Asset Price Fragility in Times of Stress: The Role of Open-End Investment Funds—Online Annex

Online Annex 3.1 Data Sources and Sample Description

Online Annex Table 3.1.1. Data Description and Sources

Variable	Description	Source
Fund variables		
Fund net flow	Fund flow as percentage of fund total net assets of the previous quarter.	Morningstar
Fund return	Fund assets' performance as percentage of fund total net assets of the previous quarter.	Morningstar
Fund cash holdings	Deposit in portfolio base currency that can be withdrawn at any time. Consistent with the literature (Jiang and others, 2022), negative fund cash holdings are set equal to zero and fund cash holdings larger than 20 percent of the fund's total net assets are set equal to 20 percent of the fund's net assets.	Morningstar
Fund cash equivalent holdings	Fund cash and equivalents include cash held in bank accounts as well as certificates of deposit, currency, money market holdings and other high quality fixed income securities with a maturity of less than 92 days. Consistent with the literature (Jiang and others, 2022), negative fund cash and equivalents holdings are set equal to zero and fund cash and equivalents holdings larger than 20 percent of the fund's total net assets are set equal to 20 percent of the fund's net assets.	Morningstar
Swing pricing (dummy variable)	Dummy variable which is equal to one when the fund is domiciled in a country in which the use of swing pricing is permitted by regulators and common across funds, and equal to zero otherwise. In the baseline analysis, Luxembourg and the UK are classified as swing pricing domiciles.	Morningstar
Expense ratio	The percentage of fund assets used to pay for operating expenses and management fees, including 12b-1 fees, administrative fees, and all other asset-based costs incurred by the fund, except brokerage costs. The fund's total expense ratio (in percent) is winsorized at the 1st and 99th percentiles.	Morningstar
Portfolio illiquidity	Holding-weighted average bid-ask spread excluding cash.	IMF staff calculation
ETF premium/ discount	Difference between ETF NAV and closing ETF price measured as a percentage of the ETF NAV. Observations are winsorized at the 1st and 99th percentiles.	Morningstar
Total net assets	The fund's total assets under management in USD measured at the end of each quarter.	Morningstar
Security-level variables		
Bid-ask spread	For equities, the spread is based on daily closing prices; for other asset classes, the spread is based on multiple inputs using daily closing bid-ask prices from an exchange, composite bid-ask prices, and Refinitiv's evaluated bid-ask prices.	Refinitiv
Market capitalization	Current market price multiplied by the amount currently in issue	Refinitiv
Return	Total return index. For equities, this shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date. For fixed income, this is the return on investment, including interest payments, as well as appreciation or depreciation in the price of the bond. Variable is winsorized at 1.5 percent level.	Refinitiv
Fraction MF (ETF) ownership	Fund's holding value of a security divided by the market capitalization of the security	Factset; Refinitiv; IMF staff calculation
Security ratings	S&P long-term local currency ratings for issuer and issue (in the case of fixed income)	Refinitiv
Turnover	The value of all trades for a stock or bond on a particular day	Refinitiv
Age	Age of the equity or fixed income as denoted by date of incorporation or issuance	Refinitiv
Skewness of returns	The skewness of daily or weekly returns over a quarter for a given security	Refinitiv; IMF staff calculation

Price-to-Book ratio	For equities, this is the share price divided by the book value per share	Refinitiv
Volatility	Standard deviation of daily or weekly returns over a quarter	Refinitiv; IMF staff calculation
Security-level swing exposure	The ownership of a given asset by open-end mutual funds that use swing pricing as a percentage of its total mutual fund ownership	Factset; Morningstar; IMF staff calculation
Issuer	Issuing entity of the security	Refinitiv
Coupon rate	This is the annual percentage rate payable on a bond	Refinitiv
Bond maturity	Time to maturity for a bond	Refinitiv; IMF staff calculation
Macro-financial variables		
Change in global liquidity	The BIS global liquidity indicator (GLIs) tracks credit to non-bank borrowers, covering both loans extended by banks and funding from global bond markets through the issuance of international debt securities (IDS). Quarter-over-quarter change of the variable is used in the analysis.	BIS
Commodity price shock	Pure oil price expectation shock as defined in Bauermeister (2021). To filter out the "pure" expectation component market-based surprises are regressed on fundamental oil supply and demand shocks.	Bauermeister (2021)
Domestic monetary policy shocks	Domestic monetary policy shocks are estimated by regressing the policy rate on a set of controls and use the residuals as the identified shocks. The set of controls includes contemporaneous and lagged values of inflation, log U.S. GDP, log foreign GDP, as well as lagged values of the policy rate and a quadratic time trend.	Haver Analytics; IMF staff calculations
Financial condition index (FCI)	The financial condition index is based on a principal component analysis of 11 key price-based variables to capture the price of risk. For methodology and a description of all the variables included in the financial condition index, refer to Online Annex 3.2 of the October 2017 *Global Financial Stability Report*. Alternative indicators are also constructed following the approach in Koop and Korobilis (2014). Positive values of the index indicate tighter-than average financial conditions.	IMF staff estimates
Foreign GDP growth	Average real GDP growth of foreign economies relative to a given domestic economy	Haver; IMF staff calculations
GDP growth	Quarterly real GDP growth	IMF, World Economic Outlook; IMF staff calculations
MPU	Monetary Policy Uncertainty index for the United States obtained from text analysis of newspapers articles.	Husted and others (2020)
VIX	CBOE Volatility Index	Haver Analytics
Source: IMF staff		

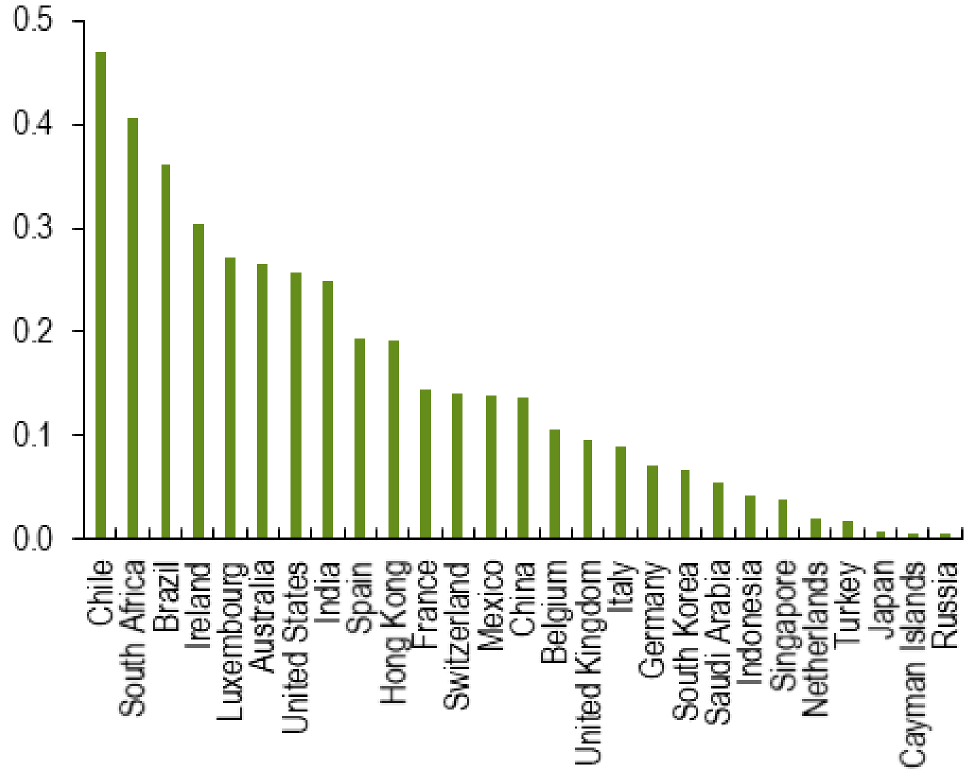
Investment fund sample description

The chapter's analysis relies on data of 17,000 open-end funds sourced from Morningstar with portfolio holdings data from Factset.[1] Of those, about 14,000 were in existence at the beginning of 2021. The sample period extends from 2013:Q4 to 2022:Q2. The OEFs in the sample are domiciled in 43 countries and can be grouped into the following global broad category groups: allocation, alternative, equity, and fixed income. Online Annex Figure 3.1.1 shows the size of open-end funds relative to the non-bank financial intermediation sector by country.

[1] Comprehensive portfolio holdings data is only available starting 2013:Q4.

Online Annex Figure 3.1.1. Total Net Asset Values of Open-End Funds Relative to Non-Bank Financial Intermediation Sector

(Percent)



Sources: FSB (2021); Morningstar, and IMF staff calculations.
Note: nonbank financial intermediation includes all financial institutions that are not central banks, banks, or public financial institutions (FSB 2022). NBFI = nonbank financial intermediation.

Online Annex 3.2 Analysis of Asset-Level Vulnerabilities

Construction of Asset-Level Vulnerability Measure

Following Jiang and others (2022), a measure of asset price vulnerability is calculated in two steps. First, a fund-level illiquidity measure is constructed as a weighted average of bid-ask spreads (illiquidity) of assets held by the fund:

$$Fund\ illiquidity_{j,t} = \frac{\sum_{i=1}^{I} Holding\ amount_{j,i,t} \times Bid-Ask_{i,t}}{\sum_{i=1}^{I} Holding\ amount_{j,i,t}}, \quad (1)$$

where $Holding\ amount_{j,i,t}$ is the market value of asset *i* held by fund *j* in quarter *t*, and $Bid-Ask_{i,t}$ is the bid-ask spread of asset *i* at the end of quarter *t*.[1]

Second, the asset price vulnerability measure is calculated based on the weighted average of investing funds' illiquidity, where the weights represent funds' relative holdings of the asset, as follows:

$$Asset\ level\ Vulnerability_{i,t} = \frac{\sum_{j=1}^{J} Holding\ amount_{j,i,t} \times Fund\ illiquidity_{j,t}}{\sum_{j=1}^{J} Holding\ amount_{j,i,t}}, \quad (2)$$

where $Holding\ amount_{j,i,t}$ is the market value of asset *i* held by fund *j* at the end of quarter *t*, and $Fund\ illiquidity_{j,t}$ is the illiquidity of fund *j* in quarter *t* (defined above).[2]

Effect of Asset-Level Vulnerability on Asset Price Fragility

Next, the chapter analyzes how the asset-level vulnerability measure affects asset-price fragility, measured as future return volatility. The following equation is estimated for each asset class (δ) separately:

$$\sigma^{\delta}{}_{c,i,t+1} = \beta_0^{\delta} + \beta_1^{\delta} Asset\ Level\ Vulnerability^{\delta}{}_{c,i,t} + \beta_2^{\delta} Controls^{\delta}{}_{c,i,t} + \gamma_i^{\delta} + \gamma^{\delta}{}_{c,t} + \varepsilon^{\delta}{}_{c,i,t+1}, \quad (3)$$

where $\sigma_{c,i,t+1}$ is the standard deviation of annualized weekly returns over the next quarter for asset *i* in country *c*, as a percent of the sample median, and $Asset\ Level\ Vulnerability_{c,i,t}$ is the standardized version of the vulnerability measure defined in equation (2). The model includes country-time fixed effects ($\gamma_{c,t}$), which absorb any time-varying country characteristics, and asset fixed effects (γ_i), which absorb any time-invariant asset characteristics. Standard errors are clustered at the quarter and asset levels. Regressions are run for various asset classes that include bonds and equities.[3]

Controls are specific to the asset class. The model for bonds includes the following controls: bid-ask spread, log of market capitalization, weekly returns, mutual fund ownership, time to maturity, and security ratings. The model for equities includes the following controls: bid-ask

[1] The chapter uses Refinitiv bid-ask spreads as the primary measures of asset liquidity. Bid-ask spreads capture transaction costs, inventory costs, and asymmetric information.

[2] There could be concerns about the liquidity of asset *i* and the asset-level vulnerability measure being too closely related—for example, in cases where funds only hold a few assets. The typical fund, however, holds a large number of assets (about 150 on average), which implies that excluding a specific asset from the fund-level vulnerability measure to construct the corresponding asset-level vulnerability measure is unlikely to impact these measures significantly.

[3] The regressions are estimated separately for all bonds, corporate bonds, high-yield corporate bonds, investment-grade corporate bonds, sovereign bonds, high yield sovereign bonds, and investment grade sovereign bonds, as well as for all equities and small cap equities.

spread, log market capitalization, weekly returns, mutual fund ownership, turnover, log age, skewness, mid-price, one-year return, and the price to book ratio.

A range of robustness checks have been performed on the baseline specification by using:

- Alternative definitions of the asset vulnerability measure: asset vulnerabilities from global equity funds only, from fixed-income funds only, from mixed funds only;
- Alternative specifications of fixed effects: country, borrower, time, borrower-time fixed effects, borrower-time and asset fixed effects;
- Alternative specifications of the dependent variable as annualized daily return volatility instead of annualized weekly return volatility;
- Alternative definitions of the asset vulnerability measure based on the definition of the portfolio-level bid-ask spread: using the average spread in the quarter before the portfolio holdings are observed;
- Alternative definitions of the vulnerability measures: including cash holdings when calculating fund-level illiquidity;
- Alternative definition of the vulnerability measures: including only funds that hold a large and diversified portfolio (at least 100 securities per quarter);
- Alternative specifications of controls in the equity and bond regressions, including using lagged volatility in the equity regression models;
- A restricted sample of securities with high mutual fund ownership.

The original conclusions are robust to these changes.

Effect of Asset-Level Vulnerability on Asset Price Fragility in Times of Stress

To test whether measures of asset price vulnerability amplify the impact of market stress events on asset price volatility, the following equation is estimated separately for each asset class:

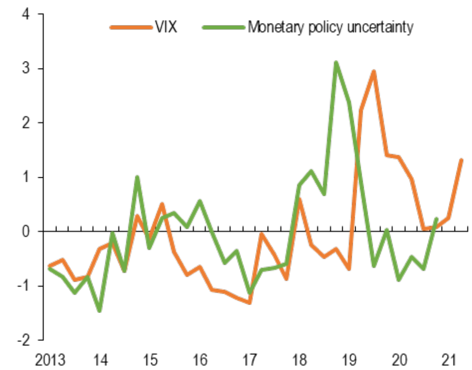
$$\begin{aligned}\sigma_{i,t+1} = \beta_0 + \beta_1 Stress_t + \beta_2 Asset\ level\ Vulnerability_{i,t} \\ + \beta_3 Stress_t \times Asset\ level\ Vulnerability_{i,t} + \beta_4 Controls_t + \gamma_i + \varepsilon_{i,t+1}\,,\end{aligned} \tag{4}$$

where i is an asset and t is time (quarter). γ_i indicates asset fixed effects. $Stress_t$ is defined as financial uncertainty (VIX) or uncertainty about monetary policy in the United States. The latter is obtained from textual analysis of newspaper articles in the daily publications of the Washington Post, Wall Street Journal, and New York Times containing the following triple of keywords: (i) "uncertainty" or "uncertain," (ii) "monetary policy(ies)" or "interest rate(s)" or "Federal fund(s) rate" or "Fed fund(s) rate," and (iii) "Federal Reserve" or "the Fed" or "Federal Open Market Committee" or "FOMC" (see Husted and others, 2020).

The VIX spiked driven by market turbulence in March 2020, when uncertainty about the effects of the COVID-19 pandemic was high. Monetary policy uncertainty was elevated in 2019 and has been rising since the end of 2021 (Online Annex Figure 3.2.1). Equation (4) is estimated by asset class using as dependent variable the next-quarter volatility of bond or equity returns relative to the median volatility of returns. The control variables are the same as those used in equation (3). The estimation is based on quarterly data and the sample period extends from 2013:Q4 to 2021:Q4. Standard errors are clustered by both asset and time.

Online Annex Figure 3.2.1. VIX and US Monetary Policy Uncertainty

(Index)



Sources: Haver Analytics; Husted and others (2020); and IMF staff calculations.
Note: Both stress variables—VIX and monetary policy uncertainty in the United States—are standardized so that the vertical axis indicates the number of standard deviations relative to the mean of the series. The monetary policy uncertainty variable is available until the third quarter of 2021.

A range of robustness checks have been performed by using:

- Alternative specifications of fixed effects: country, industry, country-time, industry-time fixed effects;
- Alternative definitions of the stress variable: defining financial stress as a dummy variable that takes a value of one when the VIX is in the upper decile of its sample distribution;
- Alternative definitions of the asset vulnerability measure: defining an asset as vulnerable if its vulnerability measure is in the upper half or top quartile of the asset vulnerability distribution by asset class and zero otherwise;
- A balanced panel of assets in the regression analysis, starting from 2013:Q4.

The original conclusions are robust to these changes.

Bond Returns During the March 2020 Dash-for-Cash Episode

Figure 3.8 shows the performance of bonds during the March 2020 Dash-for-Cash episode. To better understand if more vulnerable assets performed poorly in this episode relative to less vulnerable assets, the following regression model is estimated using weekly data:

$$\begin{aligned} Return_{i,t} &= \alpha_c + \beta_1 \ \ Asset\ level\ vulnerability_i + \beta_2\, I_{\_Stress} + \\ &\beta_3\, I_{\_Stress}\ x\ Asset\ level\ vulnerability_i \theta \ \ Controls_i + \mu_c + \epsilon_{i.t}, \end{aligned} \tag{5}$$

where $Return_{i,t}$ indicates the weekly return of security i in time t, $Asset\ level\ Vulnerability$ is the asset-level vulnerability measure defined above and control variables are the same as in equation 3 with the addition of lagged weekly returns. All other control variables are also lagged as of 2019:Q4. The model also includes industry-level (or alternatively country-level) fixed effects. Standard errors are clustered at the asset and week levels. $I_{\_Stress}$ is a dummy variable equal to 1 in the last three weeks of February and first week of March (following Jiang and others, 2022), and zero otherwise. The regression model is estimated using data for the first and second quarters of 2020.

The results show that β_3 is negative and statistically significant across all bond asset classes in, supporting the hypothesis that asset-level vulnerabilities induced by fund illiquidity lead to a decline in asset returns, that is, an increase in asset price fragility, in periods of market stress.

Spillovers of Global Investment Fund Vulnerabilities to Emerging Market Securities Markets

To assess the possible cross-border implications of open-end fund vulnerabilities, a restricted version of equation (3) is estimated for assets issued by firms of EMs and using an asset-vulnerability measure calculated only from funds domiciled in advanced economies.[4] A range of robustness checks similar to those outlined above is performed and the results are robust to these changes.

Herding as an Amplifier of Asset-Level Vulnerabilities

When investors trade simultaneously and in the same direction, their trading behaviors could amplify asset price volatility. Following Cai and others (2019) the herding behavior by open-ended mutual funds in equity and bond markets is examined. Herding is defined by how much the trading pattern of a security varies from the market-wide trading pattern in the same period. In other words, herding is the tendency of funds to trade a given asset together in the same direction (either buy or sell) more often than would be expected if they traded independently. Following Cai et al. (2019), a herding measure of asset *i* in quarter *t* is calculated as follows:

$$HM_{i,t} = \left|p_{i,t} - E\left[p_{i,t}\right]\right| - E\left|p_{i,t} - E\left[p_{i,t}\right]\right|, \tag{6}$$

where $p_{i,t}$ is the proportion of buyers among all active traders of asset *i* in quarter *t*,

$$p_{i,t} = \frac{\#\ of\ Buy_{i,t}}{\#\ of\ Buy_{i,t} + \#\ of\ Sell_{i,t}}, \tag{7}$$

and the term $E\left[p_{i,t}\right]$ is the expected level of buying intensity of asset *i*, which is estimated from the market-wide intensity of buying denoted as $\bar{p}_t$:

$$\bar{p}_t = \frac{\sum_{i=1}^{I} \#\ of\ Buy_{i,t}}{\sum_{i=1}^{I} \#\ of\ Buy_{i,t} + \sum_{i=1}^{I} \#\ of\ Sell_{i,t}}. \tag{8}$$

Since the first term of equation (5) is always greater than zero, the second term is added as an adjustment factor so that the expected value of the herding measure, $HM_{i,t}$, is zero under the null hypothesis of no herding. Under this hypothesis, funds' decisions to buy or sell assets in each quarter are made independently.[5]

The chapter also distinguishes between a buy herding measure (*BHM*) for assets with higher proportion of buyers than the market average, and a sell herding (*SHM*) for assets with a lower proportion of buyers than the market average, which are defined as follows:

$$BHM_{i,t} = HM_{i,t} | p_{i,t} > E\left[p_{i,t}\right], \tag{9}$$

[4] EMs are 53 economies included in the IMF's Vulnerability Exercise for Emerging Market Economies.

[5] In other words, under the null hypothesis, all assets are sold or bought with the same probability in a given quarter, meaning $\#\ of\ Buy_{i,t}$ follows a binomial distribution with parameter $n = \#\ of\ Buy_{i,t} + \#\ of\ Sell_{i,t}$ and $p = E\left[p_{i,t}\right]$.

$$SHM_{i,t} = HM_{i,t} | p_{i,t} < E[p_{i,t}]\,. \tag{10}$$

To test whether herding behavior amplifies the impact of asset-level vulnerability on asset price volatility, the following panel regression is estimated:

$$\sigma_{i,t+1} = \beta_0 + \beta_1 Herding_{i,t+1} + \beta_2 Asset\ level\ Vulnerability_{i,t} + \beta_3 Herding_{i,t+1} \times Asset\ level\ Vulnerability_{i,t} + \beta_4 Controls_{i,t} + \gamma_i + \gamma_{c,t} + \varepsilon_{i,t+1}, \tag{11}$$

where $\sigma_{i,t+1}$ is the asset return volatility (standardized relative to its median), and $Herding_{i,t+1}$ is one of the herding measures described above. Controls include the average bid-ask spread, log of bond issue size, bond rating, the share of mutual fund ownership, and maturity when analyzing bonds. The model includes security-level and country-time fixed effects. Standard errors are clustered by both security and time.

The Aggregate Effect of Vulnerability on Financial Conditions

Aggregate (country-level) vulnerability measures are calculated from the asset-level vulnerability measures specified in equations (2). To study whether aggregate vulnerabilities affect country-specific financial conditions, the following panel quantile regression is estimated:

$$Financial\ Conditions_{c,t+1}^{[\tau]} = \alpha_c^{[\tau]} + \beta^{[\tau]}\ Aggregate\ Vulnerability_{c,t} + \theta^{[\tau]} Controls_{c,t} + \epsilon_{c.t+1}^{[\tau]}, \tag{12}$$

where $Financial\ Conditions_{c,t+1}^{[\tau]}$ denotes the τ quantile of the financial conditions index in country *c* at time *t+1.*[6] $Controls_{c,t}$ includes the following macro-financial and external factors: domestic and US monetary policy shocks, domestic GDP growth, foreign GDP growth (averaged across foreign countries), change in global liquidity conditions, and commodity price shocks.[7] A country's aggregate vulnerability is calculated as the weighted average of asset-level vulnerabilities across all assets issued domestically, with weights representing the relative market values of the assets. Results are also reported for aggregate vulnerability measures based on asset classes. The model includes country fixed effects and coefficients that are common across countries but estimated for different quantiles (τ) of the financial conditions index.

Robustness checks have been performed to evaluate the effects of:

- Including autoregressive terms of both the dependent and independent variables;
- Including time fixed effects instead of time-varying global common factors (such as US monetary policy rate and changes in global liquidity conditions);
- Constructing alternative financial conditions indices based on a factor model with time-varying parameters that includes a broader set of macro-financial variables (as in Koop and Korobilis 2014);

[6] The financial conditions index is based on a principal component analysis of 11 price-based variables. It captures the price of risk (see Online Annex 1.1 of the October 2018 GFSR) and a larger value of the index indicates tighter financial conditions.

[7] Domestic monetary policy shocks are estimated by regressing the policy rate on a set of controls, and use the residuals as the identified shocks. The set of controls includes contemporaneous and lagged values of inflation, log U.S. GDP, log foreign GDP, as well as lagged values of the policy rate and a quadratic time trend. Commodity price shocks correspond to pure oil price expectation shocks, as defined in Bauermeister (2021). To filter out the "pure" expectation component, market-based surprises are regressed on fundamental oil supply and demand shocks.

- Using alternative asset-level vulnerability measures based on: (i) alternative aggregation of the portfolio-level bid-ask spread; (ii) more granular breakdown of asset classes; (iii) simple instead of weighted averaging across securities.

The results are broadly robust to these alternative specifications.

To examine whether fund vulnerabilities in advanced economies influence financial conditions in EMs, a modified version of equation (11) is estimated as follows:

$$Financial\ Conditions_{c,t+1}^{EM} = \alpha_c + \beta \quad Foreign\ Aggregate\ Vulnerability_{c,t}^{AE} + \theta \quad Controls_{c,t} + \epsilon_{c.t+1}, \tag{13}$$

where $Financial\ Conditions_{c,t+1}^{EM}$ denotes the financial conditions index of an emerging market economy *c*. $Foreign\ Aggregate\ Vulnerability_{c,t}^{AE}$ is the average asset-level vulnerability from funds located in advanced economies that hold assets in the emerging market economy *c*.

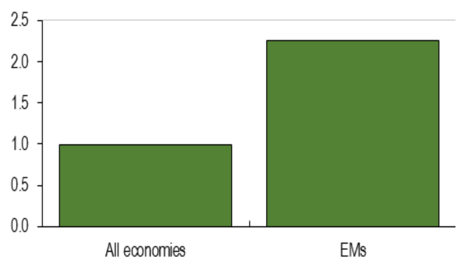
Online Annex Figure 3.2.2 shows the magnitude of the spillover effects in emerging markets compared to that estimated for all the economies.

Online Annex Figure 3.2.2 Spillovers from asset level vulnerabilities to financial conditions

Fund vulnerabilities imply larger negative cross-border spillovers for EMs than for other economies

Cross-border Spillover Effects from Fund Vulnerabilities in Advanced Economies to Financial Conditions in EMs vs. All Economies

(Index)



Sources: Bloomberg L.P., FactSet, Haver; Morningstar, and IMF staff calculations.
Note: The results from country-level panel regressions with fixed effects in which domestic financial conditions index in period t+1 is regressed on asset-level vulnerabilities averaged at the issuer country-level in period t are shown. The spillover analysis is performed by substituting domestic fund vulnerabilities with a measure capturing foreign fund vulnerabilities, which is computed as the average asset-level vulnerability from holdings of funds domiciled in advanced economies. Panel 4 compares the magnitude of the spillover effects in EMs with that estimated for all the economies. Solid dots and full bars indicate statistical significance at 10 percent or lower.

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Online Annex 3.3 Mechanisms Through Which Investment Fund Vulnerabilities Affect Asset Price Fragility

Due to strategic complementariness among investors, funds exposed to liquidity mismatches may experience more severe outflows in periods of stress (Chen and others, 2010; Goldstein and others, 2017). Funds that face outflows create selling pressures in securities markets. More illiquid funds are more likely to experience large outflows and contribute to selling pressures that can temporarily depress asset prices.

To understand these mechanisms, the chapter performs the following analyses:

Examine whether vulnerable funds—those holding relatively illiquid assets—tend to experience more extreme outflows in periods of stress. This mechanism is examined by estimating the following panel (fund-level) regression:

$$Y_{j,t} = \beta_1 Fund\ illiquidity_{j,t} + \beta_2 Stress_t \times Fund\ illiquidity_{j,t} + \beta_3 Controls_{j,t} + \mu_{c,t} + \gamma_j + \varepsilon_{i,t+1}, \quad (1)$$

where $Y_{i,t}$ denotes the outflows from fund *j* in period *t*—-the negative fund flows (with sign inverted) expressed as a percentage of the fund's size. $Fund\ illiquidity_{j,t}$ is the fund-level illiquidity measure defined in equation (1) of Online Annex 3.2. $Controls_{j,t}$ includes fund size, fund age, and past fund's returns.[1] γ_j are fund fixed effects and $\mu_{c,t}$ are country-time-fixed effects. $Stress_t$ is an indicator variable that takes the value 1 when the VIX Index is above a given percentile of its sample distribution; results are presented for the percentiles 50, 55, …, 95 to examine the presence of amplification effects of fund illiquidity on fund outflows in periods of stress. The coefficients of interest are β_1 and β_2. If illiquid funds face larger outflows in time of stress, the sum of β_1 and β_2 is expected to be positive and increasing in the level of stress (i.e. higher when the stress dummies are defined using higher percentiles of the VIX sample distribution).

Examine the relation between asset-level vulnerabilities and selling pressures. Following Jiang and others (2022), selling pressure is computed as follows:

$$Selling\ Pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\ Amt_{j,i,t}|Flow_{j,t}<25^{th}Pctl - Buy\ Amt_{j,i,t}|Flow_{j,t}>75^{th}Pctl)}{Amount\ Outstanding_{i,t}}. \quad (2)$$

$Sell\ Amt_{j,i,t}$ is the par amount of security *i* sold by fund *j* in quarter *t* (equal to zero if there is no selling). $Buy\ Amt_{j,i,t}$ is the par amount of security *i* purchased by fund *j* in quarter *t* (equal to zero if there's no buying). $Flow_{j,t}$ is the quarterly percentage flow of fund *j* in quarter *t*, adjusted for fund returns. $Amount\ Outstanding_{i,t}$ is the outstanding amount of security *i*. Intuitively, selling pressure captures the difference between sales and purchases of bonds by investment funds that experience extreme outflows or inflows. A large value indicates strong selling pressure.

The following quarterly regression on asset-vulnerability measures is performed:

[1] Results are robust to including fund's past returns as a control.

$$Selling\ Pressure_{i,j,t} = \beta_0 + \beta_1 Asset\_Level\ Vulnerability_{i,t} + \beta_2 Controls_{i,j,t} + \mu_{c,t} + \gamma_i + \varepsilon_{i,j,t}, \quad (3)$$

where $Controls_t$ include fund size (log), investment fund ownership percentage, issuer rating, average bid-ask spread and past volatility. The model controls also for country-time fixed effects $(\mu_{c,t})$ and asset fixed effects (γ_i). The coefficient of interest is β_1. If assets exposed to vulnerable funds face stronger selling pressures the coefficients of β_1 should be positive.

Examine the sensitivity of asset liquidations to pecking order and fund outflows. A pecking order of liquidation followed by funds would imply a higher sensitivity of asset liquidations to fund outflows of assets that are more liquid relative to the other assets in a fund's portfolio. To test this, the following model is estimated:

$$Y_{i,j,t} = \lambda_0 Ouflows_j + \lambda_1 Outflows_j\ x\ Pecking\ Order_{i,j} + \mu_t + \gamma_j + \alpha_i + \epsilon_{i,j,t}, \quad (4)$$

where $Y_{i,j,t}$ corresponds to the percentage change of shares of security *i* sold by fund *j* at time *t*. Pecking order corresponds to the liquidation rank of security *i* in fund *j* computed as the share of other assets held by the same fund that are less liquid:[2]

$$Liquidation\ rank_{i,j} = \sum_{g(i')} Share_{g(i'),j} x\ 1\left[Liquidity\ group_{g(i)} > Liquidity\ group_{g(i')}\right] + \frac{1}{2} Share_{g(i),j}, \quad (5)$$

where $Share_{g(i'),j}$ is the share of asset *j* in the liquidity group $g(i')$ of fund *j*.

Beyond potential confounding factors due to comoving macroeconomic variables, there is a risk that the security-level comparison of prices and liquidations washes out the price impact that is common across securities. To address such concerns, the analysis in equation (4) focuses on the COVID-19 crisis event when large sell-offs by investment funds were more likely to have impacted asset prices beyond what can be explained by fundamentals (Falato and others, 2021b; Jiang and others, 2022; Ma and others, 2022). Results from this analysis are reported in Figure 12 (panel 3). If a pecking order of liquidation is followed, the coefficients λ_0 and λ_1 should be positive.

Examine whether selling pressure has an impact on asset prices. First, as large outflows could be triggered by a deterioration in fundamentals, a measure of selling pressure is constructed taking into account the differential selling pressure of outflows on assets that are higher up in the liquidation rank of a given fund. Following Ma and others (2022), this liquidity-adjusted selling pressure measure is computed as follows:

$$Liquidation\_Adjusted\ \ Selling\ Pressure_{i,t} = \sum_j Fund\ outflow_{j,t}\ x\ (\hat{\lambda}_0 + \hat{\lambda}_1 Liquidation\ rank_{i,j}) x \frac{Holding_{i,j,t-1}}{\sum_k Holding_{i,k,t-1}} \quad (6)$$

where $\hat{\lambda}_0$ and $\hat{\lambda}_1$ are coefficients estimated from equation (4). This approach provides a more accurate measurement of the price impact of funds' asset flows since asset liquidations are

[2] To calculate the liquidation rank, funds' securities are separated into "liquidity groups" based on their level of liquidity in the sample distribution for each quarter. Asset liquidity is measured using the bid-ask spreads of the securities.

empirically estimated based not only on outflows but also take into account funds' liquidation policies, therefor reducing reverse causality concerns.

The analysis then evaluates whether the sell-off pressure measures lead to asset price pressure using the following model:

$$Abreturn_{i,t+1} = \beta_0 + \beta_1 Liquidation\_Adjusted\ Selling\ Pressure_{i,t} + \beta_2 Controls_{i,t} + \mu_i + \theta_c + \varepsilon_{i,t+1} \tag{7}$$

where $Abreturn_{i,t+1}$ is the difference between the quarterly return and the size-weighted average return of a pool of comparable securities. Controls include turnover, credit rating, amount outstanding, maturity, issuer volatility, maturity, and country fixed effects (μ_i and θ_c, respectively).[3] The model is estimated separately for each asset class. As above, the analysis focuses on the COVID-19 episode to empirically identify how fund liquidity transformation can amplify the effect of fund outflows triggered by a deterioration in fundamentals.

For robustness, the analysis in iii. and iv. is performed using ratings as an alternative measure of asset liquidity to define liquidity groups. In addition, the analysis is performed also on the full data sample (2010:Q1-2021:Q4) while controlling for differences in the sensitivity of asset liquidations to pecking order and fund outflows across time depending on the level of VIX. The results from these alternative specifications are broadly in line with the results from the baseline specifications.

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[3] For bonds, maturity fixed effects are constructed using the maturity at issuance of the securities. Maturity is discretized in seven groups with 5 years interval. The last group corresponds to securities with a maturity greater than 30 years.

Online Annex 3.4 Analysis of Liquidity Management Tools

Swing Pricing

To analyze the effect of swing pricing on fund induced asset price fragility, the following regression specification is estimated:

$$\sigma_{i,t+1} = \beta_0 + \beta_1\, Asset\_level\, Vulnerability_{i,t} + \beta_2\, Swing\_exposure_{i,t} + \beta_3\, Swing\_exposure_{i,t} \times Asset\_level\, Vulnerability_{i,t} + \beta_4\, bid - ask_{i,t} + \beta_5 Controls_{i,t} + \gamma_i + \mu_{i,t} + \varepsilon_{i,t+1}, \quad (1)$$

where, $Swing\_exposure_{i,t}$ is the ownership of a given asset *i* by open-end mutual funds that use swing pricing as a percentage of its total mutual fund ownership. γ_i is an asset fixed effect. $\mu_{i,t}$ denotes country-time fixed effects. For fixed income securities controls include log size, the lagged return, log time to maturity of the bond, issue ratings, lagged price volatility, and fund ownership. In the baseline specification, $Swing\_exposure_{i,t}$ is defined at the security level, as follows:

$$Swing\_exposure_{i,t} = \frac{\sum_{j=1}^{J} Holding\ amount_{j,i,t} \times I_j^{Swing\,country}}{\sum_{j=1}^{J} Holding\ amount_{j,i,t}}, \quad (2)$$

where $I_j^{Swing\ country}$ is a dummy variable that takes the value one if fund *j* is domiciled in a country in which the use of swing pricing by open-ended mutual funds is common, and zero otherwise. In the baseline specification, $Swing\ country = \{Luxembourg, UK\}$.

The following robustness checks have been performed:

- Using alternative definitions of the set of swing countries;
- Including time-varying global stress indicators (such as the VIX index) instead of time fixed effects;
- Using different sets of control variables.

The results are broadly robust to these alternative specifications.

The Role of Cash Buffers

To understand how funds use cash buffers to manage investor redemptions, the chapter estimates the following fund-level regression specification based on Jiang and others (2020):

$$\Delta Cash\ equiv_{j,t} = \beta_0 + \beta_1\, Net\ inflow_{j,t} + \beta_2\, Net\ inflow_{j,t} \times Stress_t + \beta_3\, Net\ outflow_{j,t} + \beta_4\, Net\ outflow_{j,t} \times Stress_t + \beta_5 Controls_{j,t} + \gamma_j + \varepsilon_{i,t+1}, \quad (4)$$

where $\Delta Cash\ equiv_{j,t} = (Cash\ equiv_{j,t} - Cash\ equiv_{j,t-1})/Cash\ equiv_{j,t-1}$ is the percentage change in fund *j*'s holdings of cash and equivalents in quarter *t*.[1] Controls include log fund size, quarterly returns, expense ratio and portfolio illiquidity, all in lags. Portfolio illiquidity is measured as the average bid-ask spreads of securities excluding cash equivalents held by the fund. The results are robust to changes in specification that focus only on specific fund types (e.g., bond or equity funds).

[1] All variables are measured at the fund portfolio level, except the expense ratio which is based on the oldest share class.

Exchange-Traded Funds

In periods of stress, assets with higher ETF ownership may be less fragile than those that are mostly owned by open-end mutual funds. [2] To test this hypothesis, the chapter examines how fragility is affected by open-end fund and ETF ownership in both tranquil and stress times. The regression analysis is carried out using the following specification:

$$\sigma_{i,t+1} = \beta_0 + \beta_1\, MF\_own_{i,t} + \beta_2\, ETF\_own_{i,t} + \beta_3\, MF\_own_{i,t} \times Stress_t + \beta_4\, ETF\_own_{i,t} \times Stress_t + \beta_5\, bid - ask_{i,t} + \beta_6 Controls_{i,t} + \gamma_i + \varepsilon_{i,t+1}, \qquad (5)$$

where $MF\_own_{i,t}$ and $ETF\_own_{i,t}$ denote the percentage ownerships of asset *i* at time *t* corresponding to open-end mutual funds and ETFs, respectively. These are calculated at the security level as follows:

$$ETF\_own_{i,t} = \frac{\sum_{j=1}^{J} Holding\ amount_{j,i,t} \times I_j^{ETF}}{Market\ Cap_{i,t}} \qquad (6)$$

$$MF\_own_{i,t} = \frac{\sum_{j=1}^{J} Holding\ amount_{j,i,t} \times I_j^{OEF}}{Market\ Cap_{i,t}} \qquad (7)$$

A key concern with this specification is that ETFs and open-end mutual funds could endogenously self-select into assets with different and unobservable levels of fragility. The chapter addresses such endogeneity issues by exploiting variation in ownership bases across nearly identical bonds (i.e., by matching different corporate bonds held by ETFs and open-ended mutual funds, while holding constant fund issuer, maturity, and coupon rate). In addition, all regressions control for various security-specific illiquidity proxies, including bid-ask spreads.

References

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[2] While open-ended mutual funds are redeemable directly from the fund company at the fund net asset value (NAV), ETFs are traded on the secondary market at the prevailing market price. As a result, ETFs are not subject to the same first-mover advantage that gives rise to run risks in, and fire sales by, open-ended mutual funds. In contrast, to ensure that the secondary market price of ETFs remains close to the fund NAV, ETFs have a built-in arbitrage mechanism that functions through so-called authorized participants (APs). APs are often large broker-dealers that have exclusive rights to create and redeem ETF shares directly with the fund sponsor in exchange for a basket of portfolio securities in primary markets. Thus, even though ETFs are not subject to first-mover advantages and run risks, there exists evidence that APs' arbitrage activities also lead to increased volatility of security prices (see Ben-David and others, 2018). The differential impact of open-ended mutual funds and ETFs on security price volatility is an empirical question addressed by this chapter.