Vulnerability and Contagion Risk in the U.S. Equity Mutual Funds

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Abstract

We study the vulnerability of different styles of the U.S. domestic equity mutual funds over the period 2003 - 2018. We first perform a macroprudential stress-test by following the framework developed by Fricke and Fricke (2021) in order to assess the resilience of these styles when faced to shocks. Unlike previous studies in this literature, we consider two market conditions and granular asset price impacts, which makes our empirical framework closer to real market situations. We then conduct a contagion analysis by using the Diebold and Yilmaz (2009, 2012, 2014)'s spillover approach to identify the styles which are more vulnerable than others and those which are more likely to spread distress to other funds. Our results show that in turbulent times, fund styles' vulnerability is much higher than tranquil times and can not be neglected. LargeCap are likely to be the most vulnerable, especially during the sub-prime crisis. They could exert a strong impact on the system. In contrast, the other styles appear to absorb more information from the system than transmit distress to the system.

Keywords: Mutual funds, financial stability, macroprudential stress-test, contagion analysis, systemic risk.

JEL Classification: G10, G11, G23

1 Introduction

Over the last decades, the mutual fund industry has experienced a constantly sustained growth all over the world. In the U.S., according to the Investment Company Institute fact-book, at year-end 2022, there are about 7,500 U.S. mutual funds that manage 22.1 trillion of U.S. dollars, compared to around 13.05 trillion dollars in 2012.[1] This development has resulted in an enlarged role of capital-market based financing of the real economy, as opposed to traditional bank financing. Meanwhile, this changing structure of the financial landscape raises new concerns about the systemic impact of mutual funds on the overall financial stability. These concerns thus call for a through understanding of their behavior, especially during turbulent periods. Our paper contributes to this effort by attempting to assess the vulnerability of the US open-end domestic equity mutual funds (henceforth mutual funds) and to study the shock propagation mechanism across different styles within this important sub-set of the U.S. mutual fund industry.

There have been over the last ten years significant effort researches that tackle the vulnerability of mutual funds. According to conventional wisdom, open-end mutual funds with a flexible end-of-day net asset value (NAV) and no leverage should be immune to bank-run-like crises. Unlike banks, funds make no guarantee that their customers' investment will be returned at face value. Fund managers do not hold assets on their balance sheet directly; they instead manage assets on behalf of clients. The risks and rewards rest with the investors rather than the fund. In that view, funds will never experience a run and hence never have to fire-sell assets. Yet, Zeng (2017) shows that the main reason of fund vulnerability to runs is the existence of a first mover advantage when investors want to redeem their shares and collectively behave procyclically. The first mover advantage stems from the way in which funds pay out redemptions. When investors redeem, their shares are valued at end-of-day floating NAV and paid later in cash. Investors who withdraw earlier impose various costs on investors who withdraw later. The most important is the cost of selling illiquid assets. When facing small redemptions, a fund can use its liquidity buffer to make payouts and avoid liquidation losses, but when redemptions exceed the liquidity buffer, the fund will have to liquidate assets to pay the investors. For illiquid assets, this is costly, because the fund can only sell at discounted prices. Depending on the size and speed of the redemptions, a forced liquidation of assets can significantly depreciate the values of the assets sold. The distressed selling of these assets effectively spreads the shock from one fund to the others. As a result of this, investors who arrive after the first round of sales will redeem their shares at a lower NAV than the early birds. Thus, the combination of a flexible NAV and active fund liquidity management, both of which are considered as means to mitigate financial stability risks, can make the fund prone to shareholder runs.[2] This shock propagation resulted from massive redemption demands combined with

[1] Domestic equity funds are the most popular category in the U.S, representing 46% of all mutual fund and Exchange-Traded-Fund (ETF) assets.

[2] Some of the potential risks associated with funds' liquidity mismatch can be illustrated by what happened during the summer of 2016, when a number of UK open-end funds invested in real estate experienced significant outflows and

the inherent liquidity mismatch is described by the Fig. 1.

INSERT SCHEMA 1 HERE

Regarding fund liquidity management, Jiang et al. (2021) document that mutual funds tend to reduce liquid asset holdings in favour of illiquid assets during normal market conditions. During periods of high uncertainty, mutual funds are likely to scale down their liquid and illiquid assets proportionally. As such, they encounter difficulties in selling their illiquid assets and have to pay high transaction costs. Weth and Dötz (2019) observe different liquidation strategies of German bond funds depending on their type of investors. Institutional-oriented funds sell their most liquid bonds first, thereby preserving short-term performance at the cost of increasing liquidity risk while retail-based funds maintain portfolio liquidity. Chernenko and Sunderam (2016) show that a careful liquidity management can not fully prevent funds from fire sale costs. Brunnermeier and Pedersen (2008) point out that under certain conditions, margins are destabilizing while market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals. Other theoretical papers that deal with mutual fund runs include Goldstein et al. (2017) and Morris et al. (2017).[3]

The potential bank-run-like risk of mutual funds provide therefore further impetus for financial regulators to assess their resilience in isolation as well as in interaction with other financial actors and the real economy. In this perspective, there has been a growing body of literature that deal with this topic. Closest to our paper is the work of Fricke and Fricke (2021) that adapts the stress test of Greenwood et al. (2015) developed for the banking sector to take into account the economic model of mutual funds. More specifically, their framework allows for quantifying the aggregate vulnerability of the mutual fund industry by considering the fire sales in presence of the flow-performance relationship. Using data on US equity mutual funds for the period 2003-2014, they observe a relatively small aggregate vulnerability compared to values measured for banks. This vulnerability is likely to increase during periods of low market liquidity. Larger funds and illiquid funds are both more vulnerable and more systemic. In the same vein, Lee (2020) conducts a similar stress test for the investment fund sector of Luxembourg by allowing a non-linear relationship between fund flow and fund performance. He finds that while the sector is quite resilient over the the study period 2008 - 2019, aggregate vulnerability increases over time. Fiedor et al. (2021) present a standardised framework of macroprudential stress-test for 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

In the meantime, more attention has been paid to the vulnerability of bond mutual funds as they

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.

[3]Goldstein et al. (2017) develop a static global game model in which shareholders who run will get a fixed-value claim if the fund is solvent and liquidity management is considered as absent. Morris et al. (2017) focus on managers' relative performance concerns while making no distinction between open- and closed-end funds.

are considered as more exposed to liquidity shocks. Different frameworks are developed but they all report a certain level of resilience of these funds. Cetorelli et al. (2016)'s stress test model quantifies the impact of an exogenous interest rate shock on outflows of the US corporate bond mutual funds by explicitly accounting for the provision of liquidity by broker-dealers and other potential buy-side investors. Baranova et al. (2017) develop a stress test based on a theoretical liquidity supply model with a brokerdealer and a leveraged investor and implement it on European-domiciled corporate bond funds. These works then gave rise to the Arora et al. (2019)'s test on Canadian fixed-income mutual funds. Bouveret and Yu (2021) notice that the U.S. Investment Grade corporate bond funds, municipal bond funds and government bond funds are more likely to spread distress to other fund categories than high yield, emerging market and loan funds, which in turn are more vulnerable to distress.

Meanwhile, a more recent stream of literature has emerged to investigate the interplay between banks and non-banks including mutual funds, hedge funds and insurers via overlapping portfolios held by these financial institutions. The findings all show that including heterogeneous financial institutions, and in particular non-banks, increases the magnitude of systemic risk. Several important works in this literature include Caccioli et al. (2015) Mirza et al. (2020), Aikman et al. (2019), Farmer et al. (2020), Sydow et al. (2024), Chrétien et al. (2020), Calimani et al. (2022).[4]

Our empirical work contributes to the burgeoning literature on financial instability risks posed by mutual funds in several ways. First, we perform the macroprudential stress test à la Fricke and Fricke (2021). Unlike Fricke and Fricke that only study all US equity funds as a whole, we investigate their vulnerability at the style level (by distinguishing 6 most popular declared investment styles). As such, instead of using a fixed flow-return sensitivity for all funds, we measure the flow-return sensitivity at fund individual levels by differentiating two market states (tranquil times and turbulent times) as Lee (2020), thus capturing the idiosyncratic flow sensitivity to performance of each style in response to market conditions. For computing the price impacts induced by funds' fire-sales, we compute time-varying liquidity factor at individual asset level. The use of these granular data makes our framework closer to real market situations.

Second, we conduct a contagion analysis by applying the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014) in order to identify which investment styles are more vulnerable to stress and how the vulnerability of a specific strategy spreads over the others. Our results show that in turbulent times, fund styles' vulnerability is much higher than tranquil times and can not be neglected. LargeCap are likely to be the most vulnerable, especially during the sub-prime crisis. They could exert a strong impact on the system. In contrast, the other styles appear to absorb more information from the system than transmit distress to the system.

Our results highlight the heterogeneity among the U.S. equity mutual funds in response to shocks and the importance to account for this diversity in system-wide macroprudential stress-tests. Besides,

[4]For an extensive survey of macroprudential stress tests, please refer to Aikman et al. (2023).

they provide a better understanding of the dynamics of shock transmissions within the fund industry, which will in turn contribute to a more effective macroprudential monitoring, especially when facing to shocks.

The structure of this paper is as follows. Section 2 describes the data. Section 3 presents the macroprudential stress testing framework used and discusses the aggregate vulnerability across fund styles. Sector 4 reports the contagion mechanism within the US domestic equity mutual funds. Section 5 concludes and discusses the policy implications of these results.

2 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 - 8/2018. In order to have a focus on the U.S. equity market, we restrict our analysis to the U.S. domestic equity open-end mutual funds (DEOEMF) by excluding from our sample bond, international and specialized sector funds. Funds are selected on the basis of their objective codes and their disclosed asset compositions. 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.

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. The sample finally contains on average 5 627 unique funds (see Tab. 5). Descriptive statistics on fund returns by styles are summarized in Tab. 1 while the relative weight of each style within the US. DEOEMF are reported in 3.

INSERT TAB. 5 HERE

INSERT FIG. 3 HERE

INSERT TAB. 1 HERE

Over this period, LargeCap consistently maintains the largest share of the total net asset value within the sector. Notably, this proportion has been steadily increasing, particularly following the subprime crisis in 2008. By 2018, the net asset value of these funds has reached 60% of the sector's total assets. On the contrary, the portion represented by GIncome funds remains stable, while Growth funds show a gradual decline over time, accounting for only 8% in 2018. At the same time, the other styles only represent a steadily small percentage of the sector despite their highest performance in terms of Sharpe ratio.

Data on individual stocks used to investigate portfolio composition of mutual funds are extracted from the CRSP US Stock Databases. The sample finally contains 6 890 unique stocks (see Fig. 2 for the detailed number of stocks at each month over the whole period).

3 Measuring the aggregate vulnerability of funds by styles

3.1 Fricke and Fricke (2021)'s (FF) 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 unchanged 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 denotes a $K \times 1$ vector of asset-specific returns.

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

3.1.1 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:

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

3.1.2 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, 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:

$$\begin{aligned}
R_1 &= \frac{A_1 - A_{-1}}{A_{-1}} && (15)\\
&= R_0\Big(1 + \gamma^E\Big(\frac{1}{1+B} + R_0\Big) + \gamma^D \frac{B}{1+B}\Big) && (16)
\end{aligned}$$

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 where $\gamma = \gamma^D = \gamma^E$, equation (17) reduces to:

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

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

$$R_1 = R_0\Big(1 + \gamma^E(1 + R_0)\Big) \tag{19}$$

3.1.3 Asset liquidation with fixed leverage ratio and fixed portfolio weights

In line with Greenwood et al. (2015) and according to empirical evidences about common practices used by mutual funds in liquidity management, asset managers are assumed to proceed asset liquidations while maintaining fixed leverage ratio B and fixed asset weights of their portfolios.

In order to deal with negative (positive) net inflows due to investors' reactions $\Delta E_1 + \Delta D_1$, portfolio manager 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:

$$\Delta D_1^a = D_1^a - D_1 = E_1 B - D_1 = A_{-1} B\Big(R_1 - \gamma^D R_0\Big) \tag{20}$$

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.

$$\begin{aligned}
\Phi &= \Delta E_1 + \Delta D_1 + \Delta D_1^a && (21)\\
&= \gamma^E E_0 R_0 + \gamma^D D_0 R_0 + A_{-1} B\Big(R_1 - \gamma^D R_0\Big) && (22)\\
&= \gamma^E R_0\Big(E_{-1} + A_{-1} R_0\Big) + \gamma^D D_0 R_0 + A_{-1} B\Big(R_1 - \gamma^D R_0\Big) && (23)\\
&= A_{-1}\Big[R_0\Big(\gamma^E\Big(\frac{E_{-1}}{A_{-1}} + R_0\Big) + \gamma^D\Big(\frac{D_0}{A_{-1}}\Big)\Big) + B\Big(R_1 - \gamma^D R_0\Big)\Big] && (24)\\
&= A_{-1}\Big[R_0\Big(\gamma^E\Big(\frac{1}{1+B} + R_0\Big) + \gamma^D\Big(\frac{B}{1+B}\Big)\Big) + B\Big(R_1 - \gamma^D R_0\Big)\Big] && (25)
\end{aligned}$$

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 outflow (inflow). Hence Φ represents the whole amount to be liquidated (invested) to meet the outflow (inflow).[5]

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

$$\Phi = A_{-1} R_0 \gamma^E\Big(1 + R_0\Big) \tag{26}$$

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

Thus, the net asset purchases by N asset managers can be computed as:

$$\phi = M^{'}\Phi \tag{27}$$

By doing this, we assume that γ^D and γ^E are the same for all asset managers.

[5]The equation (25) 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.

3.1.4 Fire sales generate price impact

Assume that asset 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:

$$F_3 = L\phi = LW^{'}\Phi \tag{28}$$

which gives a final return of:

$$R_3 = WF_3 = WLW^{'}\Phi \tag{29}$$

3.2 Measuring vulnerability exposures

Suppose there is a negative shock on asset prices, $F_1 = \left(f_1, f_2, ..., f_K\right)$ with $\forall f \in [-1; 0)$. 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:

$$AV = \frac{1'_N A_{-1} R_3}{E_{-1}} = \frac{1'_N A_{-1} WLW^{'}\Phi}{E_{-1}} \tag{30}$$

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

$$AV_i = \frac{1'_N A_{-1} R_3}{E_{-1}} = \frac{1'_N A_{-1} WLW^{'}\delta_i\delta_i^{'}\Phi}{E_{-1}} \tag{31}$$

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

3.3 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 (25).

3.3.1 Fund debts

Due to lack of information on funds' leverage in the CRSP MFDB database, we follow the approach of FF by considering two values of B: 0 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 second value refers to the maximum level of leverage $D/A = 0.33$ allowed by the regulatory framework.

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

3.3.2 Flow-performance sensitivity (FPS) of equity

This subsection describes the methodology that we adopt to gauge the flow-performance sensitivity of equity for each fund (γ^E). It has been established that there exists a positive relationship between funds' past performance and their future net inflows with the net inflow of fund i in month t denoted $F_{i,t}$ computed as:

$$F_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{32}$$

where $TNA_{i,t-1}$ and $TNA_{i,t}$ are the total net assets managed by the fund i in month $t-1$ and t respectively, $R_{i,t}$ is the return on the fund's portfolio for the month t.

To address the asymmetric pattern of investors' reactions, following Lee (2020), we assume the non-linearity in the flow performance sensitivity (FPS) by using a two-regime Markov-switching model with two specifications MSIA and MSIAH as follows:

- Specification MSIA (Markow Switching Intercept Autoregressive): the constant term (μ) and coefficients (γ and β) are regime-dependent while the error-term (ε) is not regime-dependent:

$$F_{i,t} = \mu_s + \sum_{q=1}^{k} \gamma_{q,s} R_{i,t-q} + \sum_{q=1}^{k} \beta_{q,s} F_{i,t-q} + \varepsilon_{i,t} \tag{33}$$

- Specification MSIAH (Markow Switching Intercept Autoregressive Heterocedasticity): μ, γ, β, and ε are all regime-dependent:

$$F_{i,t} = \mu_s + \sum_{q=1}^{k} \gamma_{q,s} R_{i,t-q} + \sum_{q=1}^{k} \beta_{q,s} F_{i,t-q} + \varepsilon_{s,i,t} \tag{34}$$

where $F_{i,t}$ is the percentage of net inflows into fund i at time t. $R_{i,t-q}$ is the return on the fund i's at time $t-q$ (with $q > 0$). s refers to the regime with s $\in \{1; 2\}$. $\varepsilon_{i,t}$ and $\varepsilon_{s,i,t}$ are normally distributed with $\varepsilon_{i,t} \sim N(0, \sigma^2)$ and $\varepsilon_{i,t} \sim N(0, \sigma^2_{s_t})$.

Under these two specifications, γ^E is gauged by the $\gamma_{1,s}$ associated to variable R_{t-1}. As such, γ^E has two regimes without any restriction neither on its sign nor on its level. A significant negative FPS which rejects the standard assumption of the past performance chasing of fund investors suggests that investors prefer the diversification or have other prevailing criteria than past performance.

The expectation-maximisation (EM) algorithm is used to estimate these equations. First, two specification tests are implemented to find the best performing model for each fund category. AIC and SBC are then used to select the optimum number of lags for a given number of regimes. Following Ang and Bekaert (2002), regime classification measure (RCM) is conducted to select the optimum number of regimes for a given number of lags. RCM is normalised between 0 and 100. In case of RCM=0, the model is perfectly discriminated between two regimes. In case of RCM=100, each regime has 0.5 chance of occurrence throughout the sample in the model.

Following these criteria, we finally choose to estimate, for each fund having at least 100 monthly observations, a two-regime Markow switching with 3 lags in each specification. In total, this exercise is run on 5 627 individual funds already classified into the 6 defined styles (Tab. 5).[6] By taking the mode of all the $\gamma_{1,s}$ estimated that are statistically significant within each style, we obtain the γ^E corresponding to the two regimes for each style as reported in Tab 2.[7] $s = 1$ refers to regime with small residual variance (normal markets) while $s = 2$ denotes regime with high residual variance (turbulent markets).

INSERT TAB. 2 HERE

The results indicate a clear existence of two regimes[8] but $\gamma_{1,s}$ in both regimes are quite small relatively to the value of 0.2748 adopted by FF.[9] For GIncome, Growth, LargeC, MidCap, $\gamma_{1,s}$ in regime 2 are much higher than in regime 1, implying that investors' reactions to past performance are much stronger in case of large shocks. For SmallCap, we also observe an asymmetric pattern but the difference between $\gamma_{1,s=1}$ and $\gamma_{1,s=2}$ is quite small. In contrast, MicroCap displays a smaller flow-performance sensibility under regime 2 than under regime 1.

3.3.3 Price impacts

Following previous studies in this literature, we gauge the price impact for each stock (denoted L in equation (30)) by its Amihud (2009) ratio obtained from the daily stock data. The Amihud ratio for stock k on day d is computed as follows:

$$\text{Amihud}_{k,d} = \frac{|R_{k,d}|}{V_{k,d}} \tag{35}$$

where $|R_{k,d}|$ and $V_{k,d}$ are respectively the absolute daily return and the total dollar trading volume of stock k on day d. It has been established in the literature that the Amihud ratio is a good proxy for the illiquidity condition of assets.

Figure 2 depicts the cross-sectional equal-weighted average of the price impact over time. The average of the price impact over the whole period is 2.2 $\times 10^{-6}$ obtained from an average of 6 890 stocks on each month.[10] This value is smaller than the results reported by FF who obtain an equal-weighted mean price impact of 4.77 $\times 10^{-6}$ over the period 2003 - 2014. It is worth noting that the price impact is likely to increase over the last decade and attains its peak in July 2017.

[6] There are also 204 funds that change the style at least once during the study period. They are thus excluded from our sample.

[7] The distribution of $\gamma_{1,s}$ of the 6 styles are highly asymmetric with many extreme values. Hence, the mode is used instead of the mean values.

[8] For 90% of these funds, the p-value associated to the probability of switching between two regimes is smaller than 0.1, implying a quite good discriminant power of the model.

[9] An FPS equal to 0.03 implies that a negative return of -5% would lead to a net outflows of $-5\% \times 0.03 = -0.15\%$.

[10] The median value of the daily price impact is 1.8 $\times 10^{-6}$.

INSERT FIG. 2 HERE

3.4 Computing the aggregate vulnerabilities (AV) under different scenarios

Following FF, we consider an initial shock of -5% on all stocks, which is the standard magnitude considered in stress tests for banking systems. This negative shock leads to a drop in the style return by 5%.[11] Then for each month, we compute the aggregate vulnerability by following equation (30) under two scenarios.

- **Scenario 1**: Style-specific FPS under two-regimes, time-varying and asset-specific price impact.
- **Scenario 2**: Style-specific FPS under two-regimes, average asset-specific price impact.

In each scenario, we consider three levels of leverage: no leverage at all ($B = 0$), an intermediate level ($B = 0.33$) and the max authorized leverage ($B = 0.5$)[12]:

3.4.1 Results of Scenario 1

Figure 4 plots the AVs obtained under scenario 1 where we consider style-specific FPS along with time-varying and asset-specific price impact. A negative (positive) AV measures the percentage of assets to be wiped out (invested in the style) due to the shock. Whatever the leverage level and the regime are, we observe, for all the six styles, the same pattern of AVs. In general, AVs display very small values with slight fluctuations around 0 at the beginning of the period. They progressively increase at the end of 2007 then attain their largest negative values (outflows) at the year-end of 2008 before a sharp return to positive values (inflows) during 2009. Since 2010, it is likely that AVs are extremely and constantly weak. This dynamic is quite different from those reported by FF.[13]

INSERT FIG. 4 HERE

As expected, AVs under regime 2 (turbulent markets) are higher than under regime 1 (normal markets), suggesting that in case of stress, the percentage of equity that would be wiped out by funds' asset liquidations is bigger. Without leverage, AVs in regime 2 can be ten times higher than in regime 1. At their peaks around the sub-prime crisis, the typical percentage of equity blown under stress is roughly about 2% but can be as high as 4% (for LargeCap), compared to the range of 0,4% to 0,6% in tranquil times.

[11] If the original return is 8% then the return used to compute AV will be equal to 3%. If the original return is -2% then the return used will be equal to -7%.

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

[13] FF observe only positive AVs. In their Scenario 1, AVs peak at the year-end of 2008 while in Scenario 2 and 3, AVs increase over time.

It comes at no surprise that leverage considerably amplifies AVs, implying that funds are more vulnerable if they use a lot of debts. In 2008, the intermediate level of debts ($B = 0.33$) produce AVs ranging already from 5% to 15% in normal markets. Facing turbulences, they exhibit a slight increase. This finding is in line with Vivar et al. (2023) and highlights the fragility of levered funds making them vulnerable whatever the amplitude of the stress.

A closer look at the dynamic of AVs for each style reveals highly heterogeneous degrees of vulnerability across different styles, especially over the period 2008 - 2010 (see Fig. 6). Unsurprisingly, LargeCap is by far the most vulnerable. It is followed by GIncome and Growth. In contrast, SmallCap, MidCap and MicroCap are much less vulnerable. Whatever the direction (upward or downward) taken by their AVs, they do not exceed 1,5%. The sensitivity of LargeCap to the sub-prime crisis can be explained by the prominent weight of financial values among large-cap U.S. stocks.[14] As a consequence of this, the financial crisis breakout resulted in large moveouts from financial stocks and translated into a direct distress for LargeCap funds.

INSERT FIG. 6 HERE

3.4.2 Results of Scenario 2

In this scenario, we consider a fixed price impact that is asset specific. For each asset, we retain the time-average of its daily Amihud ratio.

Fig. 5 suggests that changing the way of computing price impacts by ignoring their time variation does not change significantly the pattern of AVs, whatever the leverage level and the market condition are. Except for larger variations of (small) AVs at the beginning of the period, our results are qualitatively unchanged in comparison to those obtained under scenario 1. In details, we observe small changes in the range of AVs, sometimes upwards (regime 1 with no leverage or max leverage; regime 2 with intermediate leverage), i.e. higher vulnerability, sometimes downwards (regime 2 with no leverage), i.e. weaker vulnerability.[15]

INSERT FIG. 5 HERE

INSERT FIG. 7 HERE

[14]For instance, in 2008, financial values account for 12% of the S&P 500 capitalization, behind the communication services (26%) and information technology (13%).

[15]While the choice of computing the price impact is identical to the one used by FF in their scenario 2, our results are very different from those reported by FF. More precisely, they observe a constantly increasing AVs over time with higher values of AVs.

4 Interconnectedness between styles

Our findings in the previous section show that the US domestic equity funds display quite heterogeneous reactions in response to shocks, depending on their styles and their leverage levels. Some styles are much more vulnerable than others. In this section, we explore how these funds, given their different degrees of vulnerability, can impact each other and thus transmit and amplify shocks within this subset of the U.S. mutual fund industry.

To this end, we perform a contagion analysis between fund styles by following the spillover approach developed by Diebold and Yilmaz (2009, 2014). This section employs daily fund data 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 aggregate six series of fund style returns, weighted by the Total Net Assets (TNA) of each fund, covering the period from January 2, 2003, to September 28, 2008. 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.

The spillover approach allows measuring the extent to which a shock impacting style A's returns exert an effect on the volatility of style B's returns and the other way around. If both styles tend to propagate shocks to each other, they are highly interconnected. If style A transmits more shocks to style B than it receives from style B, then style A is a net transmitter (thus more systemic) while style B is a net receiver (thus more vulnerable). Since its inception, this method has proven to be an exceptionally effective tool for investigating systemic risks. Many studies have focused on examining volatility spillovers across various markets. For instance, Greenwood-Nimmo et al. (2016) examine spillover effects in foreign exchange markets, Fernández-Rodríguez et al. (2016) analyze volatility connectedness in the EMU (European Monetary Union) sovereign bond markets. Before us, Bouveret and Yu (2021) also use this approach to assess the connectedness between different categories of US bond mutual funds.

4.1 Spillover approach

Originally, Diebold and Yilmaz (2009) develop a multivariate time-series approach to explicitly account for interdependence in financial markets. This method has proven to be both effective and easily applicable, and has subsequently been extensively utilized to examine various economic systems. The approach builds upon the VAR (Vector Autoregression) framework and the widely understood variance decomposition procedure.

Consider a K variable VAR(p) model in the form:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t \tag{36}$$

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.

However, the Variance Inflation Factor (VIF) test reveals a high degree of correlation among the daily fund return series (grouped by style), leading to multicollinearity issues. As a result, a standard VAR model (like the Diebold-Yilmaz approach) could not be effectively estimated. To handle this, a Ridge VAR model is employed, which applies regularization to manage multicollinearity or when the number of variables exceeds the number of observations.

In the Ridge VAR model, a penalty term is added to the optimization problem to shrink the coefficients A_i towards zero. The objective function for estimating the Ridge VAR is given by:

$$\min_{A_1,A_2,\ldots,A_p} \sum_{t=1}^{T} \left(y_t - c - \sum_{i=1}^{p} A_i y_{t-i} \right)^2 + \lambda \sum_{i=1}^{p} \|A_i\|_F^2 \tag{37}$$

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, which is included to minimize these residuals by finding the best coefficients for the model.

The second term is the regularization penalty that discourages large values for the coefficients A_i. $\|A_i\|_F^2$ sums the squares of all elements in A_i. $\lambda \geq 0$ is the regularization (or penalty) parameter, controlling the degree of shrinkage. When $\lambda = 0$, the Ridge VAR model becomes a standard VAR model with no regularization. The larger the value of λ, the more the coefficients are shrunk towards zero, helping to reduce overfitting and improve stability in the presence of multicollinearity. The optimal value of lambda is chosen by testing a range of potential lambda values (from 10^{-4} to 10^{4}) using cross-validation. The lambda that minimizes the cross-validated mean squared error is selected as the best value for each variable in the system. This ensures that the Ridge VAR model avoids overfitting while handling multicollinearity effectively.

Once the Ridge VAR model is estimated, the Generalized Forecast Error Decomposition Method (GFEVD) introduced by Diebold and Yilmaz (2009) is applied to measure the interconnectedness of the variables in the system. Unlike the traditional Cholesky decomposition, which is sensitive to the ordering of the variables, the GFEVD approach offers an order-invariant solution, ensuring that the contribution of shocks to the variance of each variable remains robust regardless of the order in which the variables are modeled.

The GFEVD for a forecast horizon H is computed for each variable i in the system due to shocks from variable j using the following formula:

$$\theta_{i,j,H}^{g} = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} \left(e_i' \Phi_k \Sigma_u e_j \right)^2}{\sum_{l=1}^{K} \sigma_{ll}^{-1} \sum_{k=0}^{H-1} \left(e_i' \Phi_k \Sigma_u e_l \right)^2} \tag{38}$$

Where: $\theta^g_{i,j,H}$ is the generalized variance decomposition for horizon H, representing the contribution of shocks from variable j to the forecast error variance of variable j; σ_{jj}^{-1} is the inverse of the standard deviation of residuals for variable j; e_i and e_j are selection vectors that isolate variable i and j from the system (1 in the respective position and 0 elsewere); Φ_k is the impulse response function at lag k, each element $\Phi_k[i,j]$ captures the dynamic impact of a shock to variable j on variable i after k periods; Σ_u is the covariance matrix of the residuals, capturing the contemporaneous relationships between the variables'errors. So $(e_i'\Phi_k\Sigma_u e_j)$ extracts the impact of a shock from variable j to variable i, incorporating both the impulse response and the contemporaneous shock correlation. The denominator is the total contribution of shocks from all variables l (including i) to the forecast error variance of i sums to 1.

From the GFEVD results across the system, Diebold Yilmaz propose constructing a connectedness matrix where $\theta^g_{i,j,H}$ represents the percentage of 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 three supplementary measures that demonstrate the relative importance of each variable within the system:

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

$$CH_{i\leftarrow\cdot} = \sum_{j=1}^{K} \theta^H_{ji}, \quad j \neq i \tag{39}$$

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

$$CH_{i\rightarrow\cdot} = \sum_{j=1}^{K} \theta^H_{ij}, \quad j \neq i \tag{40}$$

- Net directional connectedness (NDC): difference between the outward and inward connectedness of each variable. It indicates whether a fund is a net transmitter or a net receiver of shocks. If the result is positive, fund i is a net transmitter of shocks, while a negative result indicates it is a net receiver.

$$CH_i = CH_{i\rightarrow \cdot} - CH_{i\leftarrow \cdot} \tag{41}$$

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

$$\text{Total Connectedness} = \frac{\sum_{i=1}^{K} \sum_{j=1, j\neq i}^{K} \theta_{ij}}{N} \tag{42}$$

Where θ_{ij}^{H} represents the contribution of variable j to the forecast error variance of variable i over the horizon H, and the numerator sums the off-diagonal contributions, indicating shocks transmitted between variables. $N = 6$ is the total number of variables in the system (GINCOM, GROWTH, LARGEC, MIDCAP, SMALLC, and MICROC)

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

4.2 Results

To verify the stationarity of all VAR components, an augmented Dickey–Fuller (ADF) test is used. The results show clearly that all return series satisfy this condition. Tab. 3 presents a basic correlation matrix for these return series. The matrix reveals that there are strong connections between all the funds, with correlation coefficients consistently exceeding 0.9. These high correlations suggest the presence of multicollinearity, as variables that are highly correlated often lead to problems in regression analysis. This suspicion is confirmed by the Variance Inflation Factor (VIF) results in Tab. 4, where all variables exhibit extremely high VIF values, far exceeding the common threshold of 10. Some variables even have VIFs exceeding 100, clearly indicating severe multicollinearity. This multicollinearity complicates the interpretation of individual variable effects and can lead to unreliable model estimates, highlighting the need for techniques such as Ridge Regression to mitigate the issue..

We then perform pairwise Granger causality tests to assess the relationships among the six return series of the six types of funds.

INSERT TAB. 3 HERE

INSERT TAB. 4 HERE

INSERT TAB. 5 HERE

Tab. 5 displays the p-values resulting from the pairwise Granger causality tests. Each p-value denoted as p_{ij} evaluates the null hypothesis under which variable j causes variable i. To illustrate, $p_{12} = 0.0011$ represents the p-value assessing whether the returns of Growth Granger-cause the returns of GIncom. To determine the presence of causality between all pairs in both directions, we employ the common 5% significance level as a reference point. A p-value (p_{ij}) less than 5% indicates the existence of Granger causality from variable j to i. In such cases, we represent this relationship from variable j to i by arrows in a simple map. If the p-value exceeds 5%, no arrow is drawn, indicating no significant Granger causality between those variables. This visualization is captured in Fig. 8. The table and network diagram highlight the pivotal roles of GIncome, Growth, and Large Cap as key drivers of causality within the system, significantly affecting the other variables. Large Cap stands out as the most influential, with strong Granger causality relationships across all variables. GIncome and Growth also play substantial roles, influencing multiple variables and contributing to the overall dynamics of the system. The remaining variables, Mid Cap, Small Cap, and Micro Cap, also display significant Granger causality in certain directions but are more influenced by GIncome, Growth, and Large Cap. For instance, Mid Cap is Granger-caused by GIncome, Growth, and Large Cap, while Small Cap shows weaker causal relationships but still plays a role in influencing Micro Cap.

The Granger causality test illustrates the complex interconnections between the variables. However, these results should be interpreted with caution, as strong correlations among the style returns can bias the outcomes and do not necessarily imply Granger-causal relationships.

Given the high multicollinearity present among the returns of these fund styles, we then estimate a six-variable Ridge VAR model. This model is particularly well-suited for handling multicollinearity, as the Ridge regression technique penalizes the size of the coefficients, helping to stabilize estimates and reduce the potential overfitting caused by the interdependencies between the variables. The six variables in the Ridge VAR model correspond to the six return series (daily data) of the fund styles, allowing us to capture the dynamic relationships between them while mitigating the impact of multicollinearity on the model's performance. This approach ensures more reliable estimates of the causal interactions between the fund style returns, despite the strong correlations observed.

Prior to estimation, several VAR lag selection tests (AIC, BIC, FPE, HQIC) were performed (see Tab. 6). Based on the AIC and FPE criteria, a lag of 12 is determined to be optimal for our VAR estimates.

A forecasting horizon of twelve periods (denoted H in the VAR model) is employed for generalized forecast error variance decomposition, serving as the basis for constructing the connectedness table (see Tab. 7). This choice of forecasting horizon aligns with the approach taken in Diebold and Yilmaz (2009).

INSERT TAB. 7 HERE

As illustrated by Tab. 7, the overall connectedness within the VAR system amounts to 61.95% implying strong interdependencies among the six fund styles. This value quantifies the extent of spillover effects within the system. Its high level suggests that shocks that hit one style might significantly affect the others. As such, a local disturbance can be transformed into a widespread crisis.

A more straightforward representation of these results is presented in Figures 9 and 10. Figure 9 illustrates illustrates the contributions to and from the system, measuring the transmission of shocks between each fund style and the system. The blue bars represent the contribution of each fund style to the system, while the red bars indicate the contribution received from the system. Figure 10 shows the net directional connectedness or the net contribution of each fund style, calculated as the difference between the contributions to and from the system (To - From). This graphical representation complements the quantitative analysis in Table 7, offering a clear visualization of the dynamic interactions within the system.

INSERT FIG. 9 HERE

INSERT FIG. 10 HERE

GIncome is the most dominant fund style, with a significantly positive NDC, indicating that it contributes more to the system than it receives from it. GIncome contributes 82.95% to other funds, while receiving 44.07% from the system, resulting in a strong NDC value of 38.88%. This large gap between contributions to and from the system reaffirms GIncome's leading role in driving system-wide dynamics. Its substantial contribution positions it as a key influencer of other funds and a pivotal propagator of shocks, meaning its performance changes can greatly impact the stability of the entire system, particularly during turbulent market conditions. This finding is consistent with the Aggregate Vulnerability (AV) analysis from the previous section, where GIncome, while not the most vulnerable, still exhibits a significant increase in vulnerability during periods of market stress, amplifying its systemic importance. In turbulent markets, GIncome's role as a shock transmitter becomes even more crucial due to its central influence in the system.

Growth and Large Cap also show positive NDC values, though to a lesser extent than GIncome. This indicates that, while they contribute more to the system than they receive, their impact is somewhat more balanced. The relatively large blue bars for both Growth and Large Cap in the graph indicate that they play a significant role in shaping the overall system. Growth contributes 68% to the system, while receiving 54% of its influence from the system, showing that it acts both as a transmitter and receiver of systemic shocks. The fact that Growth contributes more than it receives highlights its importance in driving market dynamics, particularly due to its focus on high-growth stocks, which tend to be more volatile. This aligns with the AV results, where Growth shows the highest vulnerability under market stress, especially in leveraged scenarios, making it the most exposed to external shocks. In periods of stress, this heightened sensitivity can amplify Growth's impact on other funds, as it transmits more of

the shocks it experiences, which is evident in both its high AV and its NDC.

Large Cap, similarly, contributes 66.84% to the system and receives 55.53% in return. This balance suggests that Large Cap funds, which tend to hold well-established, stable companies, have a moderating effect on the system. Their high contribution indicates they play a stabilizing role, distributing stability throughout the system. However, the influence they receive from other funds shows that even these larger, more established funds are not immune to the spillover effects of shocks originating elsewhere in the system. Large Cap's role as both a contributor and receiver implies that while it acts as a buffer in times of market stress, it can also be susceptible to disturbances caused by more volatile funds like Growth. This dynamic is reflected in the AV results, where Large Cap shows much lower vulnerability compared to Growth, suggesting that while it is a key player, its exposure to stress is more moderate, enabling it to play a stabilizing role.

In contrast, Mid Cap, Small Cap, and Micro Cap exhibit negative NDC values, meaning they are more influenced by the system than they contribute to it. These funds are primarily receivers of shocks rather than transmitters. Small Cap and Micro Cap are the most influenced, receiving 79.12% and 72.40% from other funds, respectively, while contributing relatively little back. The negative NDC values for Small Cap (-32.69) and Micro Cap (-21.32) reflect their dependence on the broader system's behavior, making them more vulnerable to external shocks. This is consistent with the NDC graph, which illustrates that these smaller funds act more like shock absorbers than sources of market stress. Their lower contribution to systemic dynamics may stem from their focus on smaller, less liquid stocks, which are less influential in driving broad market trends but more susceptible to external disturbances. Similarly, in the AV analysis, these funds showed lower vulnerabilities across both normal and turbulent regimes, further reinforcing their roles as less significant drivers of systemic risk but more susceptible to being affected by the broader system.

This dynamic highlights a potential vulnerability-feedback loop: funds like Small Cap and Micro Cap, while not heavily influencing the system, are more exposed to it, meaning that they could face outsized risks in periods of market stress. This is particularly important because, as shown in the AV section, the vulnerability of these smaller funds can still increase significantly under extreme conditions, even though their overall influence is limited. Conversely, Growth, Large Cap, and GIncome play a more active role in shaping the system's behavior, with GIncome leading the way as the most dominant player. These larger funds are not only contributors to systemic stability but also potential amplifiers of systemic risk, especially under adverse conditions, as their interconnectedness and vulnerabilities amplify their impact on the system.

Thus, the interconnectedness of these funds underscores the importance of monitoring both their contributions and their susceptibility to shocks. GIncome's dominant position makes it crucial for system-wide stability, while Growth and Large Cap serve as key intermediaries that transmit and moderate market dynamics. Mid Cap, Small Cap, and Micro Cap, while less influential, are essential

to understanding how market shocks propagate throughout the system, as they provide insights into the vulnerabilities that may emerge from funds more reliant on systemic conditions than their own performance.

5 Conclusion

In this paper, we study the vulnerability of different styles of the U.S. DEOEMF over the period 2003 - 2018. We first perform a macroprudential stress-test by following the framework developed by Fricke and Fricke (2021) in order to assess the resilience of these styles when faced to shocks. Unlike previous studies in this literature, we consider two market conditions and granular asset price impacts, which makes our framework closer to real market situations. Our results show that the percentage of equity blown under stress conditions can be significantly higher and non-neglected than during normal times. The extent of the shock impact varies over time, across styles and is amplified by leverage. It is relatively weak, except for the sub-prime period during which LargeCap is the most vulnerable, followed by GIncome and Growth. It is worth noting that we do not observe any increase in fund vulnerability after the sub-prime crisis, whatever the style and the scenario considered. This finding is thus very different from the result reported by Fricke and Fricke (2021).

In addition, we conduct a contagion analysis by using the Diebold and Yilmaz (2009, 2012, 2014)'s spillover approach to identify which styles are more vulnerable and which are likely to propagate shocks. Our findings reveal two distinct patterns. On one side, GIncome stands out as the most dominant style, contributing significantly to the system while being less affected by others, thus serving as a key transmitter of shocks. On the other side, Growth and Large Cap funds also play important roles, as their performance is crucial in shaping market dynamics and can impact the stability of the system. Conversely, Mid Cap, Small Cap, and Micro Cap act primarily as net receivers of shocks, absorbing more influence from the system than they transmit. These patterns reflect the differing characteristics of the underlying assets in these funds, with GIncome, Growth, and Large Cap influencing systemic dynamics. This finding is consistent with the previous results on Aggregate Vulnerability (AV), which indicated that these fund styles are the most vulnerable to systemic shocks. Their sensitivity to market fluctuations makes them more susceptible to external pressures, thereby amplifying their potential impact on the overall stability of the financial system.

These findings provide regulators with better understanding of the propagation mechanism within the U.S. DOEMF. They also highlight the heterogeneity among the U.S. equity funds in response to shocks and the importance to account for this diversity in system-wide macroprudential stress-tests.

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[H]

Style	Nb. of funds in each style	Average nb. of obs within a fund	Nb. of obs in each style
GIncom	1 401	143.394	219 250
Growth	2 205	149.644	368 274
LargeC	147	159.412	24 390
MidCap	759	149.914	132 674
SmallC	1 076	155.695	186 367
MicroC	39	155.051	9 148

Table 1: Descriptive statistics on fund monthly returns by styles

	Obs	Mean	Std. Dev.	Min	Max	Sharpe
GINCOM	225	0.0046	0.0382	-0.1710	0.1007	0.1204
GROWTH	225	0.0047	0.0435	-0.1808	0.1155	0.1080
LARGEC	225	0.0052	0.0412	-0.1704	0.1093	0.1262
MICROC	225	0.0084	0.0546	-0.2021	0.1793	0.1538
MIDCAP	225	0.0066	0.0489	-0.2062	0.1325	0.1350
SMALLC	225	0.0074	0.0521	-0.2045	0.1507	0.1420

Note: Sharpe ratios are computed by assuming a risk-free rate equal to zero.

Table 2: Flow - performance sensitivity by styles and regimes

Style	Regime s=1	Regime s=2
GINCOM	0.0299	0.0887
GROWTH	0.0439	0.0870
LARGEC	0.0184	0.0901
MIDCAP	0.0456	0.0709
SMALLC	0.0624	0.0767
MICROC	0.0681	0.0592
Mean	0.0447	0.0788

Table 3: Correlations between styles

	GINCOM	GROWTH	LARGEC	MIDCAP	SMALLC	MICROC
GINCOM	1.0000	0.9680	0.9731	0.9558	0.9212	0.8826
GROWTH	0.9680	1.0000	0.9861	0.9843	0.9530	0.9184
LARGEC	0.9731	0.9861	1.0000	0.9648	0.9268	0.8857
MIDCAP	0.9558	0.9843	0.9648	1.0000	0.9807	0.9496
SMALLC	0.9212	0.9530	0.9268	0.9807	1.0000	0.9863
MICROC	0.8826	0.9184	0.8857	0.9496	0.9863	1.0000

Table 4: Variance Inflation Factor (VIF)

Variable	VIF
GINCOM	20.4956
GROWTH	87.4906
LARGEC	50.4615
MIDCAP	105.6933
SMALLC	143.1572
MICROC	54.7188

Table 5: Pairwise Granger Causality Test (p-values)

	GINCOM	GROWTH	LARGEC	MIDCAP	SMALLC	MICROC
GINCOM	0	0.0011	1.94E-07	0.0016	0.0148	0.0126
GROWTH	0.0007	0	1.36E-18	0.0028	0.0002	0.0001
LARGEC	5.50E-07	1.04E-18	0	1.59E-07	2.96E-06	1.92E-06
MIDCAP	4.62E-05	0.0002	1.73E-09	0	1.51E-05	0.0002
SMALLC	0.0023	9.97E-06	1.22E-07	5.49E-05	0	0.2456
MICROC	0.0020	2.05E-05	1.27E-06	0.0007	0.1866	0

Note: p-values (p_{ij}) are reported for the null hypothesis "Does j Granger cause i?".

Lags are automatically selected based on AIC.

Table 6: VAR Lag Selection

Order	**AIC**	**BIC**	**FPE**	**HQIC**
0	-70.73	-70.72	1.915e-31	-70.73
1	-70.83	-70.76*	1.738e-31	-70.80
2	-70.86	-70.73	1.686e-31	-70.81*
3	-70.86	-70.68	1.685e-31	-70.79
4	-70.87	-70.63	1.671e-31	-70.78
5	-70.86	-70.57	1.676e-31	-70.76
6	-70.86	-70.51	1.679e-31	-70.74
7	-70.86	-70.45	1.679e-31	-70.72
8	-70.86	-70.39	1.685e-31	-70.69
9	-70.86	-70.34	1.681e-31	-70.67
10	-70.87	-70.28	1.673e-31	-70.66
11	-70.86	-70.22	1.683e-31	-70.63
12	-70.87*	-70.17	1.665e-31*	-70.62
13	-70.86	-70.11	1.678e-31	-70.60
14	-70.87	-70.06	1.672e-31	-70.58
15	-70.87	-70.00	1.666e-31	-70.56

Table 7: Connectedness across funds

	GINCOM	GROWTH	LARGEC	MIDCAP	SMALLC	MICROC	To	NDC
GINCOM		14.162	14.452	16.775	19.501	18.063	82.952	38.880
GROWTH	10.168		12.245	14.214	16.524	15.305	68.457	14.281
LARGEC	9.964	11.759		13.929	16.193	14.999	66.844	11.315
MIDCAP	8.584	10.131	10.338		13.950	12.921	55.925	-10.460
SMALLC	7.384	8.715	8.893	10.322		11.115	46.429	-32.694
MICROC	7.972	9.408	9.601	11.144	12.955		51.081	-21.322
From	44.073	54.175	55.529	66.385	79.123	72.403	**61.948**	

Note: NDC refers to the Net Directional Connectedness. Total Connectedness Index is 61.95.

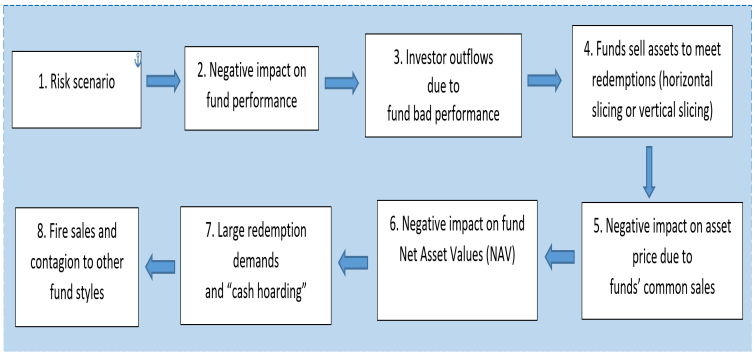


Figure 1: Mechanism of shock propagation within the mutual fund industry.

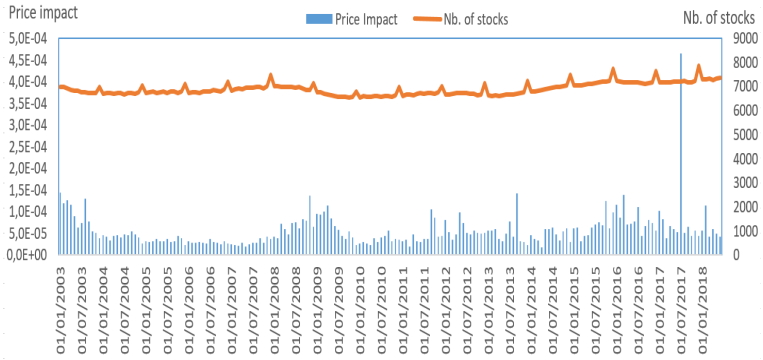


Figure 2: Monthly cross-sectional average price impact computed as mean of all stocks' daily price impact.

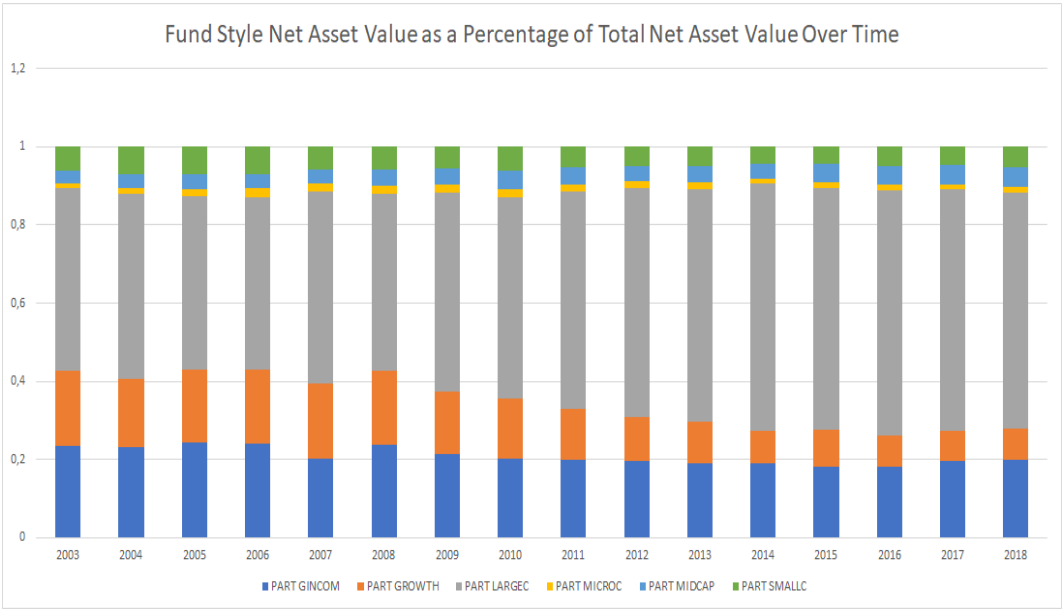
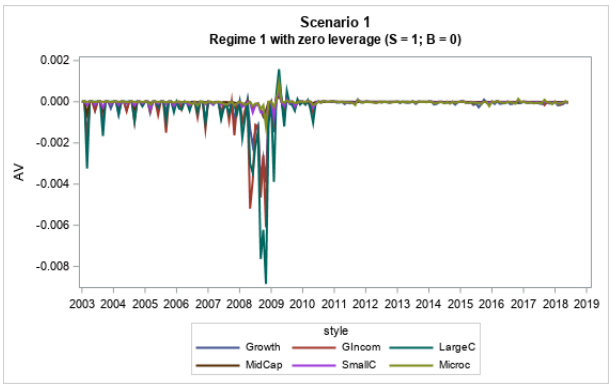
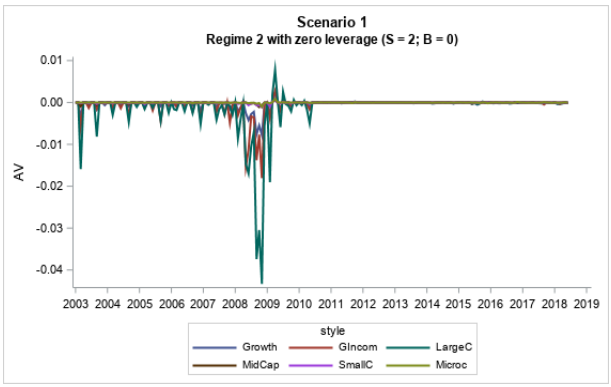


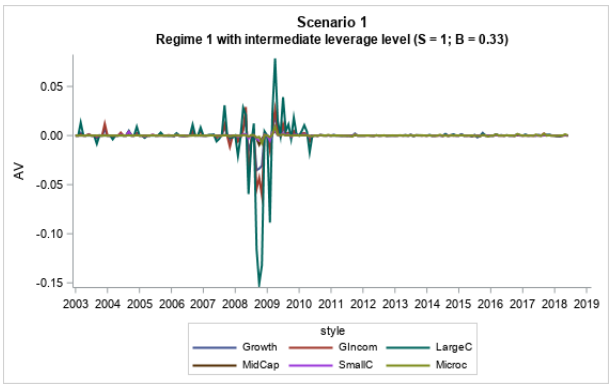
Figure 3: Fund style weights



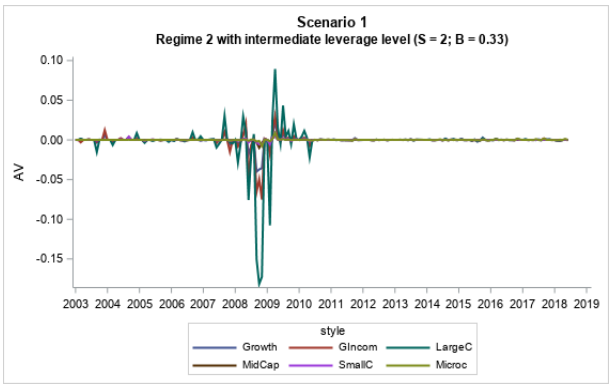
(a) Regime 1 with zero leverage



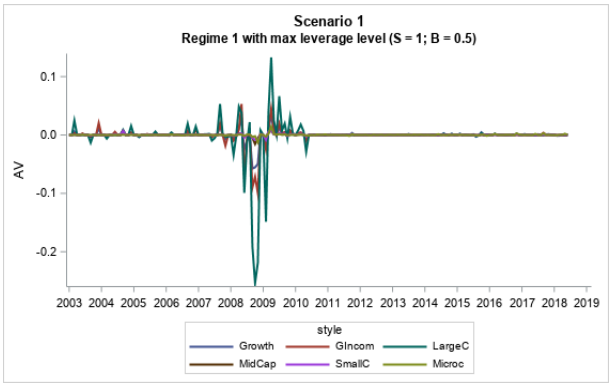
(b) Regime 2 with zero leverage



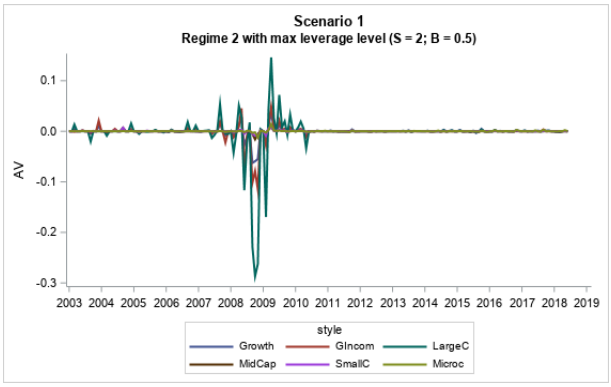
(c) Regime 1 with intermediate leverage



(d) Regime 2 with intermediate leverage

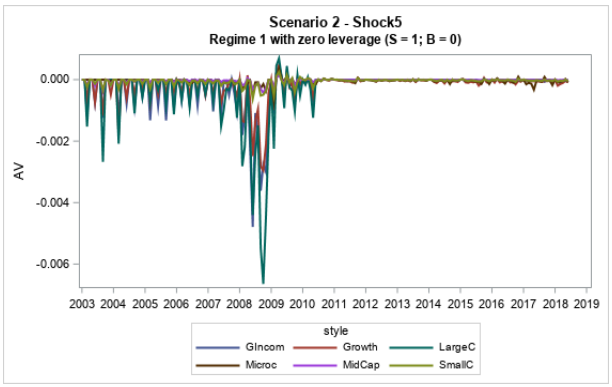


(e) Regime 1 with max leverage level

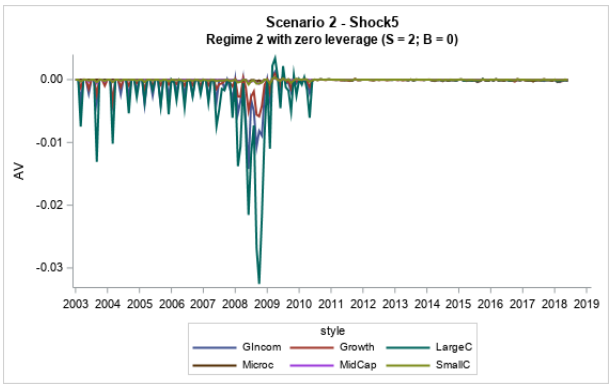


(f) Regime 2 with max leverage level

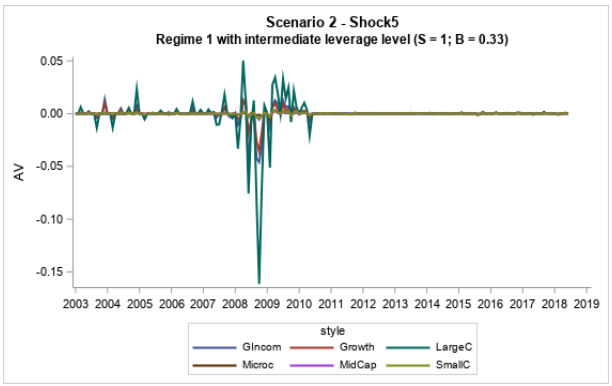
Figure 4: Aggregate vulnerabilities for scenario 1 with zero average ($B = 0$), intermediate leverage ($B = 0.33$) and max leverage ($B = 0.5$). $s = 1$ refers to regime 1 with small variance while $s = 2$ corresponds to regime 2 with high variance.



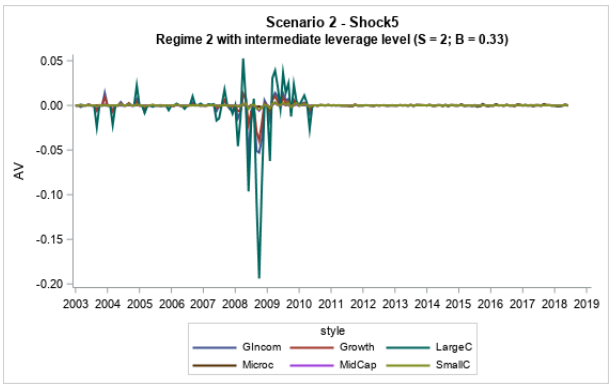
(a) Regime 1 with zero leverage



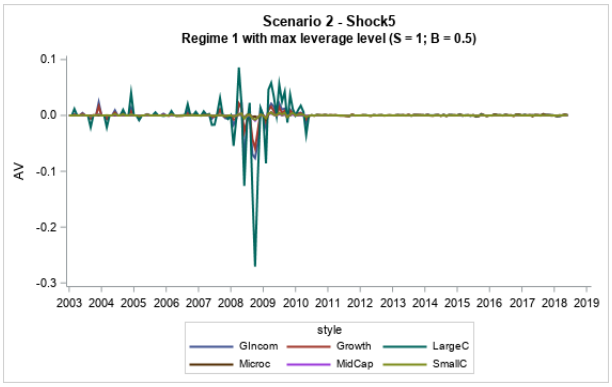
(b) Regime 2 with zero leverage



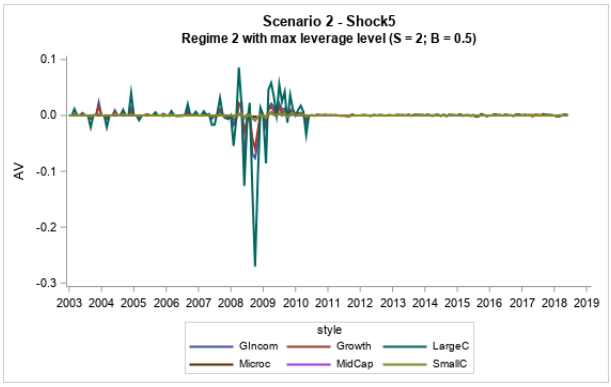
(c) Regime 1 with intermediate leverage



(d) Regime 2 with intermediate leverage

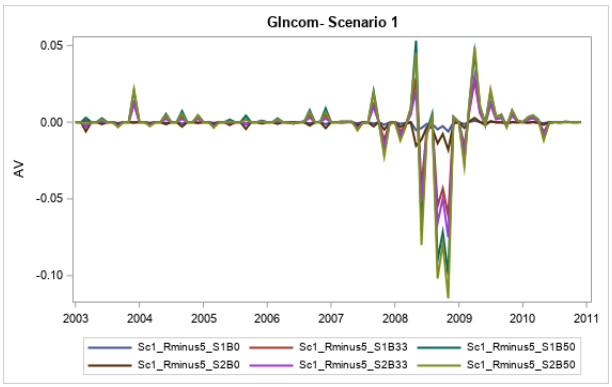


(e) Regime 1 with max leverage level

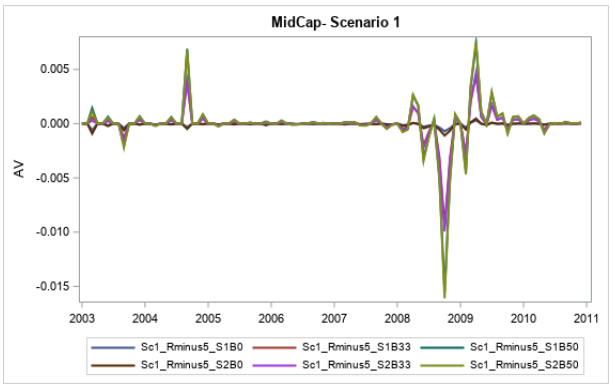


(f) Regime 2 with max leverage level

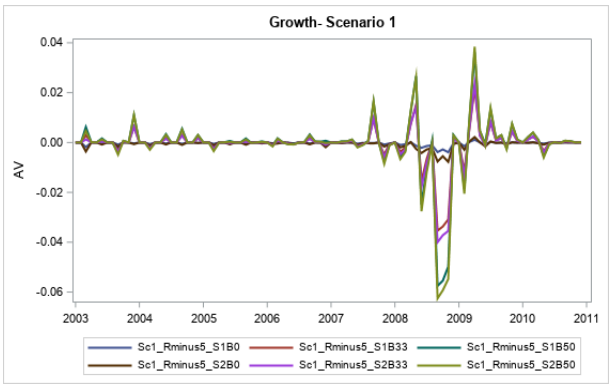
Figure 5: Aggregate vulnerabilities for scenario 2 with zero average ($B = 0$), intermediate leverage ($B = 0.33$) and max leverage ($B = 0.5$). $s = 1$ refers to regime 1 with small variance while $s = 2$ corresponds to regime 2 with high variance.



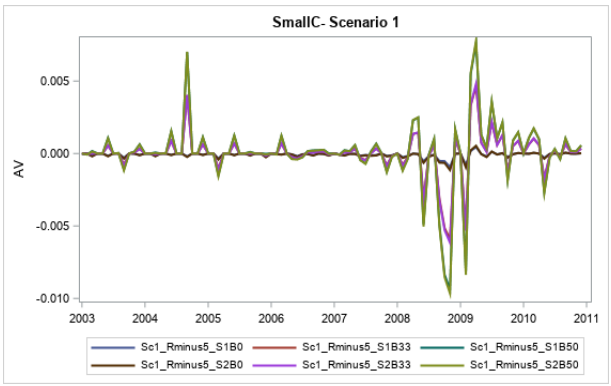
(a) GROWTH INCOME



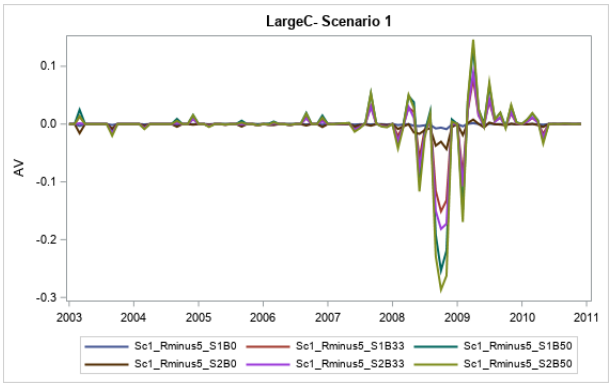
(b) MIDCAP



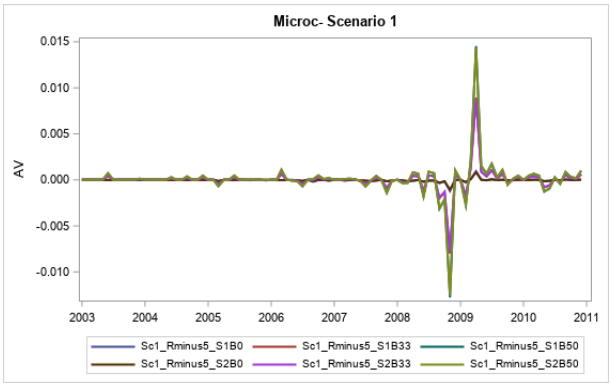
(c) GROWTH



(d) SMALLCAP

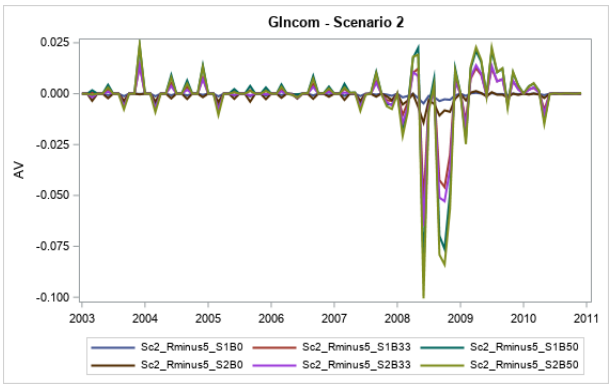


(e) LARGECAP

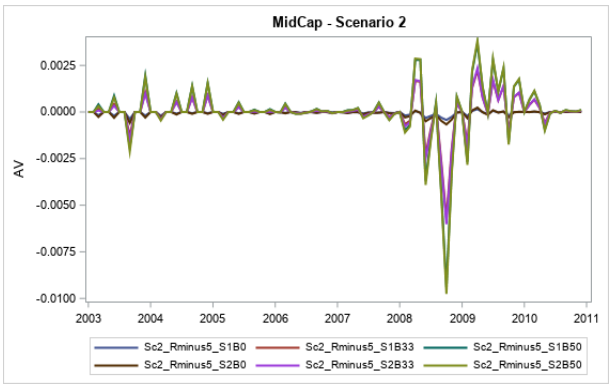


(f) MICROCAP

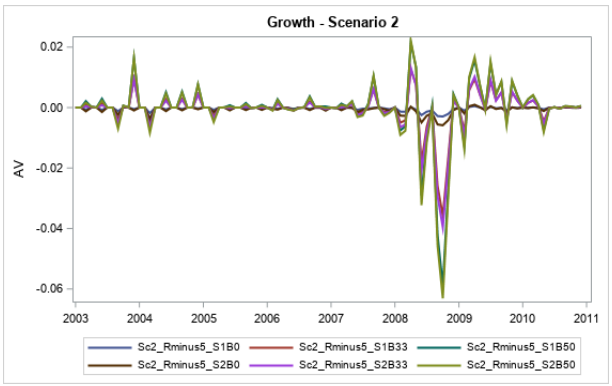
Figure 6: Aggregate vulnerabilities by styles under Scenario 1 over the period 1/2003 - 12/2010 with zero average ($B = 0$), intermediate leverage ($B = 0.33$) and max leverage ($B = 0.5$). $s = 1$ refers to regime 1 with small variance while $s = 2$ corresponds to regime 2 with high variance.



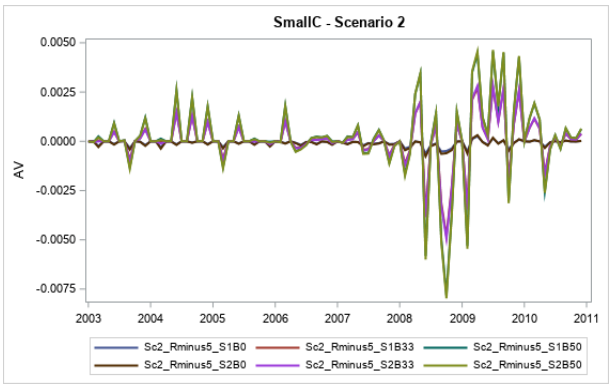
(a) GROWTH INCOME



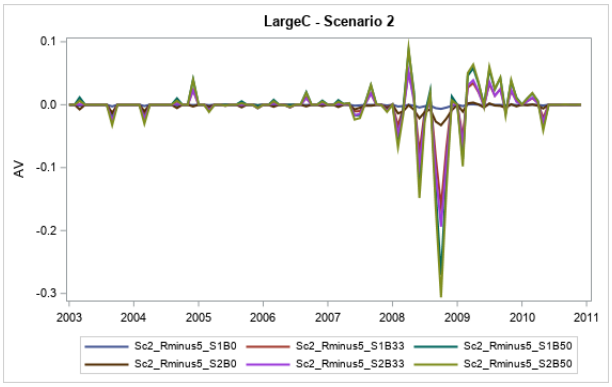
(b) MIDCAP



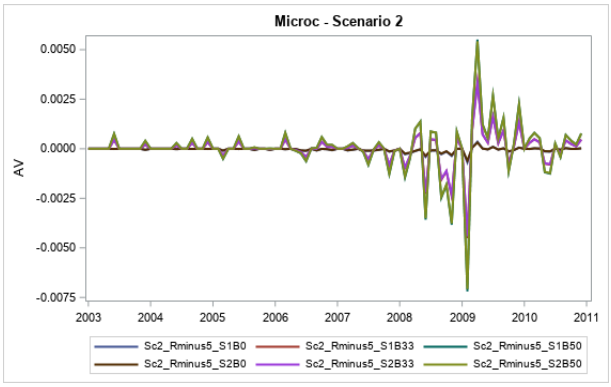
(c) GROWTH



(d) SMALLCAP



(e) LARGECAP



(f) MICROCAP

Figure 7: Aggregate vulnerabilities by styles under Scenario 2 over the period 1/2003 - 12/2010 with zero average ($B = 0$), intermediate leverage ($B = 0.33$) and max leverage ($B = 0.5$). $s = 1$ refers to regime 1 with small variance while $s = 2$ corresponds to regime 2 with high variance.

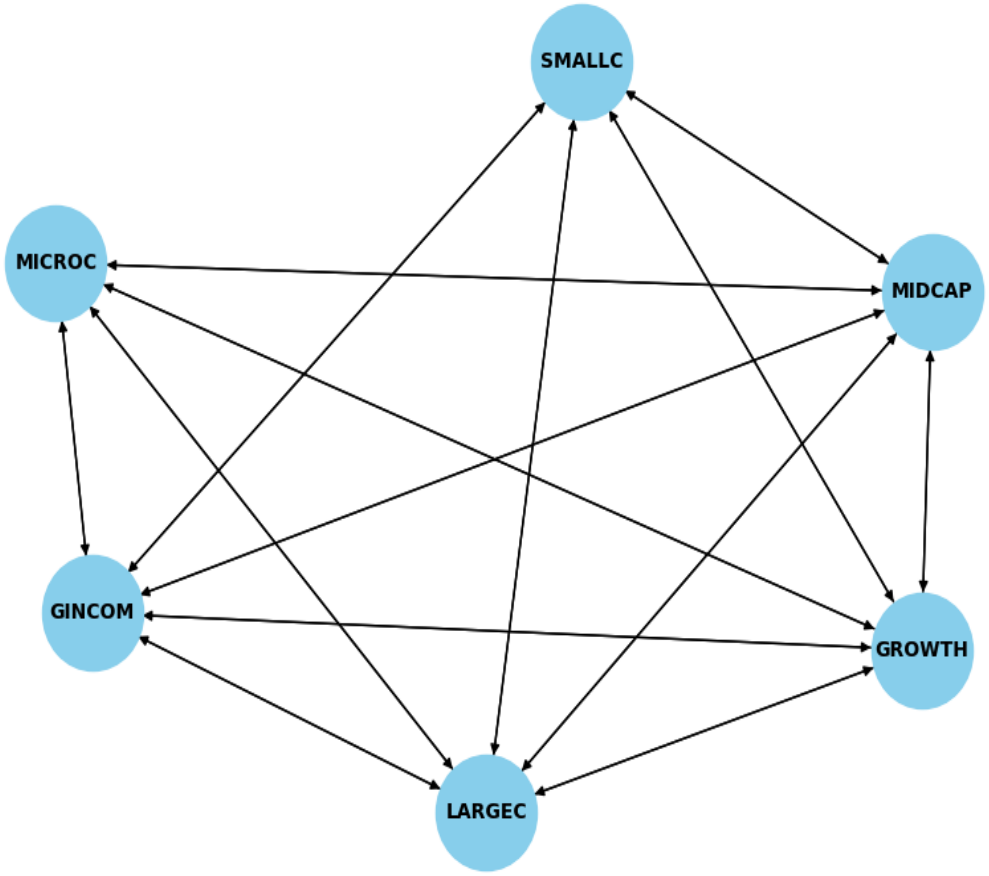


Figure 8: Pairwise Granger causality relationship (at the 5% significance level)

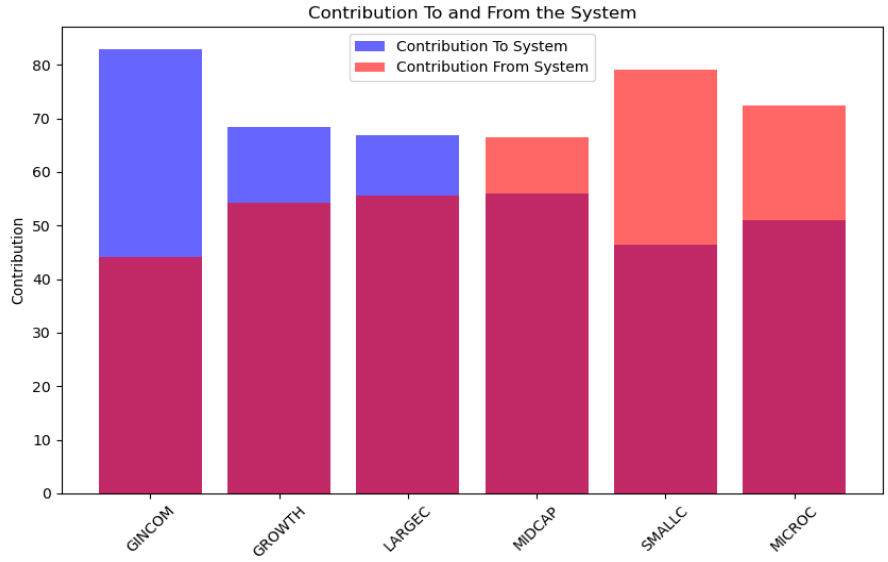


Figure 9: Contribution "To" and "From" the system

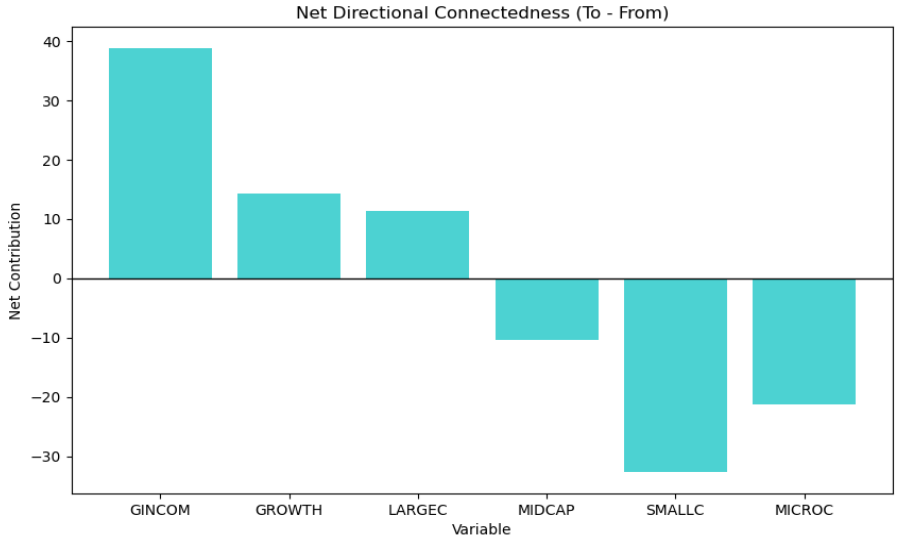


Figure 10: Net Directional Connectedness (To-From)