

Hedge Funds and Financial Stability: Online Annex

Annex 2.1 – Glossary

Table 2.1.1 Glossary of Key Technical Terms

Key term	Description
Arbitrage strategies	Trading strategies that seek to profit from pricing inconsistencies between related securities. Arbitrage generally involves buying an undervalued asset and selling a related overvalued asset, expecting the price gap to narrow over time.
Hedge fund	The term hedge fund describes a business model rather than a uniform legal category. It generally refers to a privately offered pooled vehicle for institutional or high-net-worth investors with broad flexibility to use leverage, derivatives, short selling, concentrated positions, and less-liquid investments. By contrast, public mutual funds generally serve retail investors and are subject to prospectus disclosure, tighter leverage requirements, and more frequent redemptions. Hedge funds may also face fewer product-level restrictions and may charge performance fees or impose lockups, notice periods, gates, and side pockets. These are typical rather than defining features, and the precise legal perimeter varies across jurisdictions. In the United States, for instance, hedge funds are private funds generally limited to accredited investors or qualified purchasers and classified under Form PF based on performance-fee arrangements and their permitted use of leverage or short selling; in the European Union and United Kingdom, they form part of the broader alternative investment fund category; and in the Cayman Islands, fund classification depends primarily on redemption rights, so an open-ended hedge fund falls within the legal definition of a “mutual fund,” without implying a retail offering.
Hedge fund strategies	Main hedge fund strategy groups include credit funds, which focus on fixed-income securities; equity funds, which take long and short positions in equities; event-driven funds, which trade on mergers, restructurings, distress, and corporate events; macro funds, which take positions across rates, foreign exchange, commodities, and equity markets; managed futures/CTA funds, which trade futures contracts, options, and foreign exchange derivatives; relative value funds, which exploit pricing gaps between related securities; and multi-strategy funds, which allocate capital across several strategies and asset classes.
Margin / haircut	Margin is collateral required to support a leveraged position; a haircut is the discount applied to collateral value in secured funding.
Prime brokers	Financial intermediaries, typically broker-dealer units of large global banking groups, which provide hedge funds and other institutional investors with a range of financing and operational services. These can include leverage through margin loans, financing, securities lending, custody, clearing, and execution services.
Synthetic leverage	Synthetic leverage refers to market exposure obtained through derivatives rather than direct borrowing. It is generally measured using derivatives positions expressed in terms of their equivalent exposure to the underlying assets relative to funds' gross assets.

Annex 2.2 – Data Sources

HEDGE FUND DATA

The chapter combines monthly fund and share class records from Hedge Fund Research (HFR), With Intelligence (WI), and Lipper TASS. The consolidated sample covers more than 25,000 hedge funds across 78 domiciles from January 1990 to February 2026, including both onshore and offshore vehicles, with offshore funds accounting for the majority of assets.¹ Aggregate assets under management (AUM) as of December 2025 are approximately \$2.1 trillion.

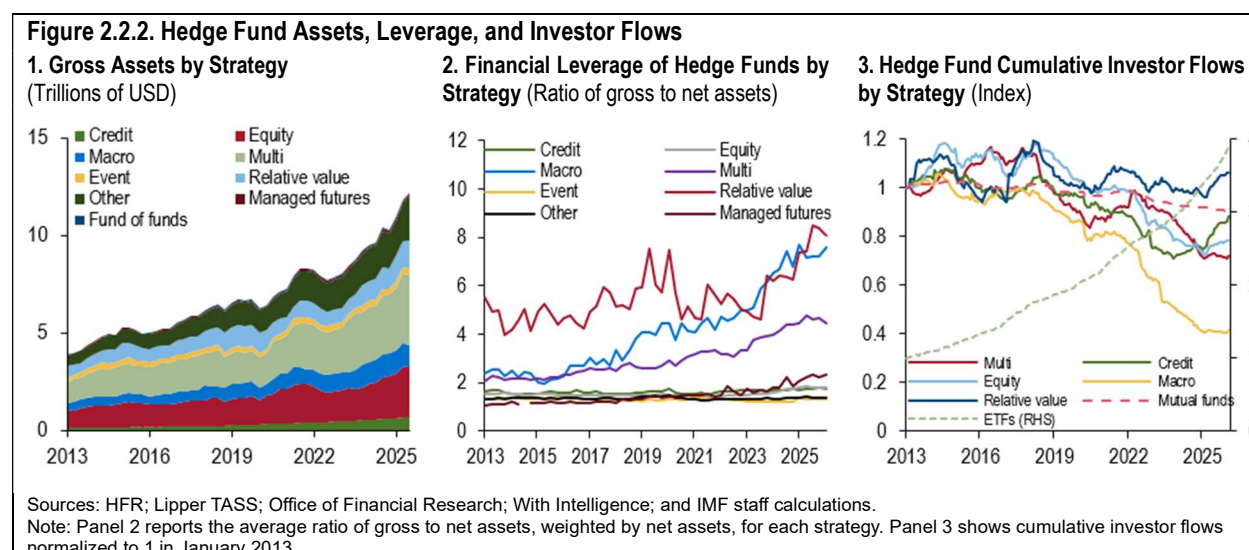
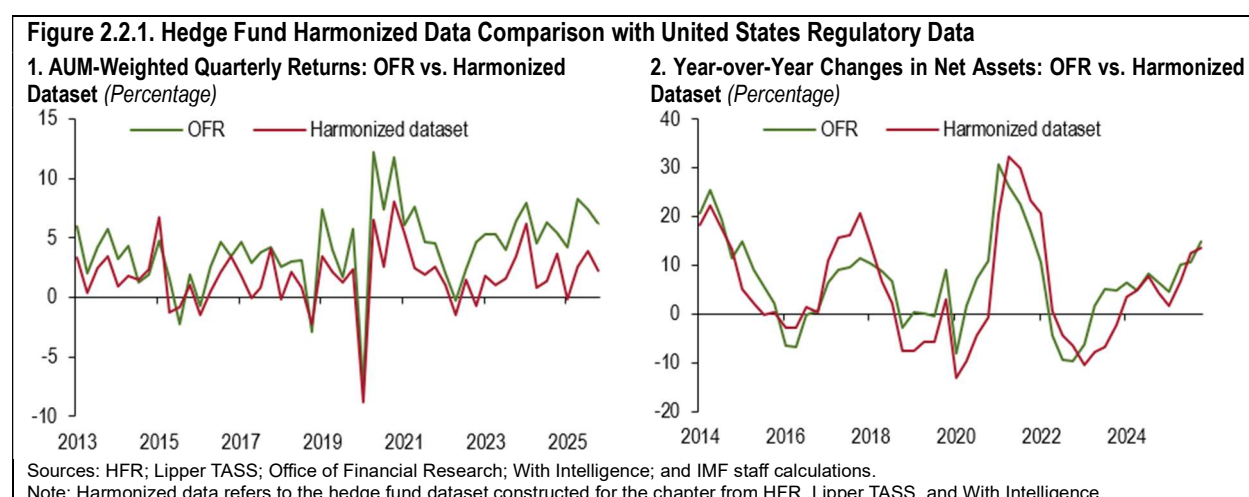
The data sources differ in their coverage, reporting units, and variable definitions and are cleaned and consolidated in multiple stages. First, backfilled HFR and TASS observations are excluded from the

¹ Offshore domiciles are Anguilla, The Bahamas, Barbados, Belize, Bermuda, the British Virgin Islands, the Cayman Islands, the Channel Islands, Curaçao, Cyprus, Gibraltar, Guernsey, Ireland, the Isle of Man, Jersey, Liechtenstein, Luxembourg, Malta, Mauritius, the Netherlands Antilles, Panama, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Martin, Saint Vincent and the Grenadines, Samoa, Seychelles, and Vanuatu.

construction of AUM and returns by setting them to missing (this rule is not applied to WI observations because no information is provided on when a fund was first added to the database; instead, the first 12 monthly observations are deleted for each fund). Funds-of-funds and quarterly-reporting funds are removed to reduce double-counting and improve comparability of monthly fund-level measures across sources. Second, share class records are linked within and across sources to identify the same underlying fund.² Third, AUM, returns, fund characteristics, and domicile are consolidated at the fund-month level.

Additionally, FactSet hedge fund investment manager information is assembled to support the analysis of ownership, affiliation, and systemic exposure within the global hedge fund sector.

The final dataset is a reconciled monthly panel of matched fund-month observations. Its aggregate returns and net asset dynamics closely mirror those reported in the Office of Financial Research (OFR) regulatory data, which are representative of the largest hedge funds in the United States (Figure 2.2.1).³ Asset concentration is also similar: as in Figure 2.5, panel 1, in the main text, the ten largest hedge funds account for about 23 percent of the sector's gross assets in the OFR data (OFR 2026).



² A share class record refers to a source-level observation. A source group refers to share class records within the same provider that are considered to belong to the same fund. A matched fund refers to the final cross-source entity used in the analysis. A manager entity refers to a standardized legal entity or firm group associated with the fund manager. A broker entity refers to a prime-broker institution.

³ The regulatory data compiled by the OFR also include information about non-US-headquartered hedge funds with US investors. As a result, the data are the most representative source on the global hedge fund sector (Barth and others 2021).

Table 2.2.1 Variable Definitions and Data Sources

Variable	Description	Source
Hedge fund variables		
Advance notice period	Required notice period before an investor may redeem capital from the fund.	HFR; Lipper TASS; With Intelligence
Age / inception date	Fund inception date and corresponding fund age, measured as the time elapsed between inception and each observation date.	HFR; Lipper TASS; With Intelligence
Assets under management (AUM)	The market value of investor capital managed by the fund as of the reporting date.	HFR; Lipper TASS; With Intelligence
Fund return	Periodic net-of-fee fund return used to measure fund performance.	HFR; Lipper TASS; With Intelligence
Gate	Restriction limiting aggregate redemptions from the fund during a specified period.	HFR; With Intelligence
Incentive fee	Performance-based fee charged by the fund, typically expressed as a percentage of investment profits.	HFR; Lipper TASS; With Intelligence
Leverage	Indicator or measure of the fund's use of borrowed funds or other financing to increase investment exposure.	HFR; Lipper TASS; With Intelligence
Lockup period	Minimum period during which invested capital generally cannot be redeemed.	HFR; Lipper TASS; With Intelligence
Management fee	Recurring fee charged for managing the fund, typically expressed as a percentage of assets under management.	HFR; Lipper TASS; With Intelligence
Offshore vehicle	Indicator identifying whether the fund is structured as an offshore investment vehicle.	HFR; Lipper TASS; With Intelligence
Redemption fee	Fee charged to investors when redeeming capital from the fund.	HFR
Redemption frequency	Number of days between permitted redemption dates.	HFR; Lipper TASS; With Intelligence
Strategy classification	Fund investment-strategy classifications mapped to a common taxonomy to support consistent comparisons across data providers.	HFR; Lipper TASS; With Intelligence
Global financial market conditions and risk factors		
Commodity price index	Broad commodity price index capturing movements across major commodity markets.	Bloomberg
Equity tail-risk or skew index	Option-implied measure of perceived tail risk in the US equity market.	Bloomberg
Variance risk premium	The difference between option-implied expected variance and expected/realized variance.	Hao Zhou's Data Library
Trend-following strategy (PTFS) factors	Return-based factors to capture the nonlinear payoff of strategies that seek to profit from persistent price trends in bonds, currencies, commodities, interest rates, and equity indices.	David Hsieh's Hedge Fund Risk Factor Data Library
G10 FX carry risk-premium index	Long-short index representing the G10 foreign-exchange carry premium.	Bloomberg
Bond indices	The JPMorgan Emerging Market Bond Index and the Bloomberg US Corporate High Yield Total Return Index.	Bloomberg
Fama-French / style factors	Fama-French factors including market excess return, size, value, profitability, investment, and momentum.	Kenneth French's Data Library
He-Kelly-Manela intermediary capital ratio	Measures of financial-intermediary capital, leverage, and risk-bearing capacity.	He-Kelly-Manela public data
International equity indices	Broad equity indices covering the S&P 500, Russell 2000, MSCI Emerging Markets, and MSCI World Index.	LSEG Datastream
Volatility indices	Option-implied measure of expected volatility in the US equity (VIX) and Treasury market (MOVE).	Haver Analytics
US dollar index	Trade-weighted measure of the value of the US dollar against a basket of major currencies.	Bloomberg
Security holding variables		
Holding market value	Market value of the holdings of a given security for a fund.	FactSet
Portfolio share	Percentage of the portfolio value attributable to each of the holdings.	FactSet
Prime broker variables		
Prime broker return	Equity return of the prime broker, expressed in US dollars.	LSEG Datastream

Country-level macrofinancial variables		
10-year sovereign bond yield	Yield on the benchmark 10-year government bond.	LSEG Datastream
Bilateral exchange rate vis-à-vis the US dollar	Bilateral nominal exchange rate of the domestic currency against the US dollar.	LSEG Datastream
Credit-to-GDP gap	Difference between the credit-to-GDP ratio and its long-run trend.	BIS
Dealer balance sheet utilization	Primary dealers' net Treasury positions scaled by dealer equity.	Federal Reserve Bank of New York
Federal Reserve's Treasury holdings	Securities held in the Federal Reserve's System Open Market Account, as a share of total marketable Treasury debt outstanding.	Federal Reserve Bank of New York
Inflation	Consumer price index level and/or consumer price inflation rate.	IMF World Economic Outlook (WEO)
Leveraged fund net short positions in Treasury futures	Net short futures position of leveraged funds across the US Treasury futures curve.	CFTC Commitments of Traders
Nominal GDP	Gross domestic product measured at current prices.	IMF World Economic Outlook (WEO)
Policy rate	Central bank policy interest rate or the closest available short-term monetary policy rate.	Haver Analytics
Sovereign bond yields	Yields of three-month, one-year, and 10-year government bonds.	LSEG Datastream
Speculative currency futures positions	Weekly speculative positions in major currency futures contracts.	CFTC Commitments of Traders
Stock market return index	Domestic equity return index.	LSEG Datastream
Treasury auction offering	Amount of each new marketable Treasury security offered for sale, together with its tenor, announcement date, and auction date.	US Department of the Treasury

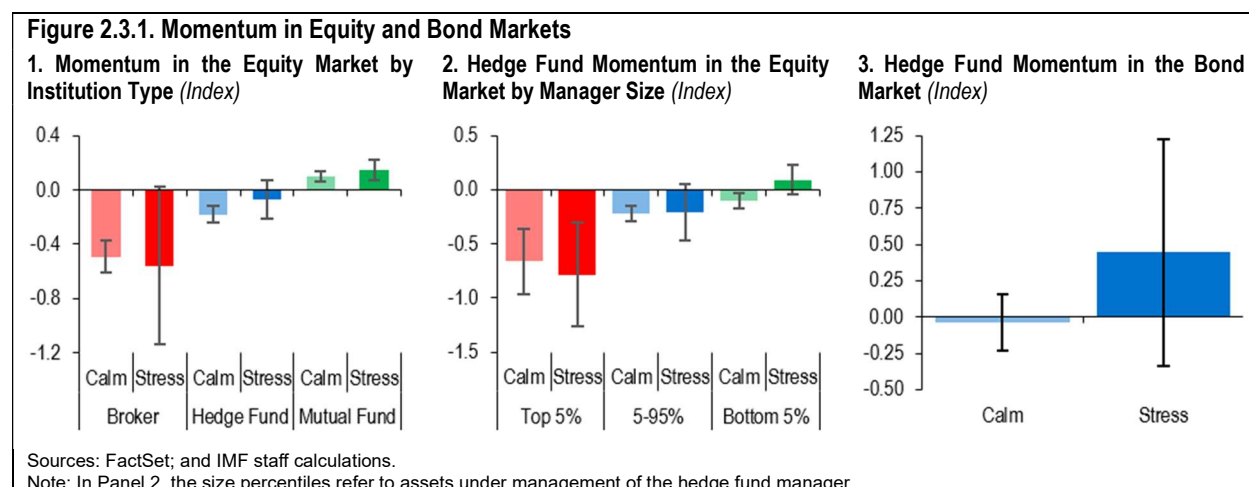
Annex 2.3 – Empirical Analysis

MARKET IMPACT OF HEDGE FUND TRADING

The market impact of hedge fund trading is assessed using three metrics: momentum; cumulative abnormal returns (CAR); and bid-ask spreads. Following Grinblatt and others (2020), momentum is defined as the co-movement between the returns of securities and the changes in their portfolio shares:

$$\text{momentum}_{f,t} = \sum_s (w_{f,s,t} - w_{f,s,t-1}) R_{s,t} \quad (2.1)$$

where $w_{f,s,t}$ is the weight of security s in the portfolio of fund f and $R_{s,t}$ the return of the security between $t - 1$ and t . Bid-ask spread is the difference between the ask and the bid price relative to the mid-price, expressed in basis points. CAR are constructed from daily equity returns using stock-specific Fama-French five-factor abnormal returns, accumulated over event windows before and after each quarter-end holdings observation.



Empirical analysis indicates that the tendency of hedge funds to be contrarian is strongest for the largest hedge funds, which continue to trade against price movements also during market stress (Figure 2.3.1, panel 2). By contrast, smaller hedge funds are significantly contrarian in tranquil periods but show some

evidence of momentum trading during times of high market volatility. The behavior of the smallest funds is, thus, more similar to that of mutual funds, while the largest funds trade more like brokers, which include proprietary trading firms. In the bond market, hedge fund trading does not appear to be strongly contrarian in calm periods but becomes more momentum-oriented during stress, although the estimates are not statistically significant.⁴

Next, changes in aggregate hedge fund ownership are related to changes in horizon-specific CAR around quarter-end holding observations:

$$\Delta CAR_{s,t}^h = \beta_h \Delta HFWN_{s,t} + \Gamma_h X_{s,t-1} + \alpha_s + \lambda_t + \varepsilon_{s,t}^h \quad (2.2)$$

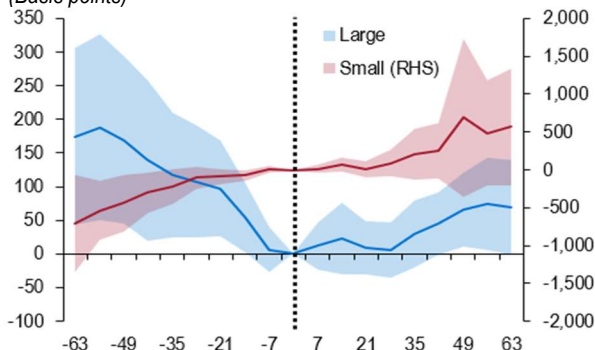
where s indexes securities, t quarters, and h the event-time horizon. $\Delta HFWN$ denotes the change in aggregate hedge fund ownership, and X denotes the vector of security-level controls.⁵ Security fixed effects, α_s , absorb time-invariant differences across securities, while quarter fixed effects, λ_t , absorb common shocks. Standard errors are computed using Driscoll-Kraay estimators with four lags.

Figure 2.3.2. Changes in Hedge Fund Ownership and Cumulative Abnormal Returns Across Fund Characteristics

The informational content of hedge fund trading varies across fund types, with trades by larger and low-turnover funds exhibiting stronger predictive power for future returns than those by smaller and higher-turnover funds.

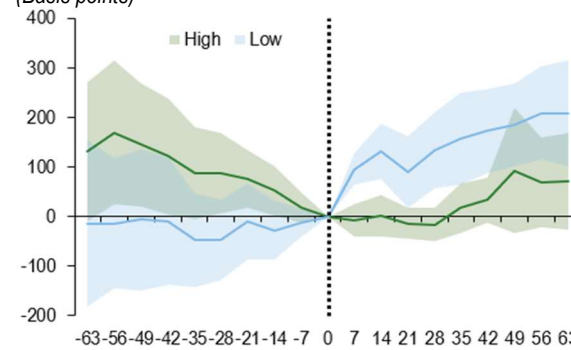
1. Large and Small Hedge Funds

(Basis points)



2. High- and Low-Turnover Hedge Funds

(Basis points)



Sources: FactSet; and IMF staff calculations.

Note: Panels show the estimated effect of a 10-percentage-point increase in hedge fund ownership on cumulative abnormal returns (CAR) at different horizons around the quarter-end ownership observations. CAR are constructed from stock-specific Fama-French five-factor abnormal returns and accumulated over horizons ranging from 7 to 63 trading days before and after the ownership observation; negative (positive) horizons denote returns before (after) the ownership observation. Estimates are obtained from security-level panel regressions of changes in horizon-specific CAR on changes in aggregate hedge fund ownership, controlling for market capitalization, turnover, price-to-book ratios, dividends, profitability, and bid-ask spreads, with security and quarter fixed effects. Large (small) funds are managed by hedge fund managers with above- (below-) median assets under management, while high- (low-) turnover funds are defined using the median portfolio turnover, measured as one-half of the sum of absolute changes in portfolio weights between consecutive reporting dates. All classifications are determined within the hedge fund sector and calculated each quarter. Shaded areas denote 90 percent confidence intervals.

The results presented in Figure 2.3.2 suggest important heterogeneity in the informational content of hedge fund trading.⁶ Large funds appear to follow more contrarian strategies, increasing ownership after prior price declines and followed by significant positive abnormal returns, consistent with identifying mispricing and contributing to price discovery. Smaller funds, by contrast, exhibit a more momentum-oriented pattern, increasing ownership after prior price gains with little evidence of subsequent price adjustment. A similar distinction emerges across turnover groups: low-turnover funds are associated with the strongest subsequent abnormal returns, suggesting that their trades reflect information that is incorporated into prices gradually, whereas high-turnover funds appear to buy after price weakness but are not followed by significant subsequent price appreciation. This pattern is consistent with low-turnover

⁴ The difference between momentum in periods of stress and during calm is, however, statistically significant at the 10 percent level. The results on bond markets should be interpreted with caution as they are based on a small sample.

⁵ Security-level controls include market capitalization, turnover, price-to-book ratios, profitability, dividends, and liquidity measures.

⁶ Heterogeneity is assessed using quarterly cross-sectional splits of hedge funds based on fund characteristics. Large (small) funds are managed by hedge fund managers with above- (below-) median assets under management. High- (low-) turnover funds are funds with above- (below-) median portfolio turnover, where turnover is measured as one-half of the sum of absolute changes in portfolio weights between consecutive reporting dates. All splits are defined relative to the median in each quarter.

funds trading on longer-horizon information, while high-turnover funds may be exploiting short-term market dislocations.

Finally, to assess whether the relationship between hedge fund trading and market liquidity differs across market conditions, changes in bid-ask spreads are related to changes in hedge fund ownership. Stress periods are defined as quarters in which the average VIX exceeds its 90th percentile. The specification allows the association between hedge fund ownership and liquidity to differ between calm and stress periods:

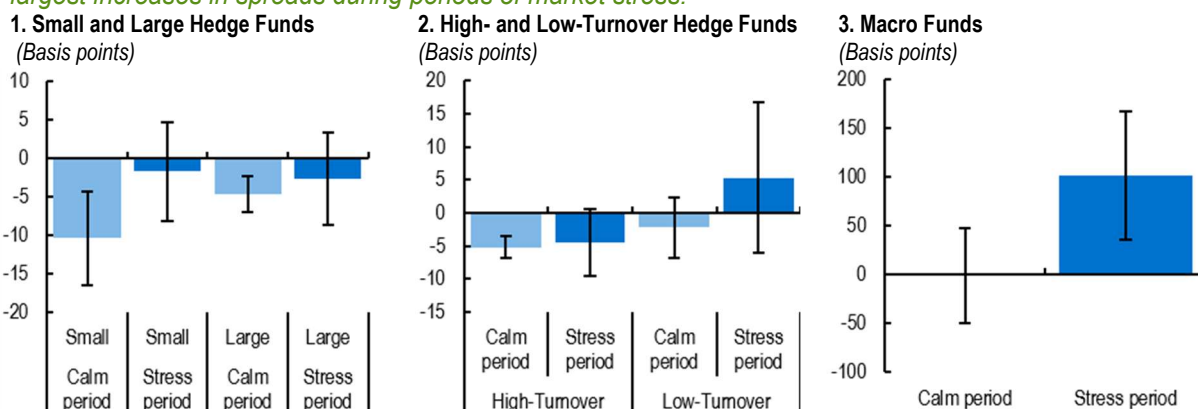
$$\Delta Spread_{s,t+1} = \beta_C \Delta HFOWN_{s,t} \times Calm_{t+1} + \beta_S \Delta HFOWN_{s,t} \times Stress_{t+1} + \Gamma X_{s,t} + \alpha_s + \lambda_t + \varepsilon_{s,t+1} \quad (2.3)$$

The specification includes the same control variables, security fixed effects, and quarter fixed effects as equation (2.2). Including the current bid-ask spread in the equation accounts for persistence in liquidity conditions and helps distinguish changes in spreads from persistent differences in average liquidity across securities. Standard errors are computed using Driscoll-Kraay estimators with four quarterly lags.

Figure 2.3.3 further illustrates that hedge funds affect market functioning through different channels. Ownership increases by smaller and high-turnover funds are associated with larger declines in bid-ask spreads during calm periods, suggesting a stronger contribution to trading efficiency, whereas macro funds are associated with the largest widening of spreads during stress episodes, potentially reflecting risk reduction or the unwinding of more leveraged positions. These differences are consistent with the broader heterogeneity documented throughout the chapter and suggest that the market impact of hedge funds depends importantly on their underlying characteristics and investment strategies.

Figure 2.3.3. Association Between Hedge Fund Ownership and Subsequent Bid-Ask Spread by Fund Characteristics

The liquidity effects of hedge fund trading vary significantly across fund types. Increases in security ownership by smaller and high-turnover funds are associated with larger reductions in subsequent bid-ask spreads in calm periods, compared to larger and low-turnover funds. Macro funds are associated with the largest increases in spreads during periods of market stress.



Sources: FactSet; and IMF staff calculations.

Note: Panels show the estimated effect of a 10-percentage-point increase in hedge fund ownership on bid-ask spreads in the subsequent quarter. Stress periods are defined as quarters in which the average VIX exceeds its 90th percentile. Estimates are obtained from security-level panel regressions of subsequent changes in bid-ask spreads on changes in aggregate hedge fund ownership, controlling for market capitalization, turnover, price-to-book ratios, dividends, profitability, and the initial bid-ask spread, with security and quarter fixed effects. Large (small) funds are managed by hedge fund managers with above- (below-) median assets under management. High- (low-) turnover funds are funds with above- (below-) median portfolio turnover, where turnover is measured as one-half of the sum of absolute changes in portfolio weights between consecutive reporting dates and captures the share of the portfolio reallocated between reporting periods. All classifications are determined relative to the hedge fund median in each quarter. Error bars denote 90 percent confidence intervals.

Figure 2.3.4 highlights substantial heterogeneity across hedge fund strategies. Relative value funds stand out for their high leverage and rapid portfolio turnover, while macro and managed futures/CTA funds also exhibit elevated leverage. Multi-strategy funds are among the largest managers, whereas event-driven funds tend to hold more concentrated portfolios. These differences help rationalize the heterogeneity documented in the previous figures. Strategies characterized by larger size or longer holding horizons tend to be more closely associated with subsequent price adjustment, consistent with a greater role in information discovery, whereas high-turnover strategies appear more closely associated with improvements in trading efficiency during normal periods. At the same time, the high leverage of macro, relative value, and managed futures funds may increase their potential to amplify market strains when positions are unwound during periods of stress.

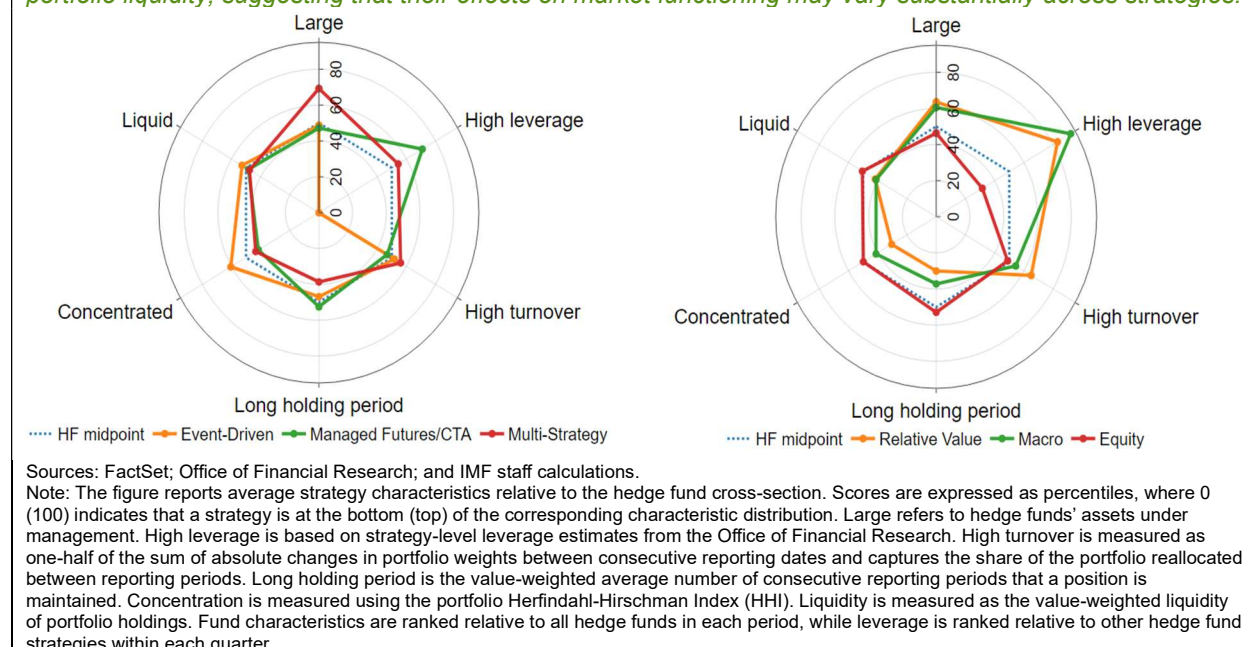
HEDGE FUND VULNERABILITIES

Return-Implied Leverage Measure

A monthly fund-level leverage measure is constructed by combining information from fund returns, reported leverage categories, and aggregate strategy-level leverage estimates from the OFR. The objective is to recover variation in leverage across funds and over time while ensuring consistency with independently observed aggregate leverage conditions and the leverage information reported by funds.

Figure 2.3.4. Characteristics of Hedge Fund Investment Strategies

Hedge fund strategies differ markedly in size, leverage, trading horizons, portfolio concentration, and portfolio liquidity, suggesting that their effects on market functioning may vary substantially across strategies.



The first step uses fund returns and a broad set of risk factors to construct a return-implied leverage score for each fund. The score is based on characteristics of fund return behavior, including volatility, downside risk, tail losses, drawdowns, and factor exposures.⁷ Reported leverage categories are used to identify the combinations of return and risk characteristics that are most strongly associated with higher reported leverage. In compact form, this step can be written as

$$Score_{i,t} = f(X_{i,t}) \quad (2.4)$$

where $X_{i,t}$ denotes the set of return- and risk-based characteristics for fund i in month t . The function $f(\cdot)$ represents the estimated relationship between these characteristics and reported leverage intensity, from strategy-specific logistic models.

To translate the score into a leverage estimate, the score is centered within each strategy-month using assets under management as weights. This centering ensures that the return-implied score determines only the distribution of leverage across funds within a strategy, rather than the aggregate level of leverage for the strategy as a whole. An unconstrained leverage target is then constructed as

⁷ Fund characteristics include both return-distribution measures and factor-exposure measures. The factor set draws on standard factor blocks commonly used in the hedge fund replication literature (Fung and Hsieh 2001; Hasanhodzic and Lo 2007) and the broader asset-pricing literature (e.g., Giglio and Xiu 2021), including equity, volatility, interest-rate, credit, foreign-exchange, commodity, liquidity, intermediary, trend-following, and Treasury basis-risk factors. Return-distribution measures include the mean excess return, volatility, downside deviation, skewness, excess kurtosis, expected shortfall, maximum drawdown, and the share of near-zero returns. Factor-exposure measures are constructed from a fund's estimated sensitivities to these factor blocks and include gross and net exposures, exposure amplification during periods of large factor movements, and tail losses conditional on such periods. Periods of large factor movements are defined as months in which the average absolute standardized movement across the factor set exceeds its 80th percentile.

$$L_{i,t}^* = L_{s,t}^{OFR} + \kappa_s \widetilde{score}_{i,t} \quad (2.5)$$

where $L_{s,t}^{OFR}$ denotes OFR leverage for strategy s , $\widetilde{score}_{i,t}$ is the strategy-month centered leverage score, and κ_s is a strategy-specific scaling parameter. This formulation assigns leverage above the strategy average to funds with higher return-implied leverage scores and leverage below the strategy average to funds with lower scores.⁸

The final step imposes consistency with the reported leverage categories. Funds with below 5 times leverage (1-2 and 2-5 categories) are constrained to remain within their reported leverage ranges. For the higher leverage categories, the procedure treats the reported category as providing a lower-bound restriction rather than a closed interval, reflecting the greater uncertainty associated with leverage at the upper end of the distribution. Funds with non-standard, unspecified, or missing leverage labels are retained in the sample and contribute to aggregate leverage calculations but are not assigned category-specific restrictions beyond non-negativity.

The unconstrained targets are then projected onto the feasible set defined by these leverage-category restrictions and the requirement that the AUM-weighted average leverage within each strategy-month equals OFR leverage:

$$L_{i,t} = \mathcal{P}(L_{i,t}^*) \text{ subject to } \sum_i w_{i,t} L_{i,t} = L_{s,t}^{OFR} \quad (2.6)$$

where $L_{i,t}$ denotes the final constrained fund-level leverage estimate, $w_{i,t}$ denotes the fund's share of strategy assets under management, and $\mathcal{P}(\cdot)$ denotes the projection that adjusts the unconstrained targets as needed to satisfy the leverage-category constraints while preserving the OFR aggregate exactly. This representation highlights the structure of the methodology: return characteristics are first mapped into a leverage score, the score is translated into an OFR-anchored unconstrained target, and the target is then projected into a final leverage estimate consistent with reported leverage categories and aggregate OFR leverage.

Equity-Level Hedge Fund Crowdedness, Investor Flow Fragility, and Leverage Exposure

To assess holdings of specific equities by funds with different levels of vulnerabilities, three quarterly stock-level measures of hedge fund vulnerability from security-level institutional holdings are constructed. Each measure is constructed to address a specific question about the funds owning a given stock: how quickly the funds could liquidate the rest of their books, how likely they are to face redemptions at the same time, and how levered they are. All three measures share a common structure. A stock is more vulnerable when it is illiquid and hedge funds own a larger share of it, and when the particular funds that own it are themselves more exposed to forced selling.

Throughout, $mv_{h,j,t}$ denotes the dollar position of hedge fund manager h in stock j at the end of quarter t , and $\theta_{j,t}$ denotes the market capitalization of stock j .⁹ Hedge fund ownership of stock j is

$$pso_{j,t} = \frac{HF_{j,t}}{\theta_{j,t}}, \quad HF_{j,t} = \sum_h mv_{h,j,t} \quad (2.7)$$

where $pso_{j,t}$ is the share of the stock's market capitalization held by hedge funds.

Crowdedness (Crowd-ADV)

Crowdedness (Crowd-ADV), following Brown, Howard, and Lundblad (2022), measures a stock's exposure to crowded liquidation by the hedge funds that own it. For each stock, the measure combines the stakes of its hedge fund co-owners with how crowded those co-owners' portfolio positions are, where crowding is proxied by hedge fund dollar holdings scaled by average daily trading volume (Days-ADV). A stock has a high Crowd-ADV when its co-owners, on average, disproportionately sit on positions that would be difficult to unwind. The measure is built in two steps.

⁸ Quarterly OFR leverage is carried forward within each quarter rather than interpolated, so monthly variation comes from changes in the return-implied score while the aggregate level remains anchored to the observed OFR series.

⁹ The holdings are from FactSet's security-level institutional ownership dataset and are reported at the management-company level.

The first step measures how crowded each individual stock is. For stock j , let $ADV_{j,t}$ be the 20-day moving average daily dollar trading volume, averaged over the quarter. The ratio of aggregate hedge fund holdings to $ADV_{j,t}$,

$$DaysADV_{j,t} = \frac{HF_{j,t}}{ADV_{j,t}} \quad (2.8)$$

is the number of trading days the hedge fund industry as a whole would need to exit its position in j at the average daily volume. *Days-ADV* is a property of the stock and of hedge fund positioning in it.

The second step asks how crowded each hedge fund's book is on average. *FundDaysADV* is defined as the book-weighted average of *Days-ADV* across its portfolio,

$$FundDaysADV_{h,t} = \sum_j w_{h,j,t} DaysADV_{j,t} \quad w_{h,j,t} = \frac{mv_{h,j,t}}{\sum_k mv_{h,k,t}} \quad (2.9)$$

FundDaysADV is high for a fund whose portfolio is concentrated in names the industry would collectively struggle to exit.

Aggregating back to the stock, each co-owner's *FundDaysADV* is weighted by that owner's stake in the stock, measured as a share of market capitalization:

$$CrowdADV_{j,t} = \sum_h mv_{h,j,t}/\theta_{j,t} \times FundDaysADV_{h,t} \quad (2.10)$$

Crowd-ADV rises both with how much of the stock hedge funds own and with how crowded those particular owners' portfolios are.

Investor Flow Fragility

Investor flow fragility measures how large a swing in demand a stock could face if its hedge fund owners were hit by redemptions at the same time. It adapts the fragility measure of Greenwood and Thesmar (2011) to hedge fund holdings. A stock is fragile when ownership is concentrated in few funds, and the flows of those funds move together.

Let $w_{j,t}$ be the vector of dollar positions in stock j across hedge fund owners, and Ω_t the covariance matrix of owner-level investor flow. Fragility is the variance of the dollar demand shock the stock would experience, scaled by its market capitalization:

$$G_{j,t} = 1/\theta_{j,t}^2 w'_{j,t} \Omega_t w_{j,t} \quad (2.11)$$

The quadratic form is what delivers the concentration property: splitting the same dollar ownership across more independent owners lowers G , while concentrating it raises G .

Investor flow for owner h in quarter t is the change in assets not explained by returns, expressed relative to assets at the start of the quarter:

$$f_{h,t} = \frac{A_{h,t} - A_{h,t-1}(1 + r_{h,t})}{A_{h,t-1}} \quad (2.12)$$

Estimating Ω_t directly is infeasible: the number of owners far exceeds the number of quarterly observations, so the sample covariance matrix is singular. A factor structure is therefore imposed. Common flow factors are constructed as AUM-weighted mean flow rates within each investment strategy, so that the common component has an economic interpretation: funds pursuing the same strategy tend to face redemptions together. Each owner's flow is regressed on these factors, and

$$\Omega_t = B_t \Sigma_{F,t} B'_t + \text{diag}(\sigma_{\varepsilon,h,t}^2) \quad (2.13)$$

where B_t collects the factor loadings, $\Sigma_{F,t}$ is the factor covariance matrix, and the diagonal term holds idiosyncratic flow variances. Substituting yields the measure:

$$G_{j,t} = \frac{1}{\theta_{j,t}^2} \left[(B'_t w_{j,t})' \Sigma_{F,t} (B'_t w_{j,t}) + \sum_h mv_{h,j,t}^2 \sigma_{\varepsilon,h,t}^2 \right] \quad (2.14)$$

Both B_t and $\Sigma_{F,t}$ are estimated on rolling 20-quarter windows, so the covariance structure is allowed to change over the sample.¹⁰ The measure enters the regressions as $\sqrt{G_{j,t}}$, in the units of a return, and as a within-quarter percentile rank.

Leverage Exposure

Leverage exposure measures a stock's exposure to levered funds. Each owner's stake in the stock is weighted by that owner's estimated leverage, and the weighted stakes are summed:

$$LevExposure_{j,t} = \sum_h \frac{mv_{h,j,t}}{\theta_{j,t}} L_{h,t} \quad (2.15)$$

where $L_{h,t}$ is the estimated leverage of manager h .¹¹

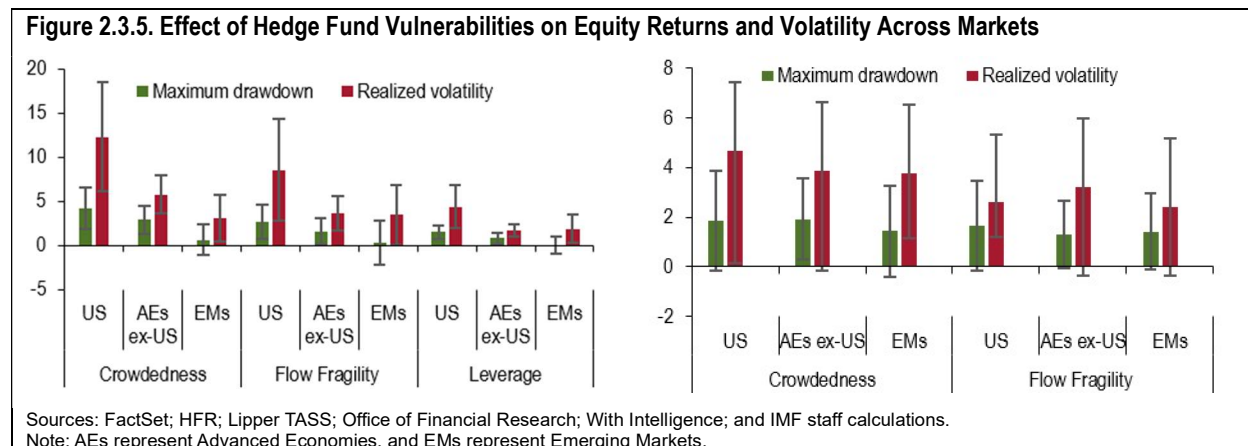
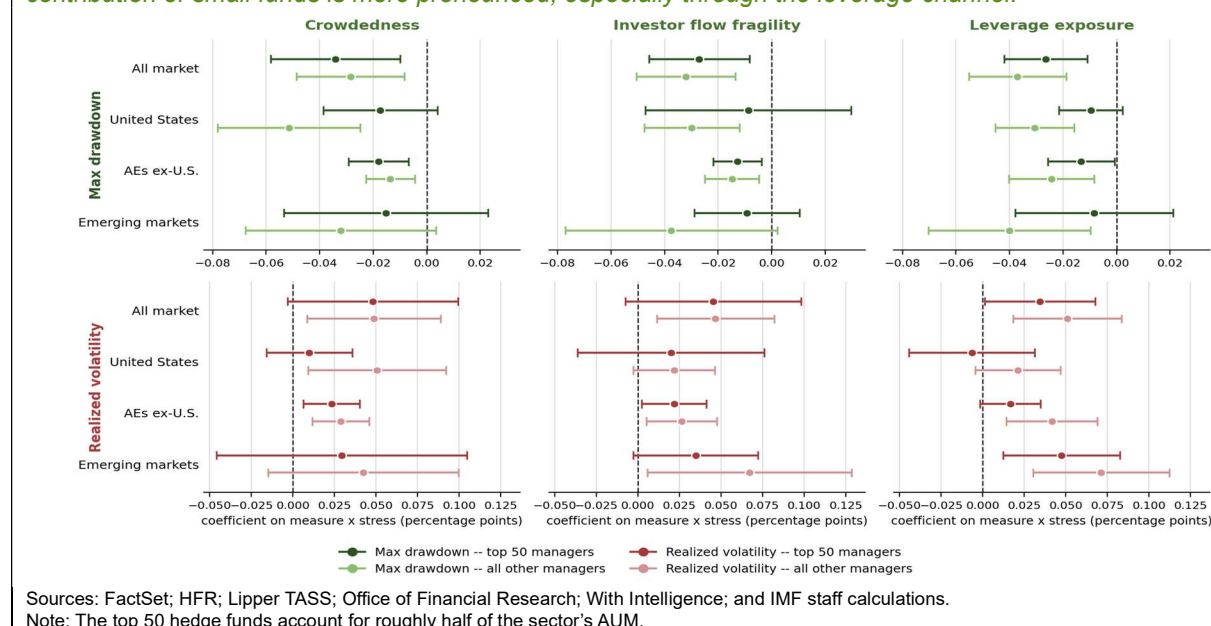


Figure 2.3.6. Effect of Hedge Fund Vulnerabilities on Equity Returns and Volatility: Largest 50 Managers and Others
Both large and small hedge funds significantly amplify tail risk in equity markets during stress, but the contribution of small funds is more pronounced, especially through the leverage channel.



¹⁰ Loadings are estimated with hierarchical shrinkage toward the mean loading of the owner's strategy group, so that funds with short or sparse flow histories are retained rather than dropped, with their loadings pulled toward the behavior of comparable funds.

¹¹ Leverage is aggregated to the manager as an AUM-weighted average across the funds mapped to that manager, and then applied to the manager's positions. Since leverage is estimated, the standard errors on its coefficient reported in Figures 2.8 and 2.9 in the main text and Figures 2.3.5 and 2.3.6 may be underestimated.

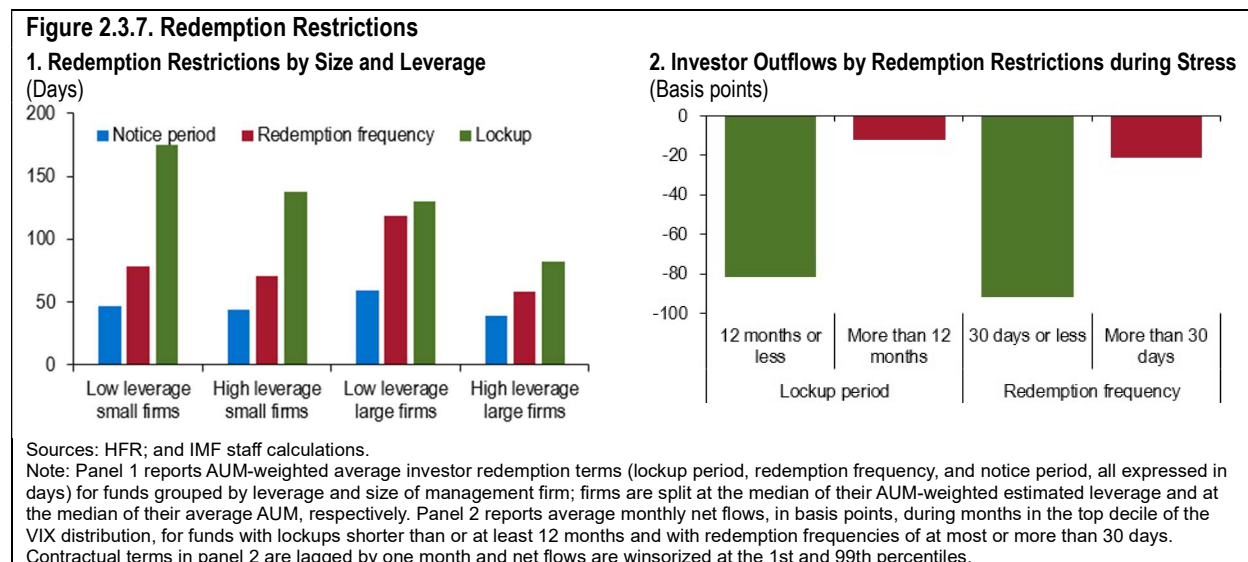
Vulnerability Regression Analysis

All three measures are constructed from information available at the end of quarter t and are related to outcomes realized over quarter $t+1$, so they are predetermined with respect to the outcomes. Each enters as a within-quarter percentile rank, so a coefficient reads as the effect of moving a stock from the bottom to the top of the cross-sectional distribution of the measure in that quarter.

REDEMPTION RESTRICTIONS AND HEDGE FUND CAPITAL STABILITY

Redemption terms shape the stability of fund capital by determining how quickly investors can withdraw capital, having implications for whether hedge funds absorb shocks or amplify them through asset sales.

Hedge funds limit investor redemptions through three contractual channels: an initial lockup period, a notice period, and the frequency at which redemptions are permitted. Figure 2.3.7, panel 1, shows that these terms vary systematically with the characteristics of the management firm, with stricter redemption restrictions adopted by hedge funds that are smaller or less leveraged. These terms appear to matter for flows: during periods of market stress (months when VIX is in the top decile of the distribution), funds with lockup periods of twelve months or less record average net outflows of about 82 basis points of assets under management, against 12 basis points for funds with longer lockup periods (Figure 2.3.7, panel 2).



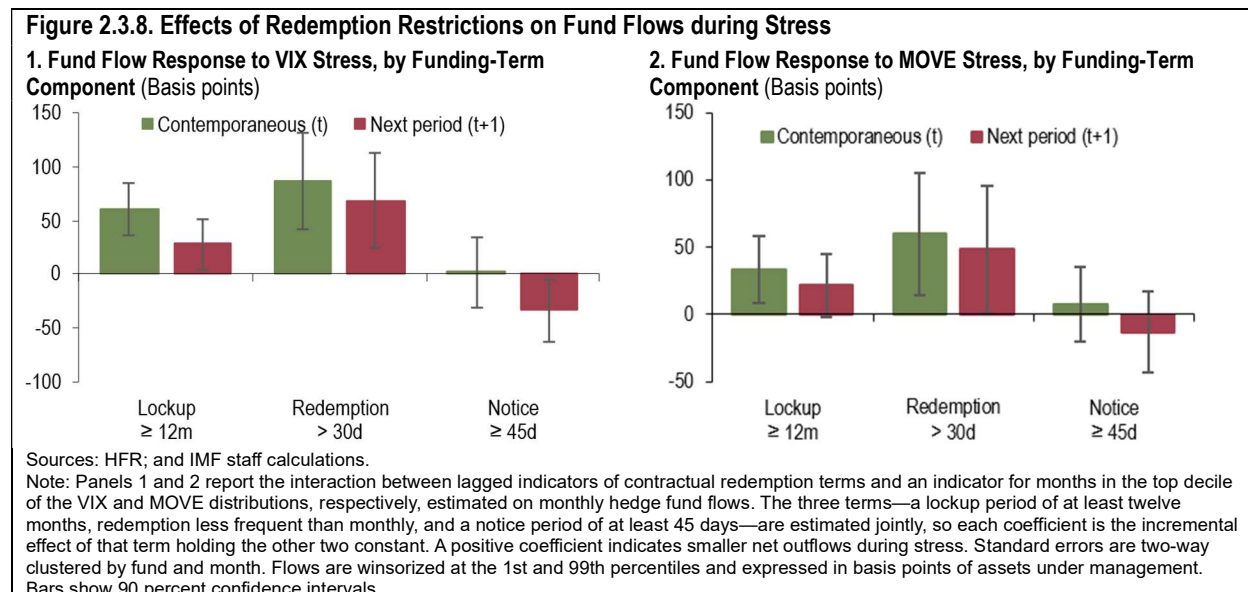
To examine the impact of contractual terms on flows during stress episodes more formally through regression analysis, the following fund-level panel specification is estimated:

$$Y_{i,t+h} = \alpha_i + \mu_{s,t} + \beta_1 R_{i,t-1} + \beta_2 (Stress_t \times R_{i,t-1}) + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t+h} \quad (2.16)$$

where $Y_{i,t+h}$ denotes net hedge fund flows, expressed in basis points, over the horizon $h \in \{0,1\}$; $R_{i,t-1}$ is a lagged rigidity indicator; $Stress_t$ is a binary indicator equal to one when the VIX or MOVE1M index is in the top decile of its sample distribution; $Controls_{i,t-1}$ include lagged log AUM, past 12-month returns, return volatility, and fund age; $\mu_{s,t}$ are strategy-time fixed effects; and α_i are fund fixed effects. Because the strategy-time fixed effects absorb all time-varying shocks common to funds within the same strategy—including the direct effect of $Stress_t$ —the interaction coefficient β_2 identifies the differential response to the same aggregate stress within the same strategy and time period. Standard errors are clustered at the fund and time levels.

Figure 2.3.8 suggests that redemption restrictions help stabilize hedge fund flows during periods of market stress, although not all restrictions are equally effective. During stress episodes, funds with lockup periods of at least twelve months or redemption frequencies longer than one month record net flows that are 61 and 87 basis points higher, respectively, than otherwise similar funds, after controlling for other contractual terms (Panel 1). In other words, these funds experience smaller outflows. By contrast, longer notice periods have no additional effect once lockups and redemption frequency are taken into account. The same pattern holds, albeit with somewhat smaller magnitudes, when stress is measured using

Treasury market volatility rather than equity market volatility (Panel 2), suggesting that the mechanism is not specific to equity market disruptions.¹²



MACROFINANCIAL EFFECTS OF HEDGE FUND STRESS

To assess the system-wide financial stability implications of hedge fund vulnerabilities, this section conducts two exercises: (i) a cross-financial institution spillover analysis that quantifies how hedge-fund stress transmits to prime brokers, and (ii) a country-level analysis that tests whether hedge-fund vulnerability strengthens the transmission of global shocks into domestic equity markets.

Effects of Hedge Fund Shocks on Prime Broker Returns

First, the spillover effects of hedge fund shocks on prime brokers—institutions most directly linked to hedge funds through financing—are examined.¹³ Following Gabaix and Koijen (2024), the analysis is implemented using a granular instrumental variable (GIV) approach in two steps. In the first step, for each prime broker, the set of hedge funds connected to that broker is identified and their returns are purged of common macrofinancial drivers by estimating the factor model:

$$R_{i,t} = \alpha_i + \sum_{f=1}^F \lambda_{i,f} f_{f,t} + \varepsilon_{i,t} \quad (2.17)$$

where the set of factors is extracted using a principal component analysis (PCA). Then, a hedge-fund-sector shock is constructed as the difference between an AUM-weighted average of the idiosyncratic innovations $\widehat{\varepsilon}_{i,t}$ and the unweighted average. The resulting aggregate shock, specific to each prime broker, captures large idiosyncratic shocks to hedge fund returns that are orthogonal to innovations in the underlying macro risk factors driving returns.

In the second step, this broker-specific aggregate hedge fund shock is used as an instrument and the effects of hedge fund shocks on prime broker returns are estimated via two-stage least squares (2SLS). The second-stage regression is given by:

$$R'_{q,t+h} = \gamma_q + \theta_h \text{Agg HF returns}_{q,t} + \beta_h \text{Controls}_t + \eta_{q,t+h} \quad (2.18)$$

¹² It is worth noting that redemption restrictions have generally eased over time. In the sample, the AUM share of funds with a rigidity index of at least 3 has declined since the mid-2000s, while the share with lockups of at least 12 months fell from about 40 percent in the early 2000s to about 15 percent recently. The data do not, however, allow to establish whether this shift reflects demand from high-net-worth or institutional investors.

¹³ Recent evidence using matched hedge fund–prime broker data documents a strong link between hedge fund leverage and prime-broker tail risk, showing that higher hedge fund leverage is associated with greater prime-broker stock-price crash risk (Karagiorgis and others 2026).

where $R'_{q,t+h}$ denotes the equity return of prime broker q , $\widehat{Agg\ HF\ returns}_{q,t}$ is the AUM-weighted aggregate return of hedge funds connected to that broker, instrumented by the corresponding broker-specific GIV shock, and $h = 0, 1, 6$ the time horizon.¹⁴ The coefficient θ_h measures the strength of the spillover from the hedge fund sector to prime brokers. While the GIV approach is designed specifically to address endogeneity arising from unobserved common shocks that drive hedge fund and prime broker returns simultaneously, the regressions further control for prime broker fixed effects and global financial conditions. The global controls include changes in the 10-year Treasury yield, the log of the VIX, changes in the US dollar index, Moody's Baa corporate bond spread, and US equity total returns. The sample period is February 2010 – February 2026, and the standard errors are clustered by broker and month. The regression results are reported in Figure 2.9 in the main text.¹⁵

The validity of the GIV approach rests on a few key considerations. First, the fund size distribution should be sufficiently fat-tailed for idiosyncratic shocks to the largest funds to matter for aggregate outcomes—a condition that holds in the dataset given the high concentration of the hedge fund industry documented in Figure 2.5 in the main text. Second, the factor model should capture a substantial share of the variation in fund returns, to ensure that the constructed instruments do not reflect exposure to common drivers. The first three principal components account for over 51 percent of the variance in connected-fund returns across all broker-specific estimations, indicating significant explanatory power. Third, the constructed shocks are not statistically significantly serially correlated, suggesting that they capture unanticipated innovations rather than predictable variation in hedge fund returns. To the extent that common macrofinancial factors are themselves typically serially correlated, this also provides some reassurance that residual exposure to such factors is limited. Finally, the instrument should be sufficiently strong, a condition satisfied in all specifications, with first-stage F -statistics exceeding conventional thresholds.

The analysis also examines whether these spillovers vary with the risk profile of a broker's client base, by re-estimating the baseline specification on subsamples of brokers split along two dimensions: the riskiness of client returns and client leverage. Client riskiness is measured as the average variance of past returns across the hedge funds connected to each broker. Client leverage is measured as the AUM-weighted share of a broker's clients whose estimated leverage exceeds the median for their strategy, where fund-level leverage estimates described above are utilized. Brokers are split at the median of the resulting time-averaged leverage, and each subsample regression retains the same broker-specific GIV instrument, fixed effects, and global controls as in the baseline. As shown in Figure 2.9 in the main text, the spillover effects of hedge fund stress are larger for prime brokers with a riskier client profile along both dimensions, with the contrast sharper along the leverage dimension.¹⁶

Effects of Hedge Fund Ownership on Domestic Equity Returns under Stress

This analysis examines whether higher aggregate hedge fund ownership amplifies the transmission of global shocks to domestic asset prices by estimating the following regression:

$$Stock\ returns_{c,t} = \alpha_c + \alpha_t + \beta HFOwnership_{c,t-1} \times GlobalShock_t + \theta Controls_{c,t} + \epsilon_{c,t} \quad (2.19)$$

where the dependent variable is the percentage change in total equity return index of country c at quarter t and $HFOwnership_{c,t-1}$ is the first lag of the aggregate hedge fund ownership share (both in percentage points). The global shock is measured by a dummy variable equal to 1 if the VIX is above its 90th percentile. The regressions control for country and quarter fixed effects, time-varying domestic macrofinancial factors (policy rate, real GDP growth, inflation, credit-to-GDP gap) and $HFOwnership_{c,t-1}$, with the standard errors clustered by country and quarter. The sample period is 2010:Q1–2025:Q4, covering 22 economies.

¹⁴ The construction of the instrumental variable at the prime broker level is motivated by evidence that hedge funds sharing a prime broker exhibit strong return comovement that is distinct from market-wide, strategy, and fund-family effects (Chung and Kang 2016). Doing so hence allows the factor model to better capture and remove the return comovement common to a broker's clients.

¹⁵ For comparison, the analysis is repeated for non-prime broker banks, constructing the GIV shock from the full universe of hedge funds. In contrast to prime brokers, their returns are not significantly affected by hedge fund shocks at any horizon, suggesting that transmission operates through direct hedge fund–prime broker linkages rather than a sector-wide repricing of bank equity.

¹⁶ The effect on prime brokers with a more leveraged hedge fund client base is also statistically significantly different from that on prime brokers with a less leveraged client base.

To construct an aggregate measure of hedge fund footprint, the analysis relies on FactSet securities holdings data. Given uneven coverage across asset classes, the analysis focuses on equities, which have the most comprehensive coverage. For comparison, an analogous ownership measure is constructed for mutual funds.

The analysis also examines whether the effects of hedge fund ownership vary by the underlying domestic equity market liquidity, by re-estimating the baseline specification on subsamples of countries split by equity market liquidity. Market liquidity is measured using the Amihud (2002) illiquidity ratio, defined as the average absolute daily return per dollar of trading volume, aggregated to the country level as a market-capitalization-weighted average across all listed stocks. Countries are split at the median of the resulting time-averaged ratio, and each subsample regression retains the same fixed effects and macrofinancial controls as in the baseline. The regression results are reported in Figure 2.10 in the main text.

BOX 2.1. HEDGE FUND ACTIVITY AND THE FOREIGN EXCHANGE MARKET

The box examines the role of hedge funds in foreign exchange (FX) carry trades and the financial stability risks that can arise when crowded funding-currency positions unwind. It draws on two episodes marked by sharp appreciations of low-yielding funding currencies: the August 2024 yen carry trade unwind and the Swiss National Bank's removal of the franc floor in January 2015.

Empirical Approach

Following Pojarliev and Levich (2011) and BIS (2024), for each strategy index s , monthly excess returns are regressed over 36-month rolling windows w (minimum 32 non-missing observations) on the carry-factor return and the market factor, as follows:

$$r_{s,t} - rf_t = \alpha_{s,w} + \beta_{s,w} Carry_t + \gamma_{s,w} MktRF_t + \varepsilon_{s,t} \quad (2.20)$$

where $Carry_t$ is the carry factor; $MktRF_t$ is the market factor and rf_t is the risk-free rate from the Kenneth French Data Library.¹⁷ Results are shown in main text Figure 2.1.1, panels 1 and 2.¹⁸ A crowdedness indicator is constructed from rolling 36-month regressions of each of the 27 HFRI class returns on the carry factor, controlling for the market factor; for each month, it is defined as the net share of classes with statistically significant positive minus negative carry loadings at the 95 percent confidence level:

$$Crowdedness = \frac{1}{s} \sum_{i=1}^s [\mathbb{1}(t_{i,t}^\beta > t_{0.95}^*) - \mathbb{1}(t_{i,t}^\beta < t_{0.95}^*)] \quad (2.21)$$

where s is the number of HFRI strategy indices (27). Results are shown in Figure 2.3.9. Broad-based positive loadings across strategy classes indicate a crowded carry trade. The S&P FX Carry G10 index is used as the carry factor in the baseline specification.

The analysis further tests whether multi-strategy funds' Japanese-equity exposure was linked to the carry trade and whether both exposures were reduced after the August 2024 unwind, comparing 36-month rolling Nikkei 300 betas before and after controlling for the carry factor; the gap captures the carry-correlated component of equity exposure (Figure 2.3.9, panel 2). The results show a widening gap between gross and net Nikkei beta before the event, suggesting rising cross-asset carry exposure. The subsequent compression of the gap is consistent with deleveraging of the common trade.

Furthermore, a difference-in-differences specification is used to estimate post-unwind changes in Nikkei and carry loadings for offshore and onshore funds:

$$r_{g,t} = a_g + (b_g + d_g Post_t)F_t + m_g Post_t + e_{g,t} \quad (2.22)$$

where F are the Nikkei and carry factors and g refers to fund-level returns collapsed into domicile portfolios. Figure 2.3.9, panel 2, shows that multi-strategy funds, especially offshore, cut both carry and

¹⁷ The same diversified G10 carry factor is used to capture hedge funds' broad exposure to the carry strategy and ensure comparability across the yen and franc episodes. The diversified, rules-based index also provides a cleaner measure of common carry exposure than currency-specific factors, which may be more affected by idiosyncratic or policy-driven moves. Robustness analysis using currency-specific carry factors yields similar results.

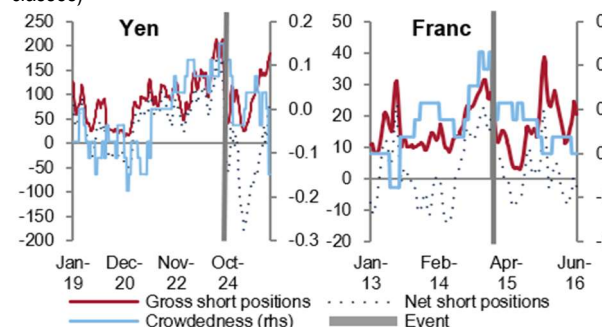
¹⁸ For robustness, equation (2.20) is re-estimated using two alternatives: replacing the diversified G10 carry factor with yen- and franc-funded carry baskets, and using equal-weighted HFRI class-index aggregates matched to the baseline strategy definitions. The results are similar across specifications.

Japanese-equity exposures, consistent with broader deleveraging of correlated FX and equity positions when margin, volatility, or VaR constraints bind.

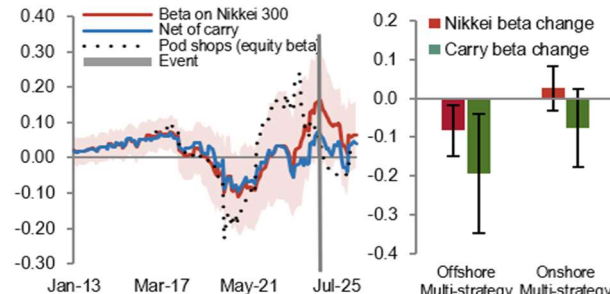
Figure 2.3.9. Hedge Funds in FX Markets: Carry Trades and Crowdedness

1. Noncommercial Positions and Crowdedness

(Left scale: thousands of contracts; right scale: net share of strategy classes)



2. Nikkei: Multi-Strategy Hedge Funds' Sensitivity to Equity Returns (Left panel: coefficient; right panel: change in beta)



Sources: Bloomberg Finance L.P.; CFTC; EUROPACE AG/Haver Analytics; HFR; Kenneth French Data Library; and IMF staff calculations.

Note: Panel 1 shows CFTC noncommercial gross and net short positions in yen and Swiss franc futures, reported in thousands of contracts as backward four-week moving averages. The blue line is the returns-based crowdedness indicator, defined as the net share of 27 HFR strategy classes with statistically significant carry loadings at the 95 percent threshold. Panel 2 left shows rolling 36-month betas of multi-strategy hedge fund excess returns to the Nikkei 300, gross and net of the FX carry factor; the gap between the two lines captures the carry-correlated component of equity exposure. Panel 2 right reports difference-in-differences estimates of changes in Nikkei and carry loadings around the August 2024 unwind for offshore- and onshore-domiciled multi-strategy funds. Vertical lines mark August 5, 2024, and January 15, 2015.

Tail-risk local projections. The analysis examines the risk of a disorderly reversal by testing whether positioning predicts the lower tail of future funding-currency and equity outcomes. The 10th-percentile quantile local projections are estimated as follows:

$$Q_{\tau}(y_{t,h}|s_t, X_t) = \alpha_{h(\tau)} + \beta_{h(\tau)} s_t + \gamma(\tau)' X_t + \epsilon_t \quad (2.23)$$

where $y_{t,h}$ in the estimations is defined as the average weekly percent change of the price level (FX or equity) over the following h weeks;¹⁹ s_t is the standardized gross short position in the funding currency. CFTC noncommercial gross shorts measure the outstanding short futures positions of reportable traders not classified as commercial hedgers.²⁰ The control vector X_t comprises the 1-month OIS interest differential versus the US dollar (basis points), the 1-month at-the-money implied volatility, the VIX, 4-week exchange-rate momentum, the weekly broad-dollar return, the MOVE index, and the own-asset lagged weekly return, all dated t . The sample is weekly, January 2013–June 2026.

Crowding amplification. To test whether crowding amplifies the tail effect, the equation above is extended to include an interaction term of positioning with a crowding dummy:

$$Q_{\tau}(y_{t,h}|s_t, c_t, X_t) = \alpha_{h(\tau)} + \beta_{h(\tau)} s_t + \beta_c c_t + \beta_t(s_t \times c_t) + \gamma(\tau)' X_t + \epsilon_t \quad (2.24)$$

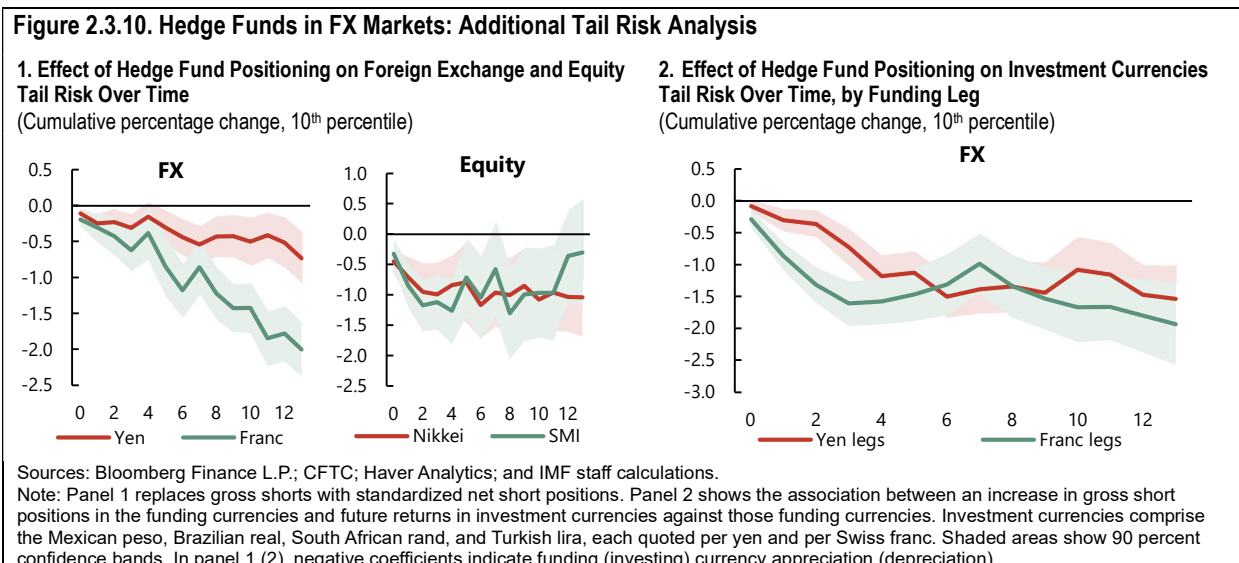
The dummy variable c_t equals one when the crowdedness indicator is above its historical upper tercile of the distribution. Results are shown in Figure 2.1.1, panel 4, in the main text. Bars report the normal and crowded-state effects, cumulated over four weeks, with 90 percent confidence intervals.

Additional analysis. Robustness checks using alternative specifications, including pooled funding currencies and longer-horizon crowded-positioning states, yield similar results, with larger negative effects at the 5th percentile, consistent with positioning mattering most in severe crash states. Replacing gross shorts with net shorts yields similar results, but with smaller coefficients, suggesting that the tail signal is concentrated in the gross short leg (Figure 2.3.10, panel 1). Finally, re-estimating the analysis with a pool of high-yielding EM investment currencies as the outcome shows that a one-standard-deviation build-up

¹⁹ Exchange rates are quoted as funding-currency units per US dollar.

²⁰ The CFTC noncommercial gross shorts measure is used here as a proxy for hedge-fund and leveraged speculative carry positioning. Galati, Heath, and McGuire (2007) note that carry trades have traditionally been implemented by large institutions such as hedge funds and CTAs, and that CFTC noncommercial currency-futures positions are the most widely used futures-market measure of carry-trade activity.

in funding-currency shorts is associated with worse lower-tail outcomes for investment currencies (that is, larger depreciation, Figure 2.3.10, panel 2), in line with evidence in Aquilina and others (2024).



BOX 2.2. IMPLICATIONS OF US TREASURY CASH-FUTURES BASIS OF HEDGE FUNDS

The box examines the growing role of hedge funds in the US Treasury cash-futures basis trade and its implications for Treasury market functioning and financial stability. It first measures the evolution of hedge fund exposure to basis trading using the sensitivity of hedge fund returns to Treasury net-basis volatility and assesses how these exposures vary across strategies, leverage, fund size, and domicile. It then evaluates the market implications of hedge fund positioning, focusing on whether leveraged basis traders help absorb Treasury market dislocations in normal conditions but amplify them during periods of stress.

Hedge Fund Exposure to Basis Trading

To assess the extent of hedge fund involvement in Treasury basis trading, the analysis measures the relationship between hedge fund returns and Treasury net-basis volatility. The 10-year Treasury cash-futures basis is measured using Bloomberg's Cheapest-to-Deliver (CTD) Net Basis that captures price dislocation between the CTD Treasury security and the corresponding futures contract after adjusting for the carry associated with holding and financing the cash security to delivery.²¹ A higher value of the measure is interpreted as a wider net basis. Daily basis changes are calculated only within the same futures contract, and monthly basis volatility is measured as the square root of the sum of squared daily basis changes within each month. The resulting series is standardized and serves as a proxy for fluctuations in Treasury basis-trade conditions.

The Treasury basis-trade footprint is estimated using rolling regressions of monthly hedge fund strategy returns on Treasury basis volatility and a set of control variables. Strategy returns are measured using HFRI indices, including aggregate hedge fund, relative value, and macro strategy benchmarks. The control variables include broad equity market returns, trend-following bond strategy returns, changes in high-yield credit spreads, changes in short-term interest rates, commodity returns, and emerging market equity returns. For each strategy, regressions are estimated using a 36-month rolling window:

$$R_t = \alpha + \beta_1 \text{BasisVol}_t + \beta_2 \text{BasisVol}_{t-1} + \Gamma X_t + \varepsilon_t \quad (2.25)$$

The footprint measure is based on the incremental explanatory power of Treasury basis volatility for hedge fund returns. For each rolling window, a full specification that includes both basis variables and controls is compared with a restricted specification that includes only the controls. The Treasury basis-trade footprint is measured using the partial R^2 :

²¹ Bloomberg's carry calculation uses a bond-specific term repo rate corresponding to the futures delivery horizon and incorporates the relevant coupon and accrued-interest effects.

$$Partial R^2 = 1 - \frac{SSR_{Full}}{SSR_{Restricted}} \quad (2.26)$$

The measure captures the share of return variation unexplained by standard risk factors that can be attributed to Treasury basis-trade conditions. A joint F -test of the basis-related coefficients is also conducted within each rolling window, and the corresponding figure in the main text highlights periods in which the basis variables are jointly significant.

To examine the relationship between basis-trade activity and leverage, the estimated Treasury basis-trade footprint is related to strategy-level leverage measures from OFR. Rolling partial R^2 estimates are aggregated to the quarterly frequency and compared with contemporaneous leverage measures for relative value and macro strategies. This exercise assesses whether periods of higher leverage are associated with a greater sensitivity of strategy returns to Treasury basis-trade conditions, consistent with the use of leverage to scale Treasury basis positions.

Implications of Speculative Positioning for the Treasury Basis

Three exercises test the state-dependent role of leveraged positioning in the Treasury basis trade. The central hypothesis is that hedge fund arbitrage capital is stabilizing when dealer balance sheets have room to finance the trade, but destabilizing when that capacity is constrained.

The first exercise tests whether positioning affects the full distribution of subsequent basis changes, by estimating quantile local projections at the 10th, 50th, and 90th percentiles of the conditional distribution over horizons from one to eight weeks. The baseline model relates the future change in the 10-year net basis to the standardized four-week build-up in leveraged positioning as follows:

$$Q_{\tau}(Y_{t+h} | F_t, X_t) = \alpha_{\tau,h} + \beta_{\tau,h} F_t + \gamma'_{\tau,h} X_t + \epsilon_t \quad (2.27)$$

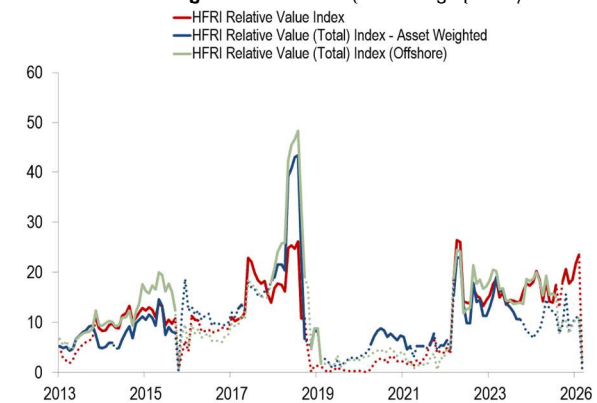
where Y_{t+h} is the change in the 10-year net basis and F_t is the standardized four-week change in the positioning-to-debt ratio.²² X_t contains the standardized level of the leveraged book, lagged basis changes, lagged VIX, MOVE level and change, an issuance-wave control, and the auction-size surprise. Results are shown in Figure 2.2.2, panel 1, in the main text. The analysis measures hedge fund activity in the basis trade using CFTC leveraged-fund Treasury futures positions, converted into DV01 and scaled by privately held marketable Treasury debt.

The second exercise tests whether the effect of leveraged positioning is stronger under stress and amplified when the Federal Reserve's Treasury-market footprint is smaller. The specification is:

$$Y_{t+h} = \alpha_h + \beta_h F_t + \delta_h D_t + \kappa_h f p_t + \theta_h F_t D_t + \lambda_h F_t f p_t + \mu_h D_t f p_t + \nu_h F_t D_t f p_t + \gamma'_h X_t + \epsilon_{t+h} \quad (2.28)$$

where D_t is a VIX-based stress indicator and $f p_t$ refers to the Federal Reserve footprint in the Treasury market, measured by the share of SOMA Treasury holdings relative to marketable debt. The plotted paths compare the effect of a positioning build-up in calm periods, in stress at the average footprint, and in

Figure 2.3.11. Explanatory Power of Treasury Basis Factors in Relative Value Hedge Fund Returns (Percentage points)



Sources: Bloomberg; HFR; and IMF staff calculations.

Note: This figure reports 36-month rolling partial R^2 estimates, defined as the share of residual hedge fund return variation explained by contemporaneous and lagged Treasury net-basis volatility after controlling for broad equity market returns, trend-following bond strategy returns, changes in high-yield credit spreads, changes in short-term interest rates, commodity returns, and emerging market equity returns. Treasury net-basis volatility is measured as the monthly realized volatility of Bloomberg's 10-year Treasury futures net basis and is computed from daily changes in the same-contract net basis to exclude mechanical variation associated with futures contract rolls. Solid (dotted) lines denote periods when Treasury net-basis volatility factors are jointly significant (insignificant) at the 10 percent level. Offshore and asset-weighted indices are HFR relative value sub-indices that proxy for offshore-domiciled funds and larger funds, respectively. Error bands are omitted for visual clarity.

²² Specifically, the ratio is defined as DV01-weighted leveraged-fund net short Treasury futures positions scaled by privately held marketable Treasury debt outstanding.

stress when the footprint is one standard deviation smaller. Results are shown in Figure 2.2.2, panel 2, in the main text.

The third exercise focuses on Treasury supply shocks and dealer capacity at a daily frequency:

$$Y_{t+h} = \alpha_h + \beta_h S_t + \rho_h \Delta E_t + \chi_h C_t + \varphi_h (S_t \times \Delta E_t) + \psi_h (S_t \times \Delta E_t \times C_t) + \zeta'_h Z_t + \gamma'_h X_t + \varepsilon_{t+h} \quad (2.29)$$

where S_t is the auction-size surprise (that is, DV01-weighted change in announced offering size), ΔE_t is the change in the standardized positioning-to-debt ratio, C_t equals one when dealer utilization is in its top tercile, and Z_t includes the remaining pairwise interactions. Supply shocks refer to auction-size surprises defined as the DV01-weighted change in offering size relative to the previous auction of the same tenor and reopening status. Results are shown in Figure 2.2.2, panel 3, in the main text. Effects are cumulative over the horizon.

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