory liquidity buffers.

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Table 1: Number of U.S. DEMF and their economic importance over the study period 1/2003 - 12/2023. This table reports, for each style and at each December, the number of funds (*Nb*) and their weight as a percentage of the total assets managed (*TNA*, in billions of dollars) by the whole sector (%). We restrict our analysis to DEMF that are actively managed, and exclude all balanced, bond, international, sector and index funds. The classification of funds into the six styles is done as follows: Large Cap having Lipper Code = SP; Mid Cap having either Lipper Code = MC or SI Code = GMC; Small Cap having either Lipper Code = SG or SI Code = SCG; Micro Cap having Lipper Code = MR; Growth having Lipper Code = CA, G or SI Code = AGG, GRO; Growth Income having Lipper Code = GI or SI Code = GRI, ING. For funds having different share classes, we aggregate all the observations pertaining to different share classes into one observation, since they have the same portfolio composition and manager names.

Year	Growth		Growth Income		Large Cap		Micro Cap		Mid Cap		Small Cap		Total	
	Nb	%	Nb	%	Nb	%	Nb	%	Nb	%	Nb	%	Nb	TNA
2003	433	42	1 020	28	68	11	35	0.52	304	7.7	475	11.0	2 335	2 462
2004	404	41	1 040	27	66	11	41	0.52	308	8.3	481	11.9	2 340	2 870
2005	409	41	1 022	28	61	11	39	0.46	289	8.8	474	11.8	2 294	3 128
2006	439	39	1 015	29	57	11	43	0.47	323	8.7	500	11.6	2 377	3 578
2007	521	41	1 228	28	62	11	47	0.37	404	9.0	580	10.4	2 842	3 948
2008	632	39	1 272	28	59	13	48	0.29	396	8.3	548	10.5	2 955	2 376
2009	609	39	1 219	28	52	12	39	0.27	346	9.2	506	11.0	2 771	3 073
2010	628	38	1 213	28	52	12	38	0.28	341	10.0	489	12.0	2 761	3 550
2011	633	37	1 226	29	51	13	43	0.25	331	9.3	496	11.6	2 780	3 418
2012	666	36	1 153	30	49	13	39	0.20	319	9.5	495	11.2	2 721	3 879
2013	729	35	1 164	29	45	14	40	0.24	318	9.9	496	11.7	2 792	5 316
2014	742	36	1 159	30	44	15	43	0.21	319	9.5	515	10.3	2 822	5 857
2015	850	35	1 232	30	48	15	41	0.18	331	10.0	510	9.6	3 012	5 835
2016	891	32	1 219	32	47	16	39	0.18	333	9.8	522	10.1	3 051	6 529
2017	866	32	1 246	32	45	17	42	0.16	326	9.5	517	9.5	3 042	7 940
2018	925	32	1 264	33	41	17	39	0.15	323	8.9	515	8.9	3 107	7 508
2019	905	31	1 218	33	42	18	37	0.13	318	9.3	485	8.1	3 005	9 618
2020	824	33	1 202	32	38	18	34	0.12	315	9.1	456	8.1	2 869	11 130
2021	840	33	1 258	32	37	19	33	0.12	311	8.7	441	7.7	2 920	13 789
2022	1 279	21	760	46	40	18	33	0.10	412	8.7	517	7.0	3 041	12 029
2023	1 328	20	778	45	42	20	33	0.09	426	8.0	540	6.8	3 147	14 552

Table 2: Summary statistics of fund characteristics by styles.

This table shows the summary statistics of U.S. DEMF over the study period 1/2003 - 12/2023. *Total net assets* (TNA) is equal to the fund's total assets minus total liabilities, reported in millions of dollars. *Fund flow* is computed as $Fl_t = \frac{\text{TNA}_t - \text{TNA}_{t-1}(1+R_t)}{\text{TNA}_{t-1}}$ and represents the fund's monthly cash inflow or outflow. *Age* is measured as the difference in years between the fund's first offer date and the date of the fund's last available return in the sample. *Expense ratio* captures the fund's operating expenses, including 12b-1 fees, waivers, and reimbursements, as a percentage of total investment. *Turnover ratio* is the minimum of the fund's total purchases or total sales expressed as a percentage of 12-month average total net assets from CRSP. *Mean return* and *Median return* are respectively the annualized average and the median values of the net monthly returns of all funds. *Return volatility* is the standard deviation of a fund's monthly net returns, multiplied by the square root of 12. The *Sharpe* ratio is calculated as the fund's average monthly excess return over the 3-month U.S. T-bill rate, divided by the standard deviation of the fund's monthly returns. *Total net assets, Fund flow, Age, Expense ratio, Turnover ratio, Sharpe* are reported as the average value of all funds.

	Growth Income	Growth	Large Cap	Micro Cap	Mid Cap	Small Cap
Total net assets ($mil)	784.64	613.24	5 202.48	161.40	514.70	376.74
Monthly fund flow (%)	12.07	9.66	16.78	-31.64	0.84	-0.35
Age (years)	9.32	9.89	13.21	10.65	10.46	10.66
Expense ratio (%)	0.80	1.20	0.60	1.60	1.30	1.30
Turnover ratio (%)	52.42	81.15	11.59	71.11	81.49	80.75
Mean return (%), annualized	8.13	9.44	10.03	9.66	10.19	10.14
Median return (%), annualized	12.07	14.36	15.84	15.10	15.26	15.93
Return volatility (%), annualized	14.17	16.64	14.71	21.03	18.45	19.91
Sharpe	0.14	0.14	0.17	0.11	0.14	0.13

Table 3: Stock betas.

This table provides the distribution statistics for the 23,534 unique beta values obtained from the regression $F_{k,t} = \alpha_k + \beta_k \ F_{\text{market},t} + u_{k,t}$ where $F_{k,t}$ represents the asset k's return at time t, $F_{\text{market},t}$ denotes the market's return at time t, represented here by the S&P 500 index; $u_{k,t} \sim N(0, \sigma_k^2)$; α_k stands for the asset's return that is independent of the market; β_k measures the asset's sensitivity to market movements. The regression is run on monthly returns.

Number of stocks	23,534
Mean	0.92
Median	0.90
Minimum	-86.86
Maximum	58.17
Standard-deviation	1.60
Skewness	-3.82
Kurstosis	586.45
Value of 99th percentile	4.44
Value of 95th percentile	2.58
Value of 1th percentile	-2.57
Value of 5th percentile	- 0.20

Table 4: Flow - performance sensitivity (FPS) by styles and regimes.

This table reports the flow-return sensitivity for each fund style and market state (regime). We estimate a two-regime Markov-Switching Intercept Autoregressive Heteroscedasticity model with the following specification:

$Fl_{i,t} = \mu_{s_t} + \sum_{q=1}^{k} \gamma_{i,q,s_t} R_{i,t-q} + \sum_{q=1}^{k} \beta_{i,q,s_t} Fl_{i,t-q} + \varepsilon_{i,t}$

where $Fl_{i,t}$ denotes the percentage of net inflows into fund i at time t. $R_{i,t-q}$ represents the return on fund i at time $t-q$ (with $q > 0$). s refers to the regime with $s_t \in \{1;2\}$. $\varepsilon_{i,t}$ are normally distributed with $\varepsilon_{i,t} \sim N(0, \sigma^2_{i,s_t})$. Note that μ, γ, β and σ^2 are all regime-dependent. We measure fund past performance by one lag of monthly return. Other lagged returns and lagged flows are also included in the explanatory variables to account for flow persistence and investor sensitivity to fund returns over longer horizons. Under this specification, FPS is gauged by the coefficient $\gamma_{i,1,s}$ associated with the one lagged return R_{t-1}. We estimate the model using the expectation-maximisation (EM) algorithm. To select the optimal number of lags and regimes, we apply the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Regime Classification Measure (RCM). Based on these criteria, we estimate a two-regime Markow switching model with three lags for each fund having at least 100 monthly observations. For 90% of these funds, the p-value associated with the probability of switching between two regimes is below 0.1, suggesting the strong discriminatory power of the model and the existence of two distinct regimes. In total, this exercise is run on 9,075 individual funds belonging to the six predefined styles. Due to the highly asymmetric distribution of $\gamma_{1,s}$, we take the median of all the estimated $\gamma_{i,1,s}$ that are statistically significant at the 95% level. Regime 1 refers to a state with low residual variance (i.e., normal market conditions) while regime 2 corresponds to a high-variance state (i.e., turbulent market conditions).

Style	Regime 1	Regime 2
Growth Income	0.0512	0.0470
Growth	0.0540	0.0900
Large Cap	0.0254	0.0202
Mid Cap	0.0576	0.1145
Small Cap	0.0548	0.1369
Micro Cap	0.0670	0.2067
Mean	0.0517	0.1026

Table 5: Correlations between styles.

This table reports the correlation coefficients between the six fund style return series, reflecting the degree to which the returns move together. High correlations suggest the presence of multicollinearity, which can create problems in standard VAR analysis by distorting estimation results.

	Growth Income	Growth	Large Cap	Mid Cap	Small Cap	Micro Cap
Growth Income	1	0.9698	0.9760	0.9592	0.9250	0.8838
Growth	0.9698	1	0.9869	0.9777	0.9428	0.9030
Large Cap	0.9760	0.9869	1	0.9600	0.9197	0.8743
Mid Cap	0.9592	0.9777	0.9600	1	0.9812	0.9475
Small Cap	0.9250	0.9428	0.9197	0.9812	1	0.9845
Micro Cap	0.8838	0.9030	0.8743	0.9475	0.9845	1

Table 6: Pairwise Granger causality test.

This table reports the p-values (p_{ij}) for the null hypothesis "Does variable j Granger cause variable i?". A p-value less than 5% indicates the existence of Granger causality from variable j to i. A p-value exceeding 5% indicates no significant Granger causality between those variables.

	Growth Income	Growth	Large Cap	Mid Cap	Small Cap	Micro Cap
Growth Income	0	0.622	0.000	0.002	0.001	0.001
Growth	0.348	0	0.000	0.000	0.000	0.002
Large Cap	0.021	0.000	0	0.000	0.000	0.000
Mid Cap	0.000	0.000	0.000	0	0.031	0.010
Small Cap	0.000	0.000	0.000	0.047	0	0.018
Micro Cap	0.005	0.001	0.000	0.094	0.041	0

Table 7: Augmented Dickey-Fuller test.

This table reports the Augmented Dickey-Fuller test statistics, p-values, and critical values for the six (daily) return series of fund styles. The p-values below 0.05 indicate that all series are stationary and suitable for further analysis.

	ADF Statistic	p-value	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)
Growth Income	-17.67	0.00	-3.43	-2.86	-2.57
Growth	-16.42	0.00	-3.43	-2.86	-2.57
Large Cap	-18.72	0.00	-3.43	-2.86	-2.57
Mid Cap	-16.09	0.00	-3.43	-2.86	-2.57
Small Cap	-16.10	0.00	-3.43	-2.86	-2.57
Micro Cap	-15.50	0.00	-3.43	-2.86	-2.57

Table 8: VAR Lag Selection.

This table reports the values for different lag lengths based on several selection criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC). The optimal lag order is indicated with an asterisk (*) for each criterion. We finally chose 4 as the number of optimal lags, based on the Akaike Information Criterion (AIC).

Order (p)	AIC	BIC	FPE	HQIC
0	-69.96	-69.95	4.149e-31	-69.95
1	-70.05	-70.00*	3.766e-31	-70.04
2	-70.09	-69.99	3.651e-31	-70.05*
3	-70.09	-69.95	3.631e-31	-70.04
4	-70.10*	-69.91	3.594e-31*	-70.04
5	-70.10	-69.86	3.612e-31	-70.01
6	-70.09	-69.82	3.621e-31	-70.00
7	-70.09	-69.77	3.627e-31	-69.98
8	-70.09	-69.72	3.637e-31	-69.96
9	-70.09	-69.68	3.618e-31	-69.95
10	-70.09	-69.64	3.620e-31	-69.93
11	-70.09	-69.59	3.636e-31	-69.91
12	-70.09	-69.55	3.624e-31	-69.90
13	-70.09	-69.50	3.640e-31	-69.88
14	-70.09	-69.45	3.635e-31	-69.87
15	-70.09	-69.41	3.630e-31	-69.85

Note: Optimal lag (AIC) = 4

Table 9: Variance Inflation Factor (VIF).

This table reports the VIF values for each of the six styles. VIF values exceeding 10 indicate a high degree of multicollinearity between variables.

Variable	VIF
Growth Income	24.59
Growth	73.10
Large Cap	56.43
Mid Cap	99.15
Small Cap	136.79
Micro Cap	47.98

Table 10: Penalty term λ in the Ridge VAR model over the two subperiods 2003–2009 and 2010–2023. This table reports the values of the λ added to the VAR model (see eq. (39)) to tackle the multi-collinearity problem due to highly correlated return series of the six fund styles (Ballarin, 2021, 2024).

Fund styles	Lambda 2003-2009	Lambda 2010-2023
Growth Income	0.052743	16 866.98
Growth	0.000503	25.04693
Large Cap	0.000503	16 866.98
Mid Cap	0.000418	0.730131
Small Cap	0.000418	0.879446
Micro Cap	23 918.24	16 866.98

Table 11: Connectedness measures across fund styles (in percentage).

This table reports the connectedness between the six styles over the two subperiods 2003-2009 (Panel A) and 2010-2023 (Panel B). The off-diagonal elements represent the pairwise directional connectedness ($\theta_{i,j,H}$), i.e. the percent of forecast error variance of style i due to shocks form style j. The bottom row (CHO) provides the total directional connectedness from style i to the system, while the second-to-last column (CHI) gives total directional connectedness from the system to style i. The rightmost column (NDC) shows the Net Directional Connectedness for each style, which is the difference between the CHO and CHI values. The Total Connectedness Index is 81.37% for 2003-2009 and 81.66% for the 2010-2023.

	Growth Income (to)	Growth (to)	Large Cap (to)	Mid Cap (to)	Small Cap (to)	Micro Cap (to)	CHI (from)	NDC (net)
				Panel A: Subperiod 2003 - 2009				
Growth Income		16.84	17.08	16.35	15.25	14.97	80.49	-3.53
Growth	15.60		17.82	17.34	16.24	14.75	81.76	2.82
Large Cap	16.01	18.09		17.13	15.85	14.18	81.26	1.50
Mid Cap	15.22	17.33	16.95		16.96	15.94	82.40	2.43
Small Cap	14.81	16.65	16.14	17.31		17.32	82.22	-0.28
Micro Cap	15.32	15.67	14.77	16.70	17.64		80.10	-2.94
CHO (To)	76.96	84.58	82.76	84.83	81.94	77.16		81.37
				Panel B: Subperiod 2010 - 2023				
Growth Income		17.47	17.61	16.80	15.65	14.48	82.02	1.89
Growth	17.54		17.66	16.88	15.59	14.28	81.95	1.50
Large Cap	18.08	18.07		16.53	15.06	13.78	81.53	-0.82
Mid Cap	16.70	16.72	16.01		17.19	15.51	82.14	2.52
Small Cap	15.96	15.84	14.97	17.62		17.32	81.71	0.14
Micro Cap	15.62	15.34	14.47	16.82	18.36		80.61	-5.24
CHO (To)	83.91	83.45	80.71	84.66	81.85	75.37		81.66

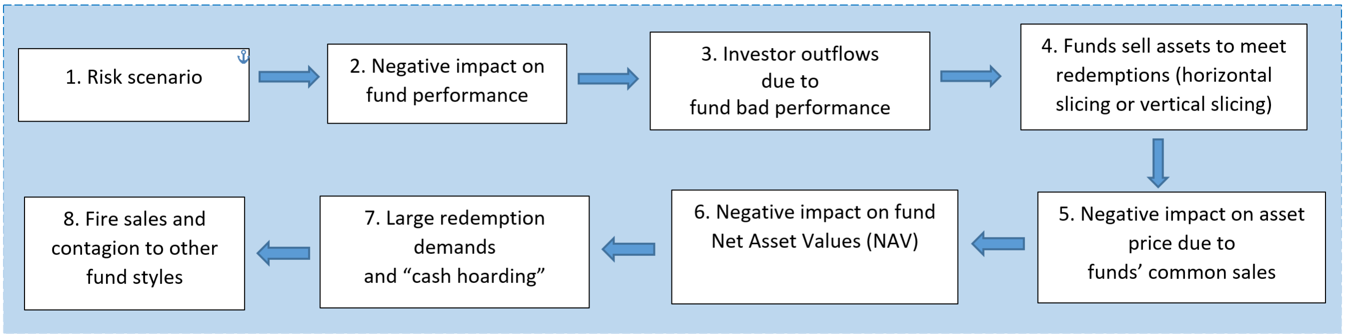
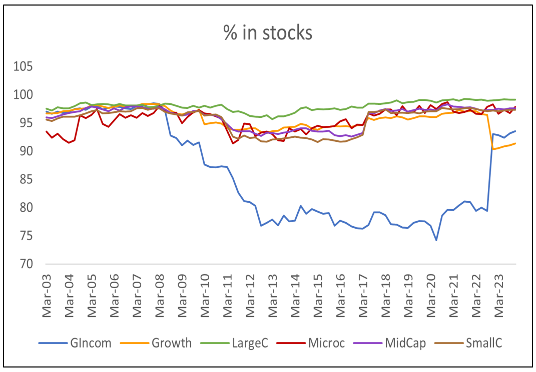
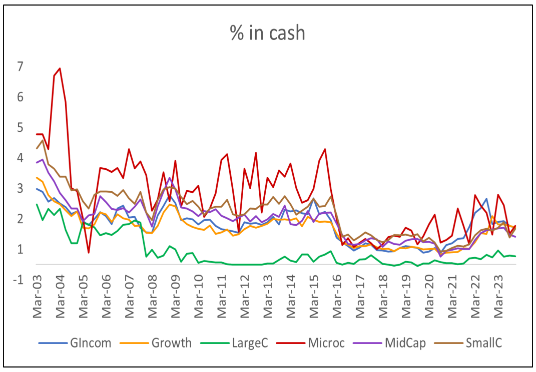
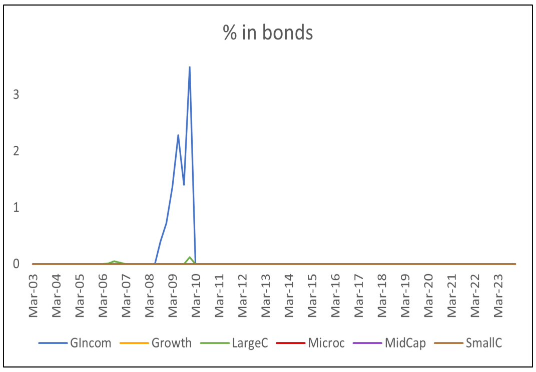


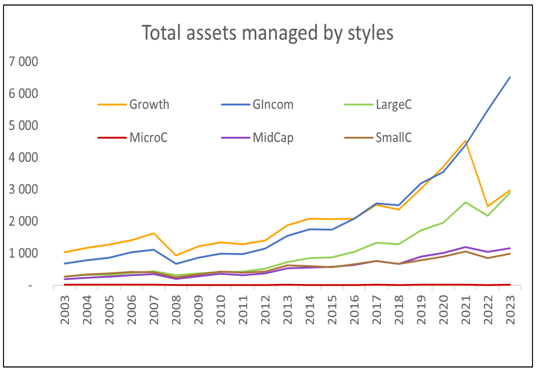
Figure 1: Mechanism of shock propagation within the mutual fund industry.





(a) (b)

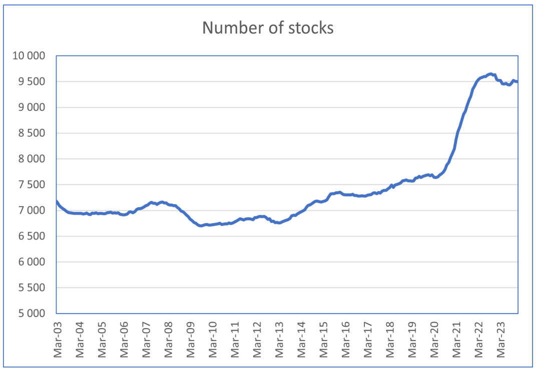




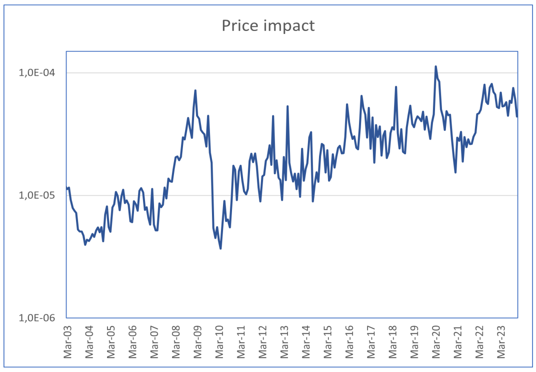
(c) (d)

Figure 2: Characteristics of funds by styles.

The figures present, for each style, the dynamics of the median value of the percentage of the portfolio invested in stocks (a), cash (b), bonds (c) and the managed Total Net Assets (TNA) (d) of funds in the sample over the study period.

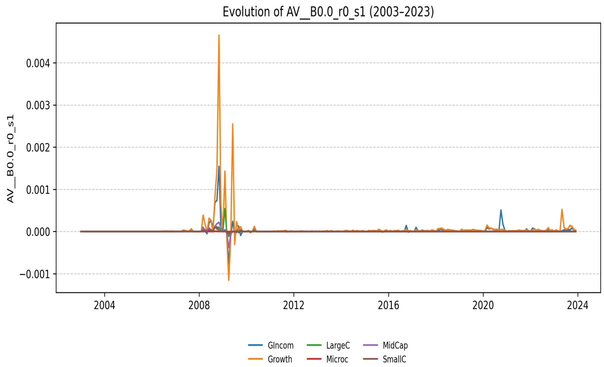


(a)

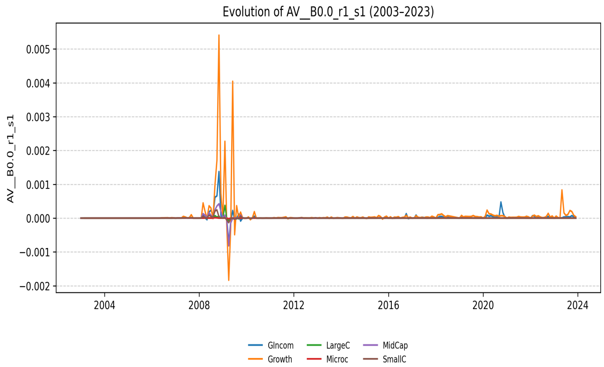


(b)

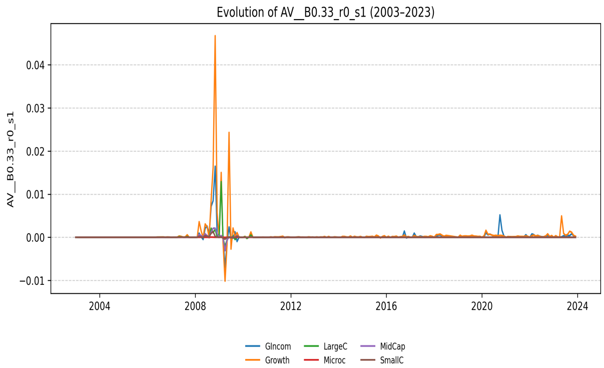
Figure 3: Monthly number of stocks and cross-sectional average price impact over time.
The left figure shows the number of stocks for each month. The right figure depicts the monthly cross-sectional average price impact computed as the monthly equal-weighted average of all stocks' Amihud ratio. The y-axis of the right figure is displayed in logarithmic scale.



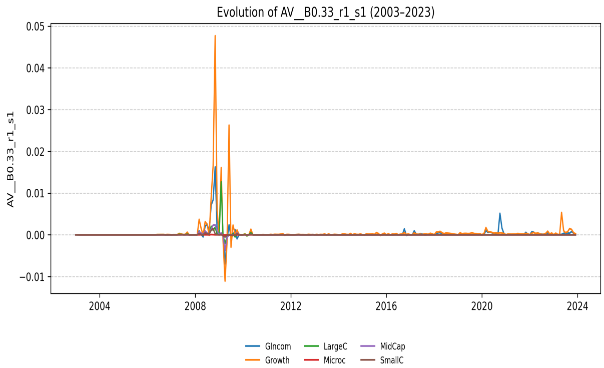
(a) Regime 1 with zero leverage



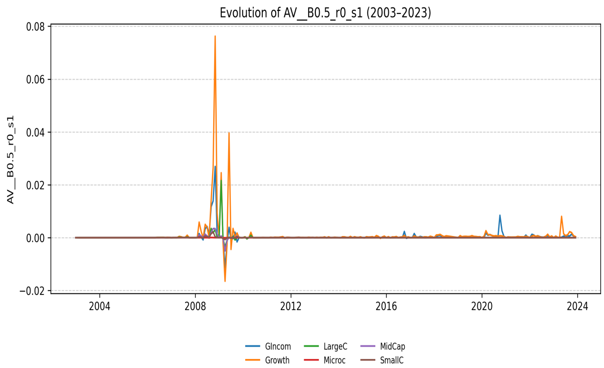
(b) Regime 2 with zero leverage



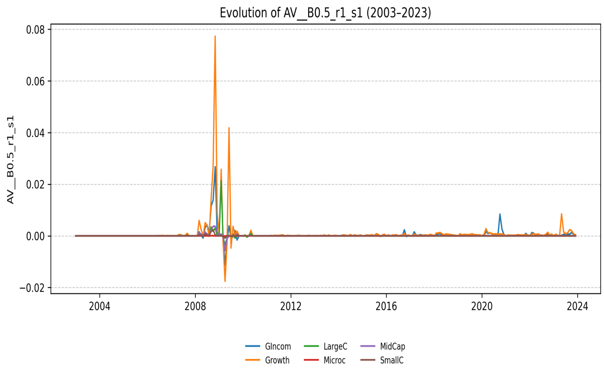
(c) Regime 1 with medium leverage



(d) Regime 2 with medium leverage

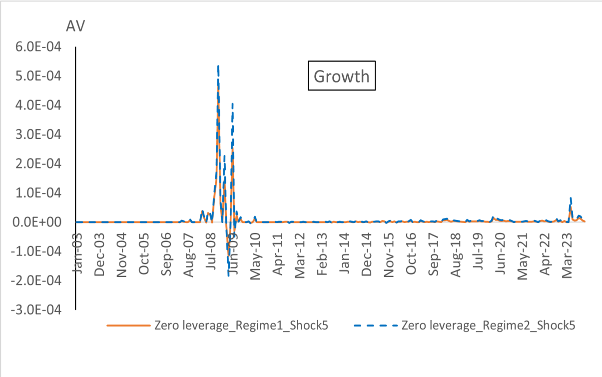


(e) Regime 1 with max leverage

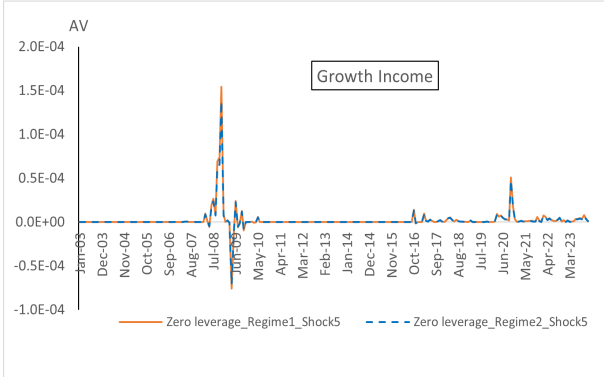


(f) Regime 2 with max leverage

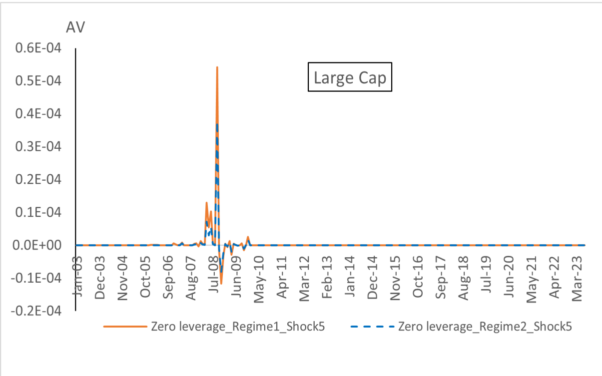
Figure 4: Aggregate vulnerabilities across market regimes and leverage levels.
This figure depicts the aggregate vulnerabilities (AV) computed under a negative shock of 5% and time-varying asset-specific price impact. We consider three leverage levels: zero average ($B = 0$), medium leverage ($B = 0.33$) and max leverage ($B = 0.5$). Regime 1 (Regime 2) is characterized by a low (high) residual variance and corresponds to normal (turbulent) markets.



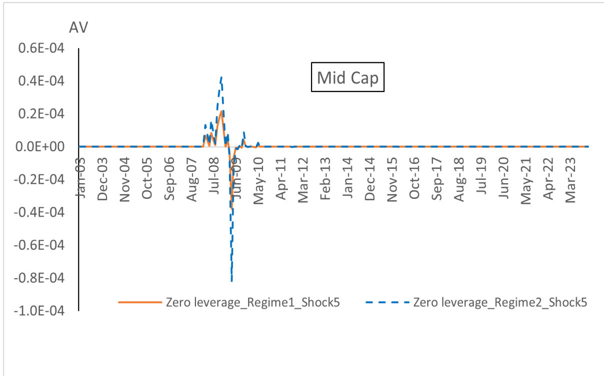
(a) Growth



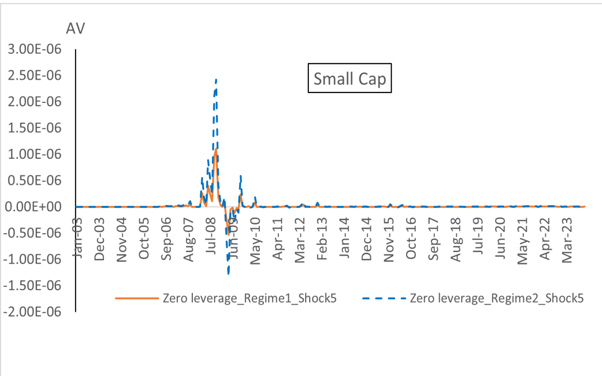
(b) Growth Income



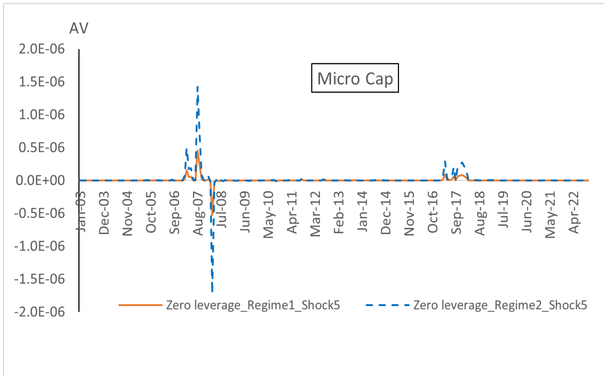
(c) Large Cap



(d) Mid Cap



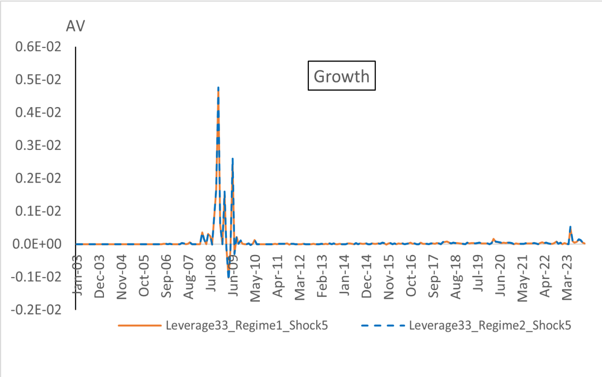
(e) Small Cap



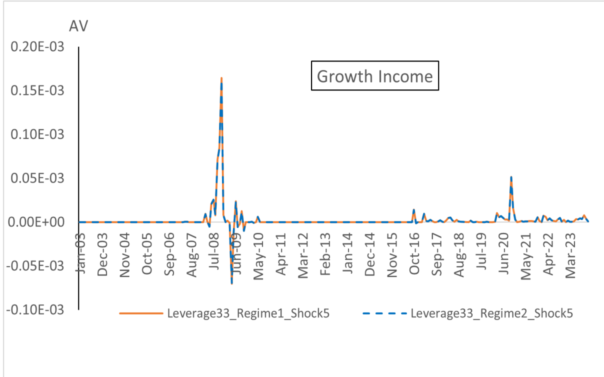
(f) Micro Cap

Figure 5: Aggregate vulnerabilities by styles with **zero leverage**.

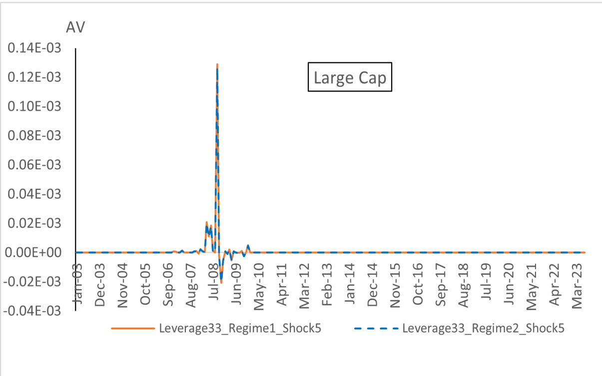
This figure depicts the aggregate vulnerabilities (AVs) computed under a negative shock of 5%, zero leverage ($B = 0$) and time-varying asset-specific price impact. For each style, we consider two market regimes. Regime 1 (Regime 2), in solid line (dashed line), is characterized by a low (high) residual variance and corresponds to normal (turbulent) markets.



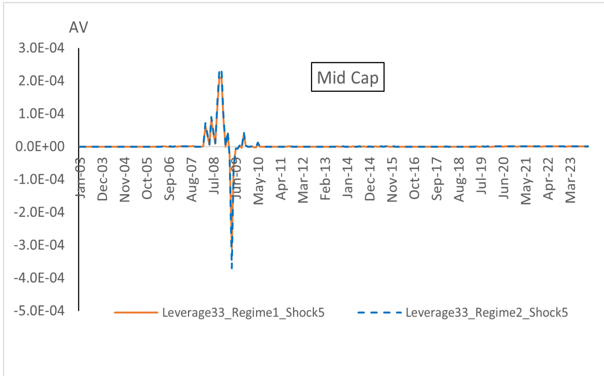
(a) Growth



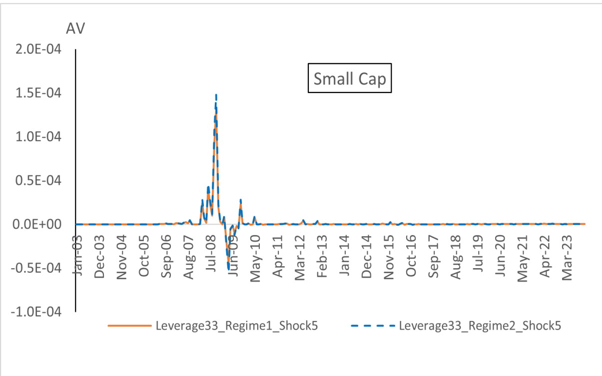
(b) Growth Income



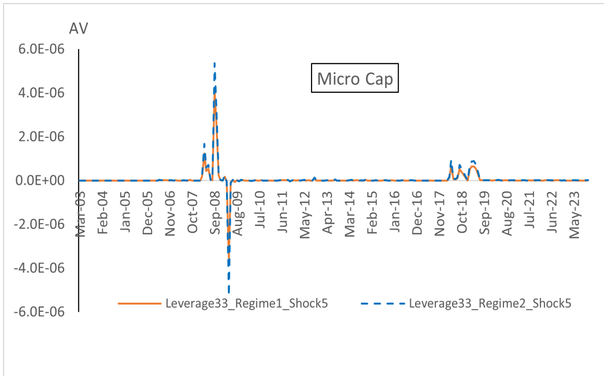
(c) Large Cap



(d) Mid Cap

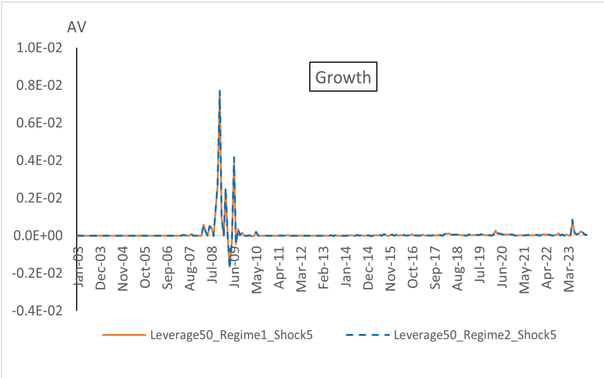


(e) Small Cap

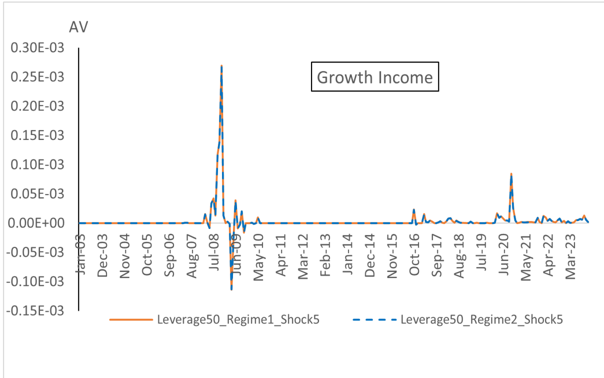


(f) Micro Cap

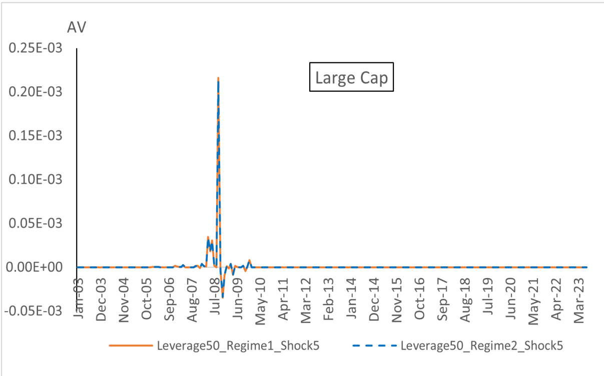
Figure 6: Aggregate vulnerabilities (AV) by styles with **medium leverage**.
This figure depicts the aggregate vulnerabilities (AVs) computed under a negative shock of 5%, medium leverage ($B = 0.33$) and time-varying asset-specific price impact. For each style, we consider two market regimes. Regime 1 (Regime 2), in solid line (dashed line), is characterized by a low (high) residual variance and corresponds to normal (turbulent) markets.



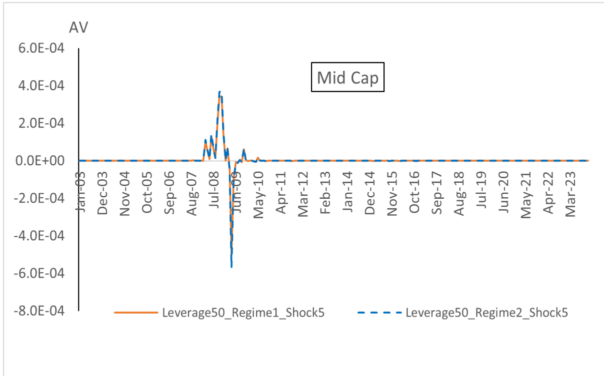
(a) Growth



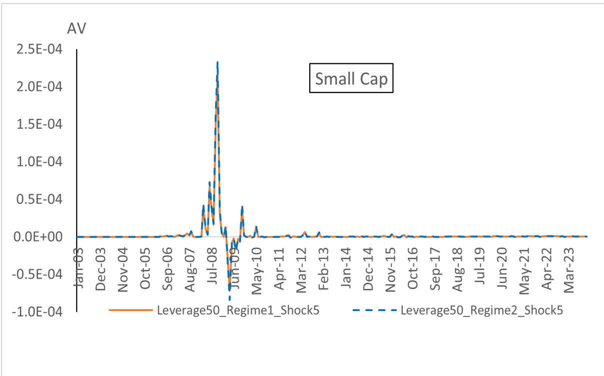
(b) Growth Income



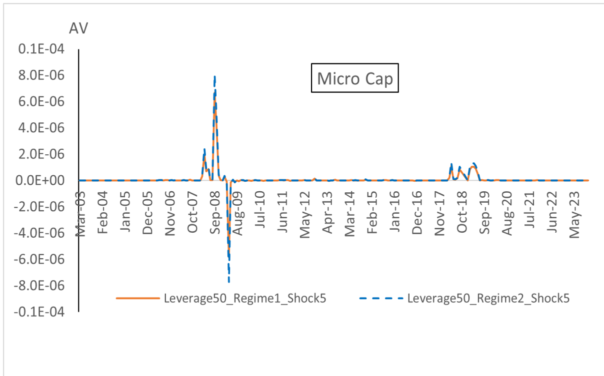
(c) Large Cap



(d) Mid Cap



(e) Small Cap



(f) Micro Cap

Figure 7: Aggregate vulnerabilities (AV) by styles with **max leverage**.

This figure depicts the aggregate vulnerabilities (AVs) computed under a negative shock of 5%, max leverage ($B = 0.5$) and time-varying asset-specific price impact. For each style, we consider two market regimes. Regime 1 (Regime 2), in solid line (dashed line), is characterized by a low (high) residual variance and corresponds to normal (turbulent) markets.