Hedge funds through tough times

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Abstract

We investigate the performance and tails of hedge funds' (HFs) strategies during 2005 – 2025, with a special focus on their left tail behavior. The agenda is on studying HFs' performance and tail responses to shocks in macroeconomic indicators. Using autoregressive Frechet (AcF), we first document the asymmetric time-varying tails for both the right and left side. Based on the tail performance, HFs posses poor market timing or tail management. We then propose a time-varying parameter vector autoregression (TVP-VAR) model to study HFs' responses to shocks in CBOE VIX, repo rate, market liquidity, and real economic expectations. We compare the left tail responses to macroeconomic shocks of the Sep 2008, Feb 2020, and Sep 2022. The results point to persistent exposure to market crises. We also find that, the 2022 market crisis had long-lasting impact on HFs' tail compared to the 2008 and 2020 crisis. Market liquidity shocks show greater persistence on tails than those of other macroeconomic indicator. Since 2022, repo rate shocks lead to large responses in HF strategies on par with VIX. While liquidity shocks have little impact on the HFs' performance, VIX and repo have a very large and asymmetric impact on different HF strategies. While equity hedge benefits from turbulent market, calm market drives up event-driven performance.

Keywords: Hedge funds; Extremes; Financial markets

JEL classification: C1; C53; E6; J15

1 Introduction

The hedge fund (HF) literature states that HFs are mainly active in the stock market (Patton & Ramadorai, 2013; Racicot & Théoret, 2016; Elyasiani & Mansur, 2017 ; Gregoriou et al., 2021; Noori & Hitaj, 2023 among older studies). Hedge funds follow a dynamic portfolio strategy where market downturns are managed using financial derivatives. In the after math of the 2008 Global Financial Crisis (GFC), HFs were blamed for creating bubble across diffident financial assets and markets. Following the 2008 GFC, the Dodd–Frank Act was signed into law on July 2010 requesting further disclosure and regulatory checks on HFs' activities[1]. The HF literature shows that, HFs take shelter in commodity market at times of crisis which can potentially lead to price bubble

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[1]Such as the Securities and Exchange Commission's form PF

in commodity futures (Büyükşahin & Robe, 2014; Noori & Hitaj, 2023). Studies also posit that hedge funds retreat to cash at times of crises and take long positions in the treasury markets (Patton & Ramadorai, 2013, Barth & Kahn, 2021, Noori & Hitaj, 2023).

Almost all recent papers that study HFs' investing styles, rely on GARCH type variance modeling conditional on (an)other financial assets. Dynamic conditional correlation (DCC), variance or correlation modeling, and volatility spillovers are the building block of these volatility models. As a result, no paper has directly modeled HFs' tail. In this paper, we directly focus on HFs' tail, estimating a time-varying tail for both upper and lower end of the HFs' return distribution. This direct tail modeling will provide a direct tool to study different HFs' performance through time. To estimate a time-varying index for both right and left tail, we utilize the autoregressive Frechet[2] introduced by Zhao et al. (2018) AcF. This distribution relies on monthly block maximum or minimums, and by following the estimate Frechet distribution parameters, we can estimate an AcF(1,1) to derive the time-varying tails.

Measuring HFs' tail directly has several implication compared to other methods like co-movements or spillovers. First, we do not need to rely on the joint distributions for estimation; second, there is no need to find assets for joint modeling; third, when we know the target distribution parameters we will have better understanding of the data generating process; finally, the time-varying tail exhibits the HF exposure to the markets directly through time. Thus the first motivation for this study is to investigate the response of the HFs' tail during the last 20 years.

To estimate HFs tail, we utlizie the maxima and minima in each month (Coles, 2001) to fit generalized extreme value (GEV) distribution and obtain the GEV parameters. Then we fit an autoregressive conditional Frechet model (AcF) using those monthly maxima to find the dynamic volatilities and tail risk indices separately for each variables (Zhao et al., 2018). Unlike previous studies, we estimate two tails instead of one for each HF strategy. One for the right tail and for the left tail. We find that there are significant asymmetries between the two tails across all strategist. Some strategies seem to have managed financial crises and turbulent market time a lot better than other strategies. Specifically, the event-driven strategy has the smallest left tail (our variable of interest) compared to the other strategy, while relative value arbitrage has the greatest and most volatile left tail.

Since the 2020 COVID crisis, numerous unprecedented number of financial and economic instabilities have inflicted financial markets. The ongoing Russian invasion of Ukraine since 2022, the unprecedented 2022 EU/US exchange rate decline, the 2023 crisis in the US banking system and the failure of the two major banks Silicon Valley Bank (SVB) and Signature Bank, the big declines in the Fed and ECB interest rates in late 2024, the 2022, 2024, and 2025 market crash all require studies on the role and behavior of the financial intermediaries in those turbulent periods. In this regard, we measure the response of the HFs' strategies to four major macroeconomic indices in-

[2] one type of Generalized Extreme Value distribution

cluding the CBOE VIX, the Amihud market liquidity index, the repurchase agreement rate as HFs borrowing rate, and the economic condition expectation index. The results of our estimations based on the time-varying parameter vector autoregression (TVP-VAR) provide insightful findings on the reactions and behavior of HFs through the post-COVID turbulent time.

Given the recent increased booms and busts in the market, we propose a time-varying parameter vector autoregression (TVP-VAR) to study the time-varying impulse response functions of the HFs strategies to four macroeconomic indicators largely involved in and influential on HFs trading. The CBOE volatility index (VIX) representing market fear in the literature, the market liquidity represented by the Amihud liquidity index, the repurchase agreement (repo) as the HFs' borrowing rate, and the expectation on economic condition as the expectation index. These macroeconomic indices can potentially reveal an aspect of how HFs managed the recent crises. For instance, during the last decade the Federal reserve has had a big effect on the financial markets from its aggressive rate to combat inflation, to the persistent quantitative targeting policies in the last decade. Thus, we include repo representing HFs' borrowing rate to study the effect of monetary policy on HFs. Our results show that since 2022, HFs' response to repo rate have increased drastically far exceeding that of VIX. The result of time-varying impulse response further reveal that different HF strategies benefit differently from market conditions. For instance we find that equity hedge performance benefits from positive shocks in VIX, negative shocks in repo rate, and negative shocks in expectations. That is, more fearful market, cheaper funding rate, and pessimism in the market, drive up equity hedge performance. While event-driven benefits from a calm market, where VIX goes down, rates are higher, and market is optimist about the future. Additionally, we witness that HFs' response to shocks have a very short-lived nature of 5-days. The 12-day response and the 24-day response are almost none.

This paper contributes to the HF literature by analyzing HFs' performance in light of the recent post-COVID crisis. We show that different HFs respond and mange their tail differently during the last two decades. The 2020 pandemic did not create great tail response in none of HFs' strategies. We also do not witness any tail jumps in HFs strategy during the Feb-April 2025 in the commencement of Trump's second term, despite the massive turbulent market or trade war. This paper contribute to the literature by analyzing and study the impact of the HFs' borrowing rate and its impact on HFs' performance. The results show that HFs' respond to repo rate exceed the usual VIX index. We also report that, HFs response to the 2020 pandemic was unexpectedly mild, while the 2022 turbulent market had a great effect on HFs' performance. We also evidence the asymmetric effect of the macroeconomic effects on different strategies. Our results are novel in the literature.

The rest of the paper is organized as follows. In Section 2 we summarize the background and some literature. In Section 3 we describe the data. In Section 4 we describe the GEV-AcF in Subsection 4.1 and the TVP-VAR modeling in Subsection 4.2. In Section 5 we discuss and disentangle the findings. Section 6 concludes.

2 Literature

HFs are among the most mature institutional investors. As a result, their performance and interactions within the financial markets is of utmost importance. On the other hand, there is not enough paper that directly studies the performance of the HFs in the financial markets directly. This is crucial given that in the aftermath of the 2008 GFC, HFs were blamed for causing price manipulation noise, bubble, and extensive speculation across several financial markets and asset classes. Tang & Xiong (2012), Singleton (2014), Büyükşahin & Robe (2014), Knittel & Pindyck (2016), Elyasiani & Mansur (2017), Zhang & Wu (2019), Noori & Hitaj (2023), and Burns & Prager (2024) among others witness direct evidence of such behavior.

In studying HFs' exposure to a range of economic indicators Bali et al. (2011) evidence proof that HFs are affected by market factors greatly (despite the claim of being market-neutral actors). Kelly & Jiang (2012) develops a time-varying tail index based on a 5% extreme case threshold. They prove that HFs have persistent exposure to extreme downside risk.

Barth & Kahn (2021) find that HFs had been trading Treasury cash-futures basis significantly pre-COVID pandemic, with its peak rising around March 2020. According to Barth & Kahn (2021), from 2017 up to the end of 2019, HFs exposure increased from 1.06 trillion to 2.02 trillion US Dollar. HFs relies on short term funding for their investment, as a result, this reliance can increase their exposure to funding constraints and financing rate risks. As the literature shows, if HFs access to short-term funding is limited, they sell their holdings at fire sales prices (Brunnermeier & Pedersen, 2009, Cao et al., 2018). This clearly leads to price noise in the stock markets especially at times of crises. Cao et al. (2013) state that HF managers increase (decrease) their market exposure when equity market liquidity is high (low), even retreating to cash holding (Patton & Ramadorai, 2013). Sadka (2010) posits that the same liquidity risk factor affects both stocks' and HFs' returns.. Cao et al. (2018) find that stocks held by hedge funds experienced large declines in price efficiency during several liquidity crises.

Studies on the HFs' tails and their response to different financial crises or market downturns are quite limited with opposing findings. Among the very few are Kelly & Jiang (2012), Cui & Yao (2020), Gregoriou et al. (2021). Kelly & Jiang (2012) conclude the negative comovements between HFs' performance and their tail risk makes them lose value during high tail risk episodes. Their tail index is based on higher-than-5th percentile extreme negative return. Cui & Yao (2020) employs the same estimator in Kelly & Jiang (2012) but the threshold based on Hill (1975) estimator. Gregoriou et al. (2021) on the other side, rely on co-skewness and co-kurtosis as HFs' tail.

3 Data

Out data covers April 1, 2003 – April 14, 2025. We employ hedgefundresearch[3] HFRX daily HF indices[4]. We utilize the HFRX UCITS[5] investable indices, including the Equity Hedge, Event Driven, Macro, and Relative Value Arbitrage, representing the four broad HFs' strategies[6]. Table 1 describes our HF data in detail[7].

Table 1: Descriptive statistics – HFs' strategies daily return

HF strategy	Mean	Return	SD	Skewness	Kurtosis	Max Drawdown
Equity hedge	1bp	0.64	0.0038	-0.9	8.8	-0.31
Event-driven	0.9bp	0.71	0.0028	-1.4	16.5	-0.29
Macro	0.2bp	0.23	0.0037	-1.01	10.0	-0.31
Relative value	0.6bp	0.38	0.0022	-2.3	45.1	-0.39

As in Table 1, the event-driven outperforms other strategies based on the return during the sample period. On the other side, macro is the worst strategy in our study. The highest uncertainty over performance belongs to the equity hedge followed by the macro. Relative value arbitrage has a large kurtosis representing tail events. This strategy also has the largest maximum drawdown compared to other HFs' strategies. The negative skewness and generally large kurtosis manifests the influence tail events across all HFs' strategies. The maximum drawdown is the maximum observed loss from a peak to the trough (of the return series) before a new peak is attained. Among the four strategies relative value arbitrage has the greatest max. drawdown of negative 45.1, which means, during the sample period one could lose 45.1% of his total investment in this strategy.

4 Method

4.1 The GEV-AcF framework

Given the specification, design, and goal of this study, we follow the recently modified and introduced work by Zhao et al. (2018) to estimate a time-varying tail index for each HF strategy. The estimation procedure relies on generalized extreme value (GEV) and block maxima/minima to compute the right/left tail index. As in Coles (2001) the GEV is needed in modeling the block maxima (minima) x_t, and it is defined by three key parameters including a location $\mu \in R$, a scale $\sigma > 0$, and a shape parameter $\xi \in R$.

[3] www.hfr.com

[4] The description of each strategy index is provided in appendix A.

[5] Undertakings for Collective Investment in Transferable Securities (UCITS) is an integrated EU directive that permits the unrestricted operation of collective investment plans across the EU on the basis of a single authorization from a single member state.

[6] Details on agenda and the investing style of each strategy is in the attachment.

[7] All data series are stationary by ADF test. Results are not reported due to space constraints.

The block monthly maxima belong and converge to the max-domain of attraction according to the GEV distribution as:

$$H(x_t;\mu,\sigma,\xi) = \begin{cases} \exp\left(-\left(1+\xi\frac{x_t-\mu}{\sigma}\right)^{-\frac{1}{\xi}}\right), & \xi \neq 0 \\ \exp\left(-\exp\left(-\frac{x_t-\mu}{\sigma}\right)\right), & \xi = 0 \end{cases}$$

The shape parameter ξ is also called the extreme value/tail index. Based on ξ the GEV distribution obtains three variants including the Gumbel distribution, Frechet distribution, and the Weibull distribution[8]. Frechet distribution is widely used for financial variable and risk management, since ξ gets large values ($\xi > 0$) pointing to possibility of extreme events.

$$H(x_t;\mu,\sigma,\xi) = \exp\left[-\left(\frac{x_t-\mu}{\sigma}\right)^{-\frac{1}{\xi}}\right], x_t > \mu, \sigma > 0, \xi > 0, -\infty < \mu < \infty$$

To estimate the GEV parameters for each variable in this study, we employ a maximum likelihood estimator.

Since the variables in our study follow Frechet distribution (evidence by the fitted GEV in table 3), we follow the autoregressive conditional Frechet (AcF) model of Zhao et al. (2018) to get the dynamic model for the block maxima. Assuming $a = 1/\xi$, the AcF(1,1) reads as:

$$Q_t = \mu + \sigma_t Y_t^{\frac{1}{a_t}} \tag{1}$$

$$\log \sigma_t = \beta_0 + \beta_1 \log \sigma_{t-1} + \beta_2 \exp(-\beta_3 Q_{t-1}) \tag{2}$$

$$\log a_t = \gamma_0 + \gamma_1 \log a_{t-1} + \gamma_2 \exp(-\gamma_3 Q_{t-1}) \tag{3}$$

where the Y_t is a sequence of iid unit Frechet random variables with $\leqslant \beta_1 \neq \gamma_1 < 1,\ \beta_2 < 0,\ \beta_3, \gamma_2, \gamma_3 > 0$. The Q_t is the sequence of monthly block maxima with Frechet parameters μ, σ_t, a_t where the scale and shape parameters are time-varying.

[8]For further explanation refer to Coles (2001)

Table 2: Descriptive statistics for HF strategies monthly blocks

	Mean	**SD**	**Skewness**	**Kurtosis**	**ADF test**
Max Equity hedge	0.0064	0.0032	2.3	12.0	0.00
Min Equity hedge	0.0067	0.0044	2.1	9.8	0.00
Max Event-driven	0.0048	0.0027	3.1	20.0	0.00
Min Event-driven	0.0050	0.0042	3.3	19.3	0.00
Max Macro	0.0062	0.0028	1.5	7.2	0.02
Min Macro	0.0073	0.0047	2.6	13.3	0.01
Max Relative Value	0.0034	0.0033	4.6	32.5	0.02
Min Relative Value	0.0032	0.0040	5.0	36.1	0.00

The block min stats are based on the absolute values. ADF is the augmented Dickey-Fuller test.

4.2 Hedge funds' response to macroeconomic indicators

In this section we study the response of the four HF strategies to the shocks in the macroeconomic indicators using the time-varying parameter vector autoregression (TVP-VAR). These macroeconomic indices include CBOE volatility index (VIX), repurchase agreement contracts (Repo) rate, Amihud market liquidity index (liquidity), and the Aruoba et al. (2009) index for expectation of real economic condition (ADS–expectations). The data for these four macro indicators comes the from Federal Reserve databases. These four indices provide a fair and complete amount of information on different aspects of economic environment for HFs. The Amihud index is calculated by:

$$\text{Amihud index} = \frac{\text{S\&P 500 daily return} \times 10^9}{\text{daily volume in \$billions}}$$

We calculate the natural log changes[9] for all the variables in our TVP-VAR estimations. Figure 1 exhibits the four macro indicators. An increase in VIX index reflects market fear for crash while an increase in the ADS-expectation index points to optimism about the economic conditions. Several periods including the 2008, 2020 mark the turbulent market conditions. The great spikes in VIX, liquidity, and the Repo rate and the large fall in the expectations index are such proofs among others. For computational feasibility and stability, we implement the TVP-VAR using the HF performance daily data after 2015. This also reflects the fact that our agenda is on study post-COVID financial instability. For each HF strategy, we estimate a TVP-VAR separately. Below, we discuss the TVP-VAR model developed by Primiceri, 2005 briefly.

[9]For the ADS expectation index that we use the arithmetic changes i.e. $\frac{P_i - P_{i-1}}{P_{i-1}}$, since the include consists of negative values.

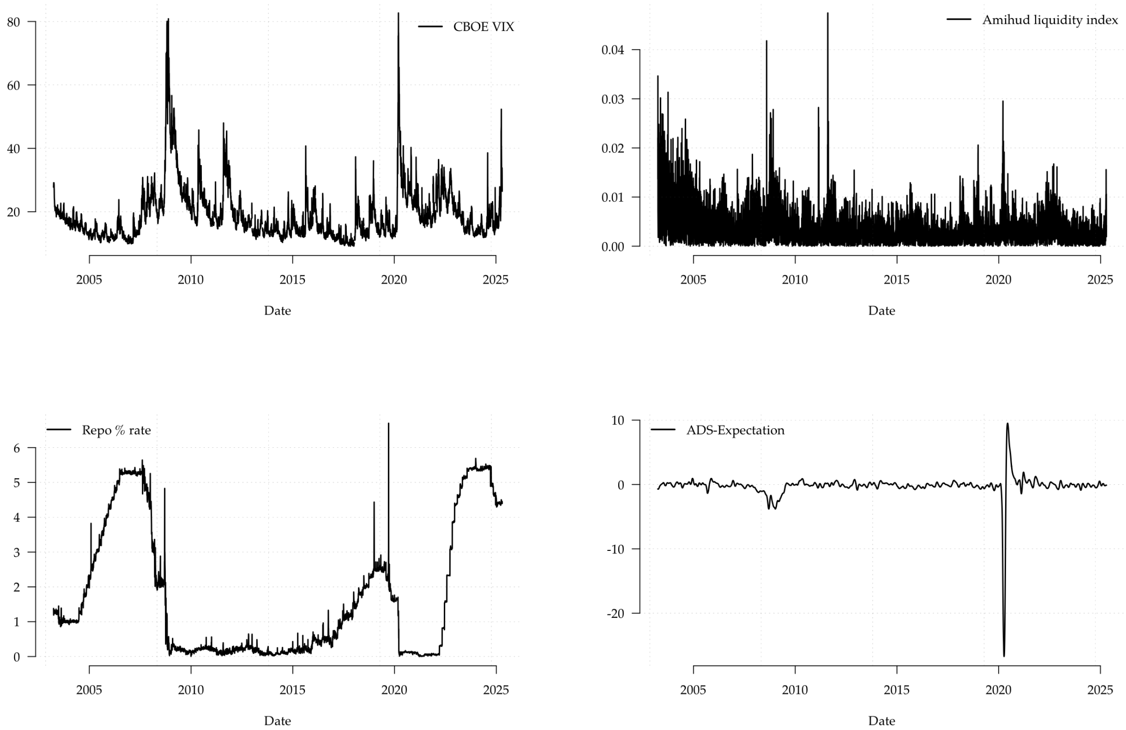

Figure 1: Macroeconomic market indicators, 2003-2025

Table 3: Frechet parameter estimates for monthly blocks

Variable	μ	σ	ξ
Max Equity hedge	0.005 (0.0001)	0.002 (0.0001)	0.14 (0.04)
Min Equity hedge	0.005 (0.0002)	0.002 (0.0001)	0.22 (0.05)
Max Event-driven	0.006 (0.0001)	0.002 (0.0001)	0.12 (0.04)
Min Event-driven	0.003 (0.0001)	0.002 (0.0001)	0.29 (0.05)
Max Macro	0.005 (0.0001)	0.002 (0.0001)	0.06 (0.04)
Min Macro	0.005 (0.0002)	0.002 (0.0001)	0.24 (0.04)
Max Relative Value	0.002 (0.0001)	0.001 (0.0001)	0.36 (0.05)
Min Relative Value	0.002 (0.0001)	0.001 (0.0001)	0.42 (0.05)

The standard errors are reported inside the parenthesis.

The TVP-VAR is classified as a non-linear VAR model, and it is able to capture the asymmetric effect of positive vs negative structural shocks either by the state of the economy or by the variables and lags. The model is so flexible that state variables can capture both gradual and sudden changes in the economy[10]. Additionally this model is developed to provide time-varying VAR coefficients (based on some stochastic process) and impulse response functions (IRFs). The evident existence of the different economic regimes, and changes in the conditional HF tails and the macro indicators all refer to the smooth structural change (Primiceri, 2005, Nakajima, 2011). Following Primiceri (2005) the TVP-VAR model is derived from structural VAR model, and reads as follow for a multivariate case:

$$\boldsymbol{Y}_t = c_t + A_{1,t}\boldsymbol{Y}_{t-1} + \cdots + A_{p,t}\boldsymbol{Y}_{t-p} + u_t \qquad t = 1, ..., T \tag{4}$$

Where $\boldsymbol{Y}$ is a $n \times 1$ vector of endogenous variables, c_t is a $n \times 1$ vector of coefficients that multiply the constant terms, the coefficients $A_{i,t}, i = 1, ..., p$ are time dependent matrices. The innovations u_t are assumed to be a zero-mean white noise process with time-varying covariance matrix, i.e. $u_t \sim (0, \Sigma_{u,t})$. To facilitate structural analysis, the error covariance is decomposed to:

$$\Sigma_{u,t} = B_t^{-1}\Sigma_{w,t}B_t^{\prime -1} \tag{5}$$

Where $\Sigma_{w,t} = diag[\sigma^2_{1,t}, ..., \sigma^2_{k,t}]$ is a diagonal matrix with the variances of the structural shocks, and B_t^{-1} is a lower-triangular matrix as follow:

[10]Even recent extension or alternatives of TVP-VAR are not as flexible and relaxed in assumption, as the original TVP-VAR model.

$$B_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ b_{21,t} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ b_{k1,t} & \cdots & b_{kk-1,t} & 1 \end{bmatrix}$$

Restrictions on B_t can be used to uniquely identify the structural shocks or $w_t = B_t u_t$, and using it, we can rewrite the model in structural form as:

$$\boldsymbol{Y}_t = c_t + A_{1,t}\boldsymbol{Y}_{t-1} + ... + A_{p,t}\boldsymbol{Y}_{t-p} + B_t^{-1} w_t \tag{6}$$

If we gather all the reduced-form VAR slope coefficients in the vector $\alpha_t = vec[c_t, A_{1,t}, ..., A_{p,t}]$ and the unrestricted elements of the B_t in $b_t = [b_{21,t}, b_{31,t}, b_{31,t}, \cdots, b_{k1,t}, \cdots, b_{kk-1,t}]'$ then the vector b_t is the $\frac{1}{2}K(K-1)$-dimensional vector of elements below the main diagonal of B_t which is row-wised such that the parameters for each individual equation are grouped together. Now having $\sigma_t = [\sigma_{1,t}, \cdots, \sigma_{k,t}]'$ as the vector of w_t's standard deviations, we can specify the dynamics of the time-varying vectors of coefficients as random walk processes for α_t and b_t, and a geometric random walk for σ_t. Restating, the model allows for stochastic volatility with considerable persistence:

$$\alpha_t = \alpha_{t-1} + \eta_t^\alpha \tag{7}$$

$$b_t = b_{t-1} + \eta_t^b \tag{8}$$

$$log\sigma_t = log\sigma_{t-1} + \eta_t^\sigma \tag{9}$$

Summing up, the co/variance matrix error terms of the model equations is block diagonal as:

$$Cov \begin{bmatrix} w_t \\ \eta_t^\alpha \\ \eta_t^b \\ \eta_t^\sigma \end{bmatrix} = \begin{bmatrix} \Sigma_{w,t} & 0 & 0 & 0 \\ 0 & \Sigma_\alpha & 0 & 0 \\ 0 & 0 & \Sigma_b & 0 \\ 0 & 0 & 0 & \Sigma_\sigma \end{bmatrix}$$

Where Σ_α, Σ_b, and Σ_σ are the positive definite covariance matrices of η_t^α, η_t^b, and η_t^σ respectively. Note that, the error terms are independent of one another with:

$$\alpha_t \sim \mathcal{N}(\mu_\alpha, \Sigma_\alpha) \qquad b_t \sim \mathcal{N}(\mu_b, \Sigma_b) \qquad \sigma_t \sim \mathcal{N}(\mu_\sigma, \Sigma_\sigma) \tag{10}$$

Assuming $Z_{t-1} \equiv (1, \boldsymbol{Y}_t, \cdots, \boldsymbol{Y}_{t-p})'$ the initial VAR in equation 15 becomes:

$$\boldsymbol{Y}_t = (Z_{t-1}' \otimes I_k)\alpha_t + u_t \tag{11}$$

With the symbol $\otimes$ referring to Kronecker product. Equation 11 and the random walk process of α_t (7) are basically a state-space model with measurement equation (10) and transition equation (7). Generally there are two ways to estimate this model, one is maximum likelihood estimation, and Bayesian estimation based on the Markov Chain Monte Carlo (MCMC), which the latter is employed given the issues with maximum

likelihood estimation. In implementing the TVP-VAR, we include one lag in our modeling. Further we follow Primiceri (2005) regarding priors and distributions of parameters.
Where i refers to the i^{th} element of the matrices. Our identification strategy is based on recursive ordering (following hedge funds' literature) of the most exogenous to most endogenous[11], with the following specification:

$$\text{VIX} \rightarrow \text{Liquidity} \rightarrow \text{Repo} \rightarrow \text{Expectation} \rightarrow \text{HF performance}$$

where we are only interested in the response of the HFs to shocks in these four macroeconomic indices[12].

5 Results

5.1 HFs' asymmetric tails

Figure 2 displays the results of the AcF(1,1) estimations for different HF strategies. For each strategy we have the time-varying tail index ξ_t for both left (solid line) and right tails (dashed line). The left tail (the point of interest in this study) is based on the block minima of the monthly returns against the right tail[13]. Note that these time-varying tails are the inverse of the a_t in equation 3. It is evident that the left and right tails are asymmetric and come from different DGP. The left tail across all strategies is greater than the right tail. This shows that the possibility of large losses is significantly greater than large gains through different points in time, which is in line with the skewness preference in the literature.

Among the four strategy, Relative Value Arbitrage owns both the greatest tail, followed by the macro, equity hedge and event-driven strategies. As it is evident, the two strategies, macro and relative value arbitrage left tails increased significantly during major market turmoils of 2008, 2020, and other financial markets crises. On the other side, the equity hedge and event-driven strategies left tails are not as sensitive as the former two strategies, to the market crises. Event-driven that had the best performance among the four strategies, has the lowest left tail as well. The right tail, which represents the block maxima time-varying tail estimation, in case of macro strategy, had the lowest ξ Frechet parameter. This is in line with our previous finding that macro has the smallest right tail, among the other HFs' strategies in 3. relative value arbitrage reacts much stronger to market crises compared to other strategies. Overall the results follow the

[11]In this VAR structural shock identification, VIX affects liquidity, repo, Expectation, and HF tail; then market liquidity affects repo, expectations, and HF tail; finally, Expectation affects HF tail. In this regard, with economic intuition, market liquidity responds to VIX, repo rates respond to market liquidity, and expectation responds to the three variables in the preceding order. For instance, expectations formation go through VIX, market liquidity, and repo rates.
[12]For the estimation, we employ Nakajima, 2011 codes.
[13]We use the absolute value of the returns in case of the block minima, to fit a GEV/Frechet.

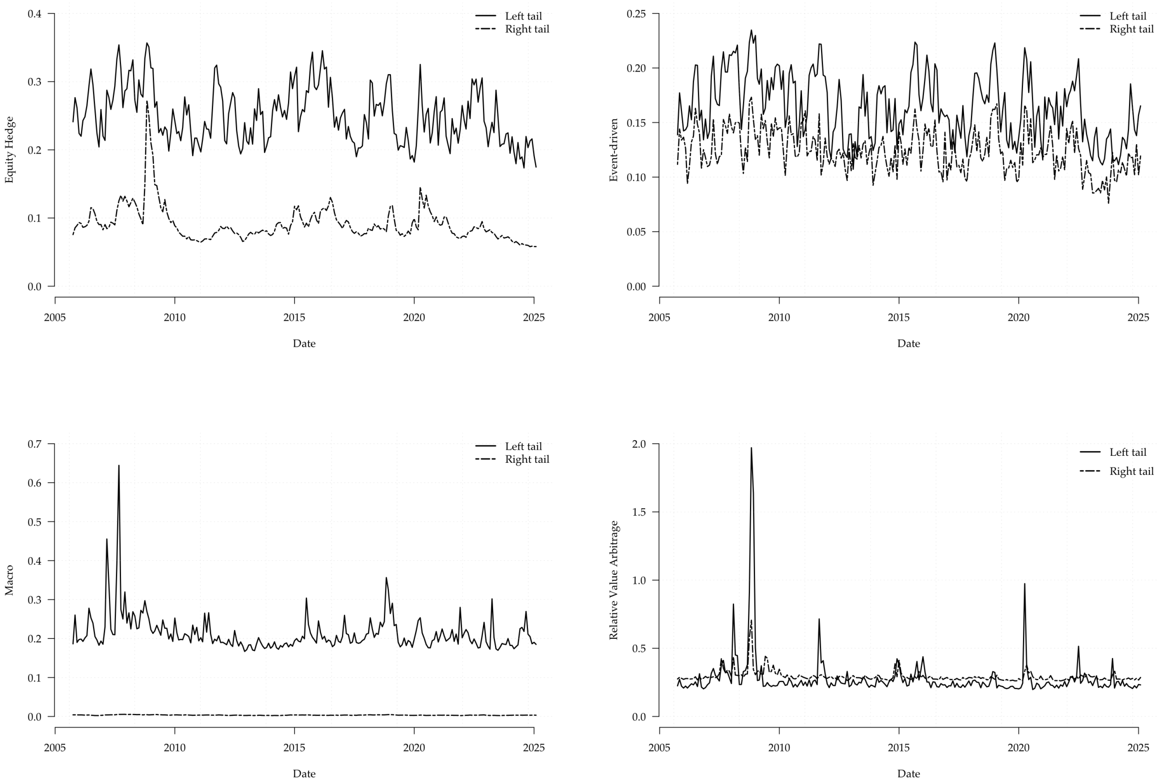

Figure 2: HF strategies tails, 2005-2025

investment agenda for each HF strategy.

We also find evidence of spikes in HFs' left tail in the post-COVID era. Including. That includes the left tail spikes in 2022 (all strategies) and the 2024 (except for equity hedge). The macro strategy exhibits the most modest response to the 2020 pandemic. Both the right and left tail of all strategies seem to fluctuate up during market crises. All strategies left and right tails significantly increased a few month after the 2020 pandemic. This represents the lagged impact of the pandemic on HF tails, and a clear proof against market timing capabilities of HFs. Trump's second term and Tech crashes of Feb-April 2025 do not create any big fluctuations in the tails. Our findings are in line with Kelly & Jiang (2012) who find that HFs have persistent exposure to market crises. As in Figure 2, all HFs' strategies are clearly exposed to the market systemic risk as well (Bali et al., 2011).

5.2 HFs' tail through financial crises

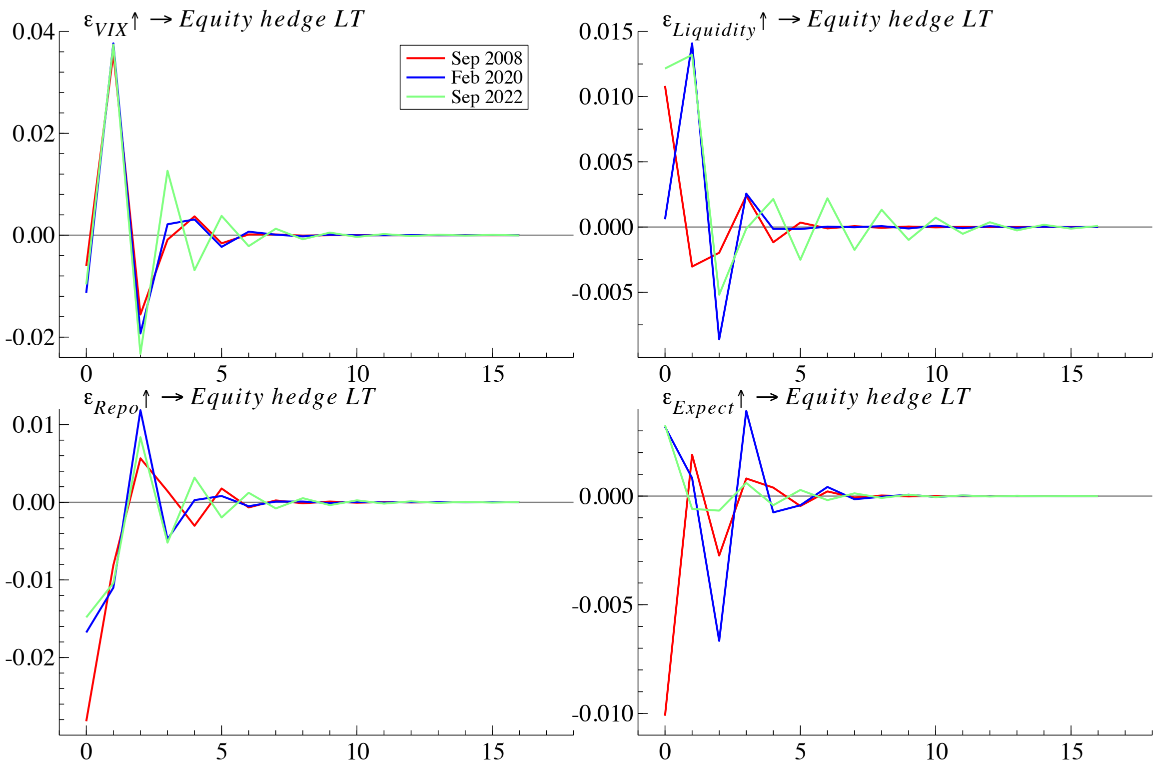

Figure 3: Equity hedge left tail response to the 2008, 2020, and 2022 greatest shocks.

Figures 3 to 6 show HFs' left tail (LT) time-point IRFs to shocks in the four macro indices at the three major financial crises, namely the Sep 2008 (response in red), Feb 2020 (response in blue), and Sep 2022 (response in green). These crashes are the major stock market drops [14] in the last two decades. All IRFs in Figures 3-6 show that the response

[14]Since our data sample stops at April 2025, we are unable to analyze the April 2025 time-point IRFs

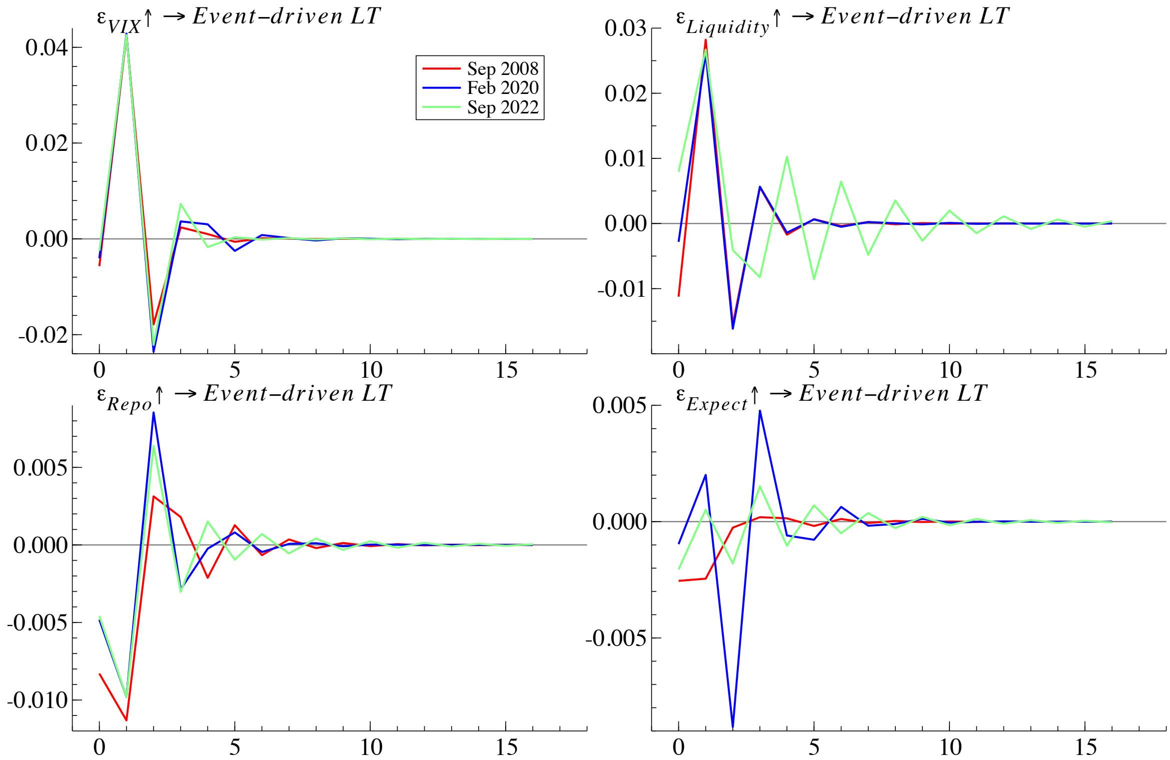

Figure 4: Event-driven left tail response to the 2008, 2020, and 2022 greatest shocks.

of different HFs' strategies to macro variable shocks oscillate[15] around and converge to zero, and by the sixth month they largely lose effect. Further it is evident that liquidity shocks take longer to dissipate, in comparison with VIX, repo, and expectation shocks. The long-lasting responses to liquidity shocks, are primarily linked to the 2022 and then 2020 market crashes. Another general pattern relates to the range of the responses. VIX (expectation) shocks during market crises create the strongest (weakest) responses across all HFs' strategies except for the macro. Positive shocks in Repo curbs the LT in all strategy. That is, an expensive funding rate during market crisis acts as a buffer against the market crises. While the IRFs do not witness different HFs' reaction to the three market crises, the 2022 market crisis has a long-lasting impact on HFs' left. This finding is in line with Kelly & Jiang (2012) who find persistence in HFs' exposure to downside tail risk in different financial crashes.

3 shows the IRFs of equity hedge strategy LT to shocks in macroeconomic variables during market crises. VIX, repo, liquidity, and expectation shocks create the strongest response in this strategy respectively. In this regard, a positive shock in repo rate curbs equity hedge LT during the first two months while increasing the LT in the third subsequent month. The pattern is similar during the three market crises. After the 4th subsequent months, the effect gradually reverts to zero. Shocks in VIX during those periods, have a damping effect. A contemporaneous lowering impact on the LT while

[15]Damped oscillation

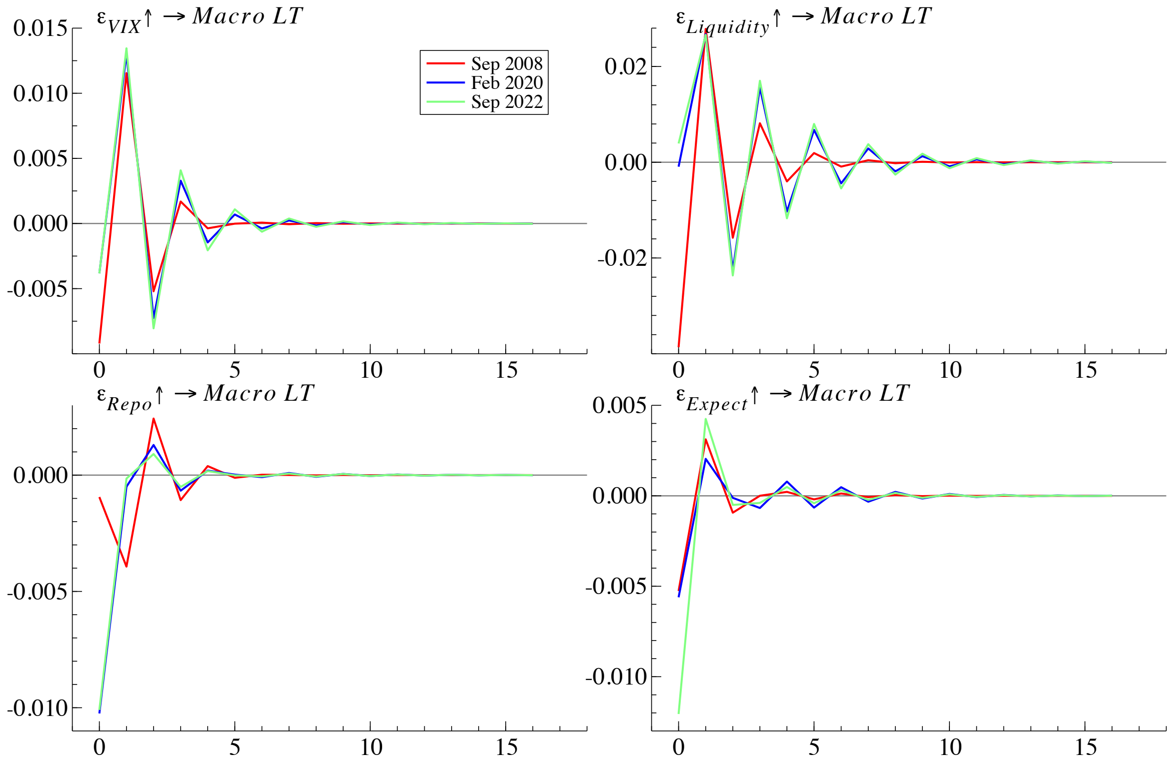

Figure 5: Macro left tail response to the 2008, 2020, and 2022 greatest shocks.

a greater increasing effect in the first and third month. Liquidity shocks increase the LT contemporaneously, though for the 2020 and 2022 crashes, the effect follows up. The 2022 market crash seems to have a long lasting effect on equity hedge strategy, as it takes much longer for the shocks to dissolve. Expectation shocks are the weakest, and have a non-homogeneous pattern on equity hedge strategy in the firts two periods. The 2008 crash (red line) shows that the contemporaneous effect is decreasing the tail, while in case of the 2020 and 2022 the LT increases as a result of the shocks.

The IRFs of the event-driven strategy (Fig. 4) has its strongest response in the first month, except for expectation shocks. VIX, market liquidity, repo, and the expectation shocks create the largest response in this strategy, in the respective order. Similar to equity hedge strategy, (the 2022) liquidity shock takes much longer than the other three macro shocks, to disappear. Figure 5 exhibits the response of the macro strategy to macroeconomic shocks during market crises. Liquidity shocks create the strongest response in this strategy, followed by VIX, repo, and expectation shocks. Macroeconomic shocks during market crises show a similar pattern overall. Unlike other strategies, expectation shocks in different market crises have homogeneous negative effect. Finally, Figure 6 depicts the relative value arbitrage IRFs. The 2008 macro shocks dissipate faster than those of 2020 and 2022. The 2020 and 2022 shocks cause long-lasting responses. Liquditiy shocks linger in this strategy longer than those of other strategies.

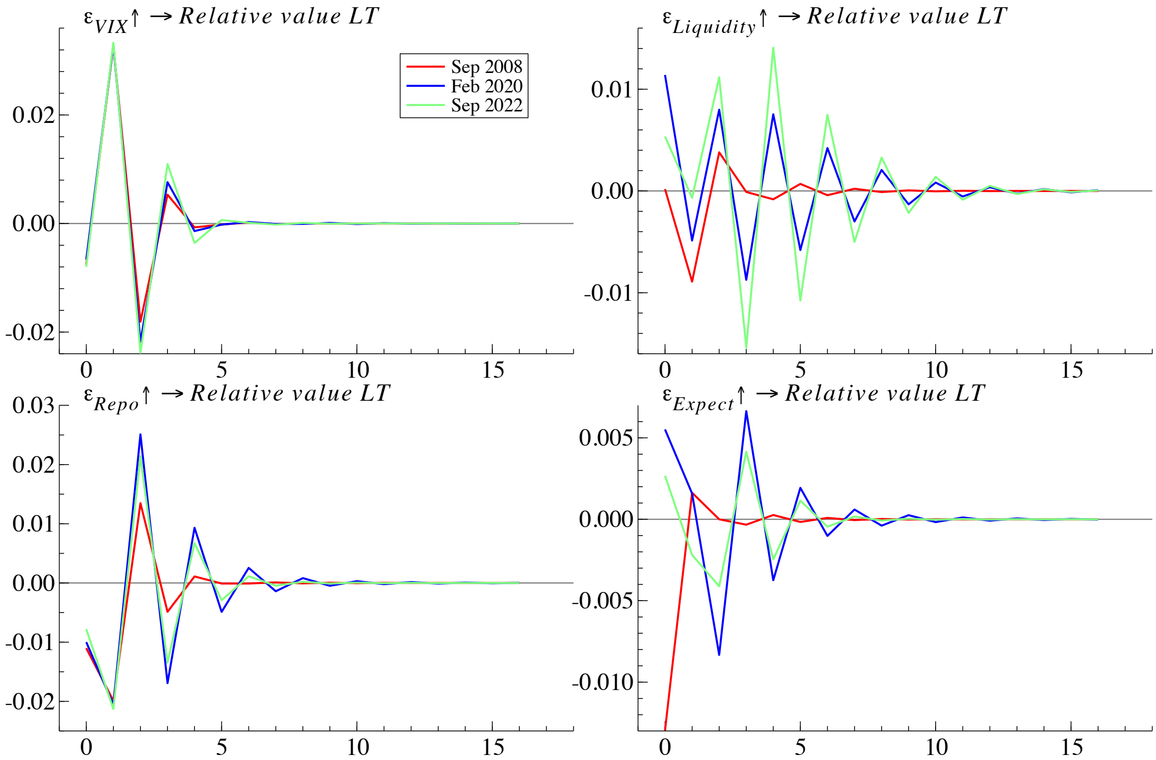

Figure 6: Relative value arbitrage left tail response to the 2008, 2020, and 2022 greatest shocks.

5.3 HFs' tail aggregate response to macroeconomic indices

In this section, we discuss the aggregate response of the HFs strategies left tail (LT) to positive shocks in different macroeconomic variables, shown in Figures 7-10 (with 75% and 95% confidence intervals). Overall, the IRFs across all strategies show that the average LT responses to macroeconomic shocks largely dissipate after the third month in line with Cui & Yao, 2020 findings. This is much faster than the LT responses to the major market crisis discussed in the previous Section 5.2. The impact of major financial shocks take 5 to 8 months to lose effect which is intuitive. On the other side, the aggregate LT responses to macroeconomic shocks largely disappear after the 3rd month. We also find out that VIX shocks have the greatest impact on HFs' LT, larger than other macroeconomic variables in this study. This is in line with the HF literature. Further, similar to the previous section, we also witness a similar pattern in the IRFs, like that of Section 5.2. Overall, all HF strategies have a strong positive response to a positive shock in VIX, in the first month. In other words, a positive shock from VIX (more fearful market) leads to LT jumps significantly. In this regard, event-driven, equity hedge, relative value arbitrage and the macro strategies respond the strongest to VIX shocks, in order. This order reflects HF strategies' investing style as well, where event-driven and equity hedge are largely active in stock market compared to the other two (Gregoriou et al., 2021; Noori & Hitaj, 2023). On the other hand, positive shock in the repo rate curbs the LT in all strategies in the first month, except the macro. Liquidity shocks

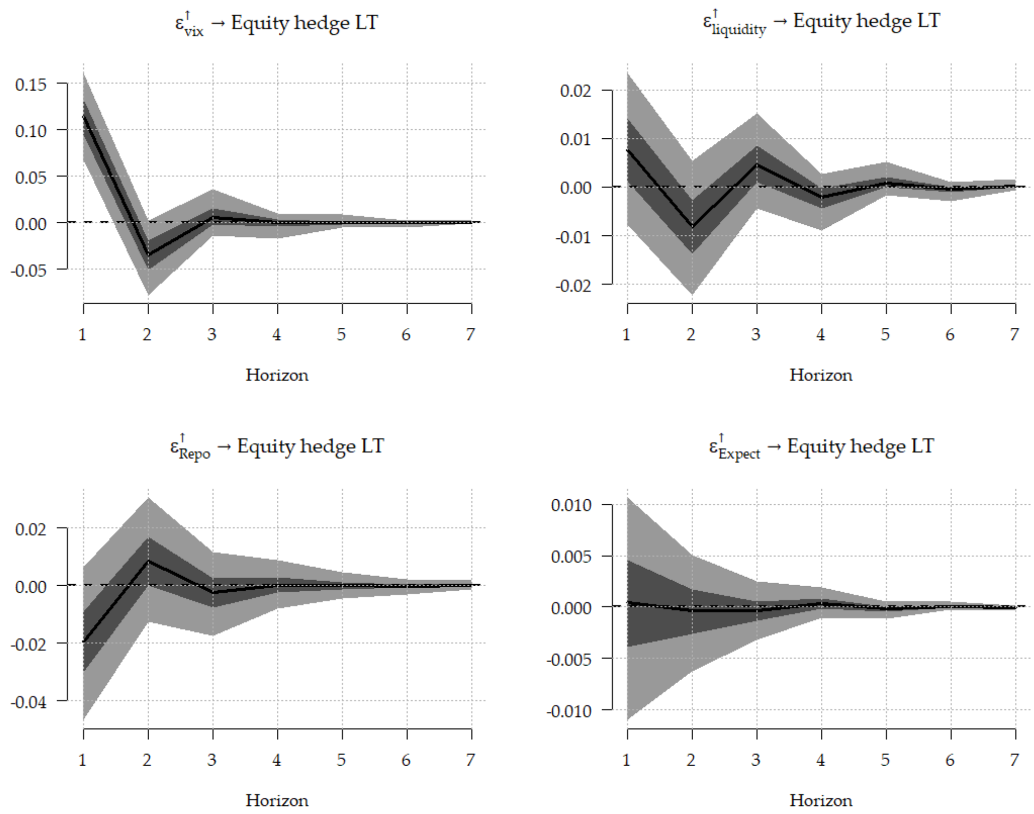

Figure 7: Equity hedge left tail aggregate response to macroeconomic shocks

show a damped oscillation behavior around the zero line, while market expectation has the smallest effect on HFs' LT. Our findings are generally in line with Cui & Yao (2020) who find short-term (up to three months) effect of tail risk exposure on fund of funds performance.

5.4 HFs' performance and macroeconomic shocks

Figure 11-14 show the estimated time-varying impulse responses of each HF strategy. In these figures, the 5-day, 12-day, and the 24-day responses are shown in red, pink, and green line respectively. That is, these are each HF strategy responses after a certain number of days when a shock from one of the four macro variables hit the HF strategy. Since HFs follow an active and dynamic portfolio management, it is no surprise to see that almost all responses other than the 5-day response have zero effect. Additionally, the impact of the 2022 financial crisis is much stronger and more persistent than the

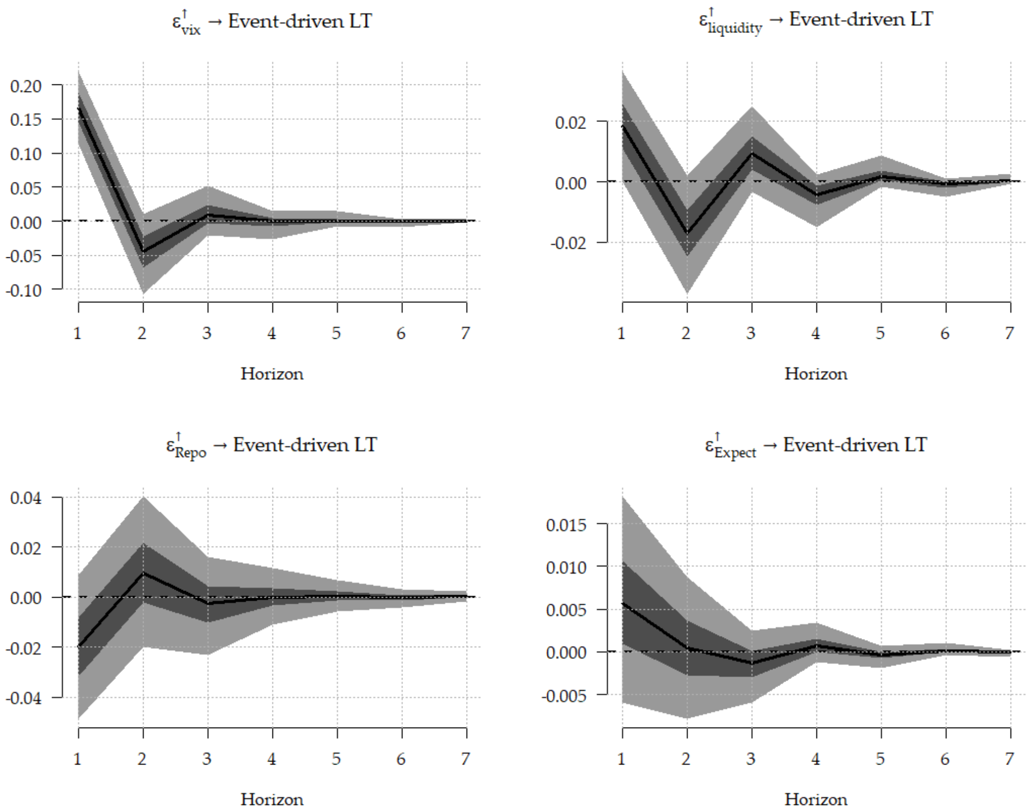

Figure 8: Event-driven left tail aggregate response to macroeconomic shocks

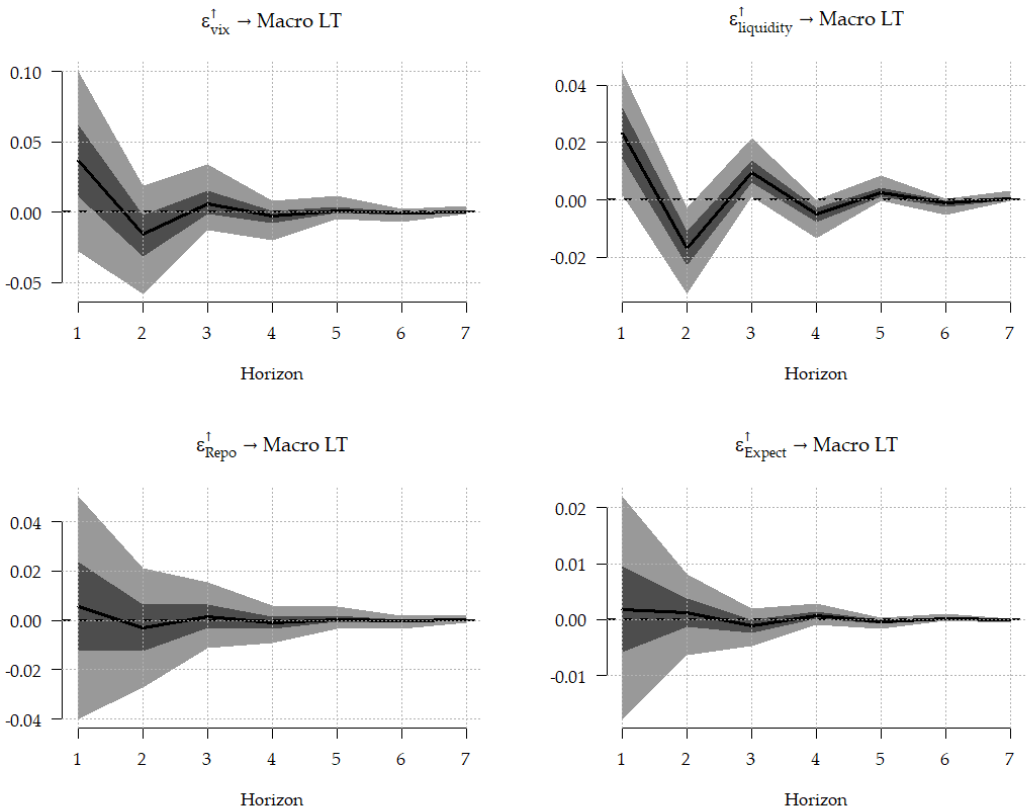

Figure 9: Macro left tail aggregate response to macroeconomic shocks

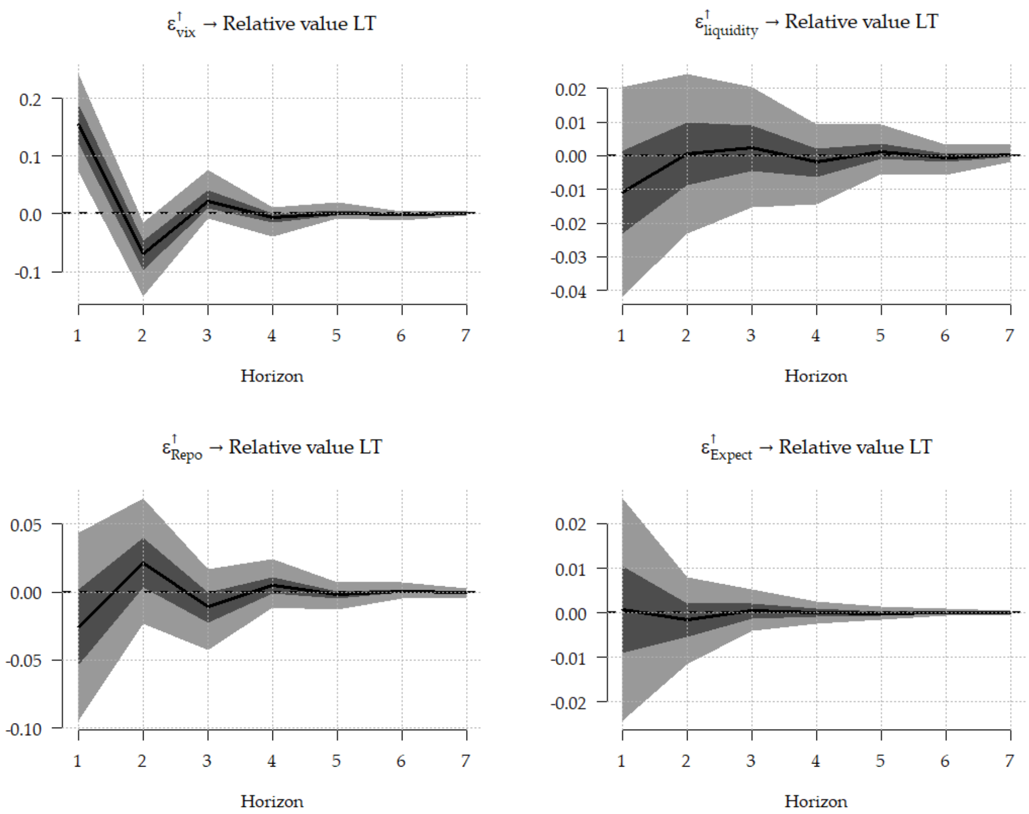

Figure 10: Relative value arbitrage left tail aggregate response to macroeconomic shocks

2020.

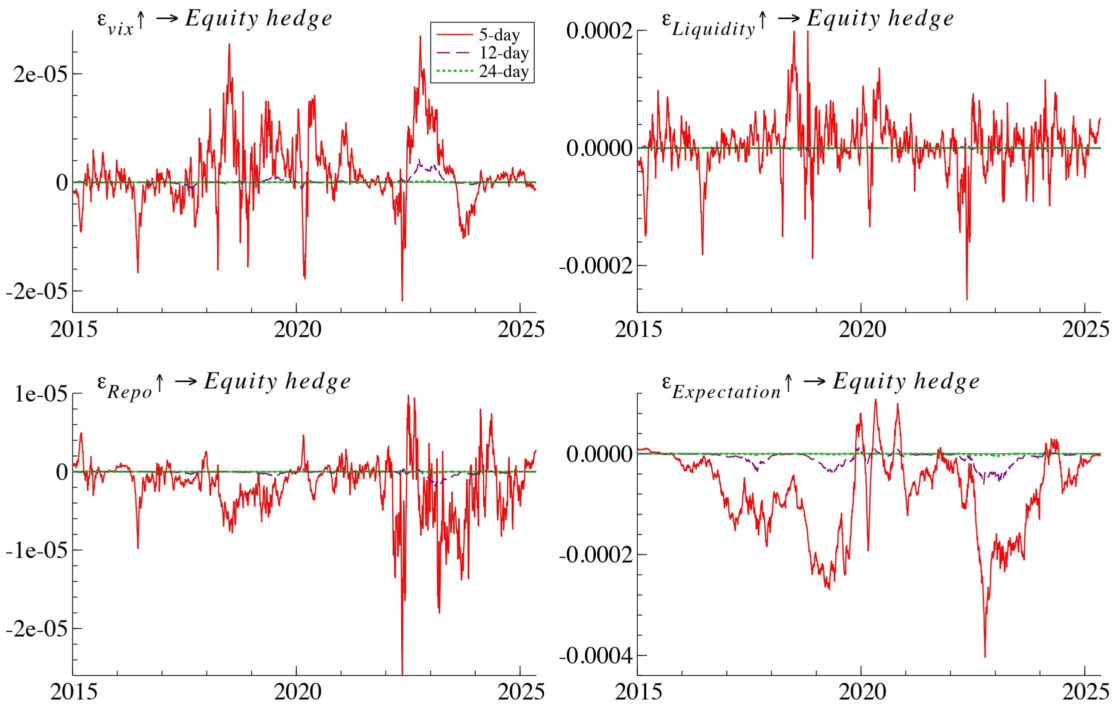

Figure 11: Equity hedge strategy time-varying impulse response function. The 5-day, 12-day, and 24-day responses are shown in red, pink, and green respectively.

Figure 11, shows the time-varying impulse response function of the equity hedge strategy. Among the four macroeconomic indices, VIX and Repo have the largest impact on this strategy. We can also see that since 2021, shocks in Repo create greater responses in this strategy. On average positive shocks in VIX and Repo lead to better and worse performance in the equity hedge strategy. In other words, a more fearful market and lower funding rate means leads to better performance in the equity hedge strategy. The impact of the expectations on the equity hedge is negative. Positive shocks (increases in the expectations) lower equity hedge performance uniformly in the past decades. So this strategy has better performance in the market downturn. Overall, equity hedge seems to follow a betting against the market strategy. More fearful, negative expectation on market performance, and somehow higher market liquidity (panic selling) increase the performance of this strategy. The 2022 market crash created long-lasting response, as evidence by the largest 12-day response.

The time-varying impulse response functions of the event-driven strategy are presented in 12. Long-run 24-day responses are almost zero, while the short-term 5-day response are quite strong, reflecting HFs' dynamic investing style. Based on the range and average 5-day responses, repo, VIX, Expectations, and Liquidity represent the de-

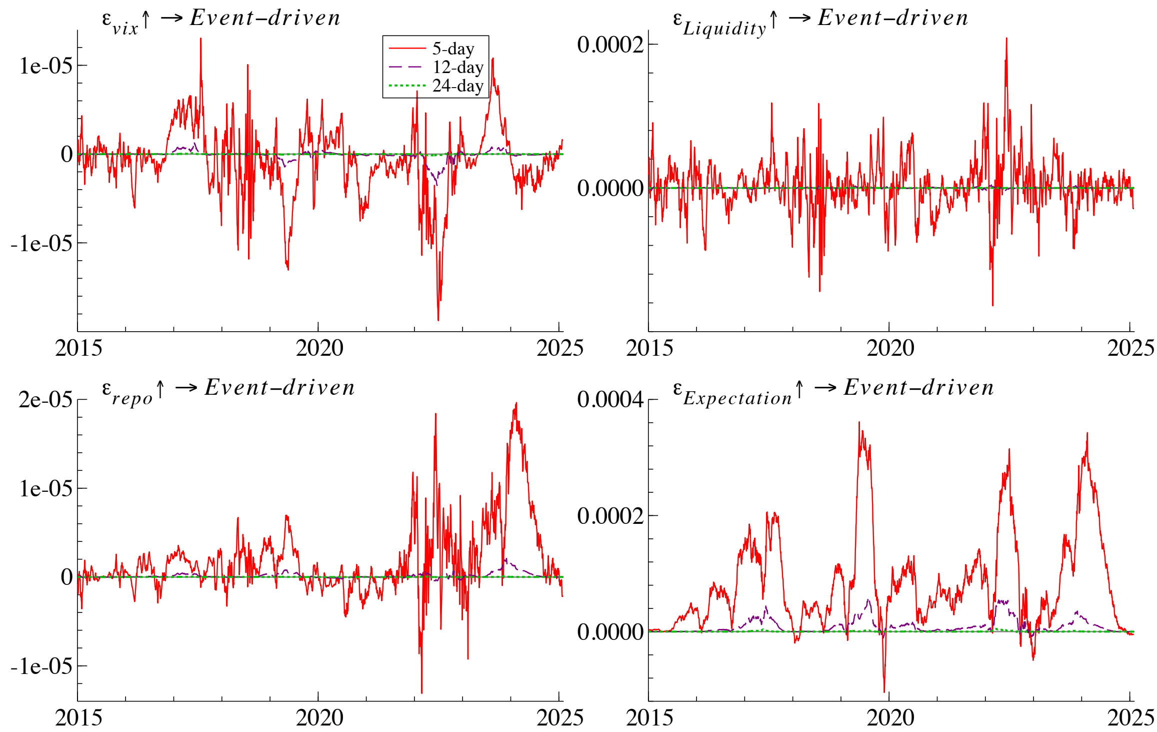

Figure 12: Event-driven strategy time-varying impulse response function. The 5-day, 12-day, and 24-day responses are shown in red, pink, and green respectively.

gree of influential macro indices. A positive shock in repo can lead to $2e^{-5}$ (0.013) of response in the event-driven strategy (during 2022 or early 2024). Similar to the equity hedge strategy, since 2022, repo shocks created strong responses in this strategy. On average, positive shocks in repo and expectation increase the performance of this HF strategy, while VIX shocks lead to worse performance in the short run. As a result, unlike equity hedge strategy, a calmer market based on optimist economic conditions, higher borrowing rate, and low VIX index drive up event-driven performance. The early 2024, shows an instance of such condition.

Figure 13 shows macro strategy's impulse responses. VIX, repo, liquidity, and expectations are in the order of creating strongest response in macro's performance. Similar to the previous strategies, shocks create asymmetric response. Shocks in VIX in the late 2018, created a very strong response from this strategy ($5e^{-5} \sim 0.033$). Brexit news, Fed 3-time interest rate, Argentine, Brazil, and Turkey monetary crises, and the first term of US-China trade war, all were among the major causes of the economic turbulence of that time. All these are in line with macro strategy investing style, that focuses on the underlying economic conditions. We do not witness clear cut impulse-response patterns during the 2020 pandemic. On the other side, the 2022 market crisis exhibits itself through very strong impulse-response patterns. Sharp negative response of the macro strategy to positive shocks in all the three macroeconomic indices are visible

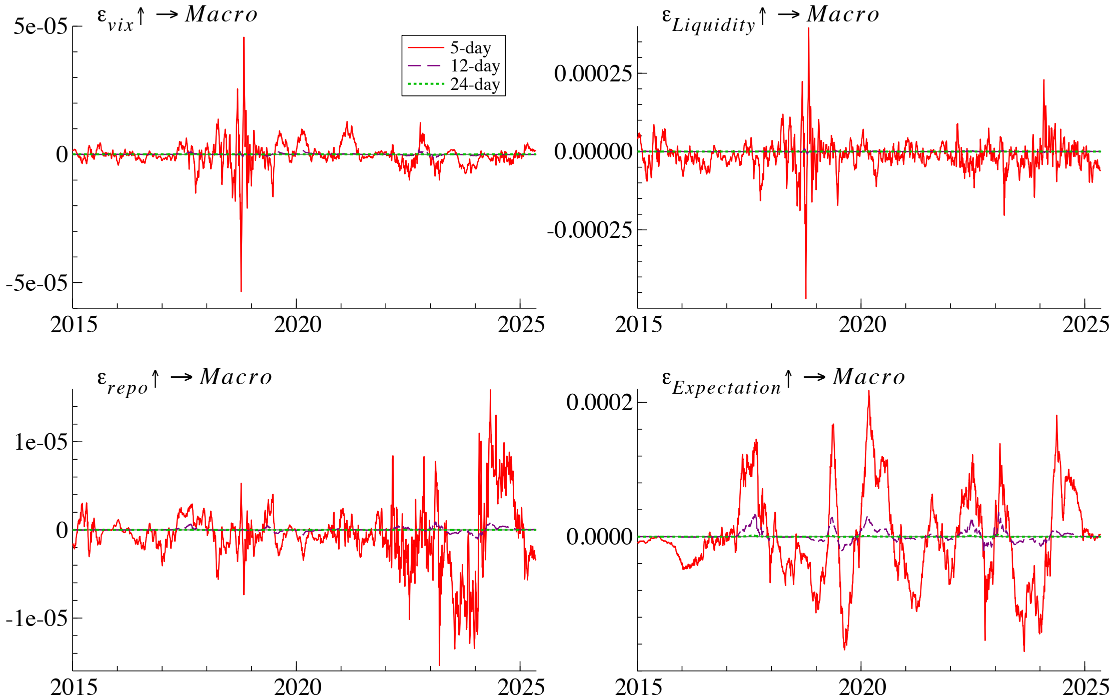

Figure 13: Macro strategy time-varying impulse response function. The 5-day, 12-day, and 24-day responses are shown in red, pink, and green respectively.

and greatest in all this recent past decade. On average positive shocks in the repo rate and expectation lead to underperformance in macro strategy. Better economic outlook, proxied by expectation adversely affects macro strategy. Trump's second term market fluctuations are not reflecting themselves in the impulse response function of macro strategy, much like other HF strategies.

Finally in Figure 14 we investigate the time-varying impulse response functions of the relative value arbitrage. Like other strategies, shocks in the macroeconomic indicators do not have long-term effects. VIX and repo, expectation, and market liquidity are the most influential variables on this strategy. Unlike other strategies, positive shocks in liquidity lead to short-term underperformance. The late 2022 market crisis is visible on in the impulse response. The greatest among all years. The 2020 pandemic didn't create great response in this strategy. Since 2022, shocks in repo create very strong response this strategy.

6 Conclusion

In this paper, we looked into the tails and performance of four representative HF strategies, with a special focus on the tails. In the aftermath of the 2020 pandemics many

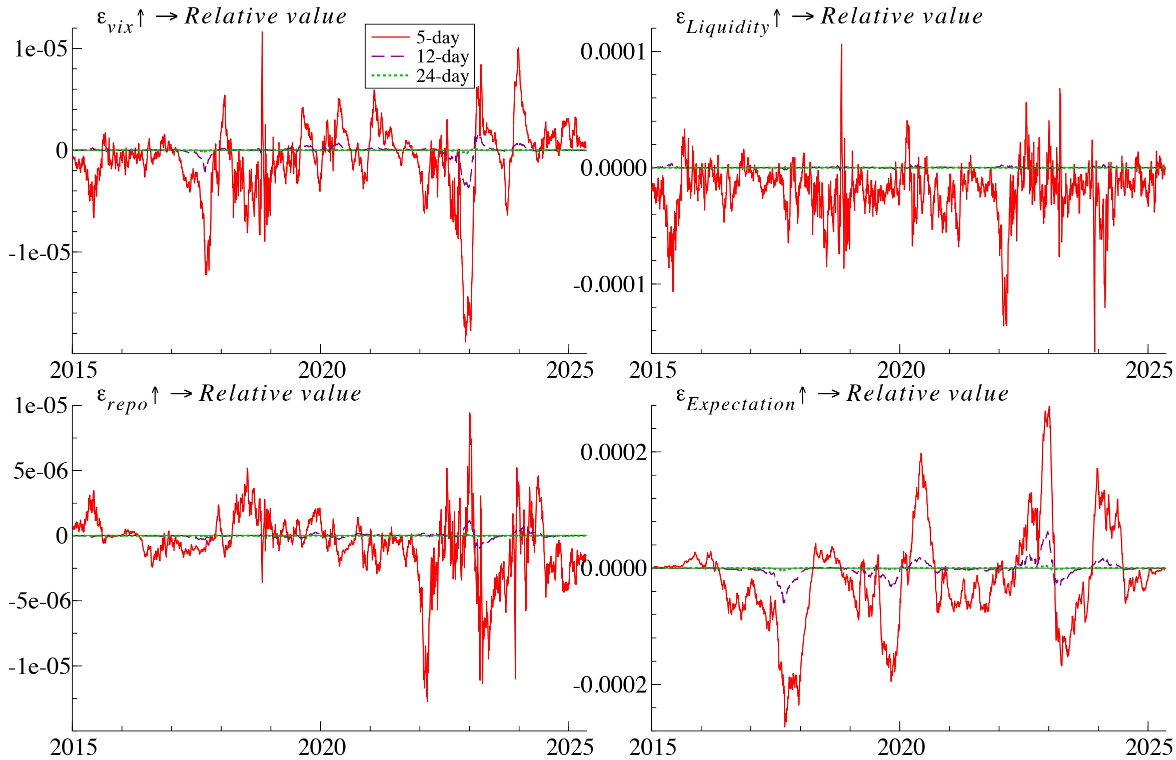

Figure 14: Relative value arbitrage strategy time-varying impulse response function. The 5-day, 12-day, and 24-day responses are shown in red, pink, and green respectively.

financial markets and assets witnessed great fluctuations. The tech company crashes in the 2022-2025, trade wars, Trump's second presidency among other exchange rate novel dynamics all require detailed investigation. HFs claim to be among the most smart investors famous for generating alpha. As a result, studying their dynamics and performance is quite important. For this reason, in this paper we study HFs strategies tails using a recently developed autoregressive Frechet distribution which builds upon block maxima and minima. We looked into the HFs tails both for the upper and lower end of their distribution from 2005 to 2025. We realized that overall, HFs have poor market timing and tail exposure. Macro and relative value arbitrage have experience strong tail jumps during market crisis. Overall the results, show that the 2008 GFC still has the largest ever effect on HF tails. We also find asymmetries between the right and left tail of all HFs, with left tail significantly exceeding its right tail range.

Given the turbulent nature of the economy during the last decade, we investigated the effect of the four macroeconomic indicator including CBOE VIX, repurchase agreement (repo), market liquidity (represented by the Amihud liquidity index), and the expectation on real economic conditions (as expectations) on each HFs strategies separately. We studied the IRFs of HFs LT to shocks in these economic indices. Our results show that, while the 2020 pandemic didn't create elevated impulse response chain behavior, the turbulent 2022 market created strong responses from HFs to shocks in the macroeconomic indices. We also witness that HFs response to the macroeconomic shocks have transitory nature and do not persist for more two weeks. This finding is in line with HFs dynamics portfolio management. The results show that, since the 2022, the repo rate shocks seem to cause great responses on the HF strategies. The literature has represented the repo rate as HFs' borrowing rate, thus this shows how HFs are getting more engaged with this rate. On the other side, the role of the Fed has had a strong impact on market conditions. This would further clarify why HFs have strong response to the repo rate. Our results show that, VIX still has the largest effect on HFs performance. We find that expectations and liquidity influence different strategies differently. Based on the average response of the HFs strategies to the macroeconomic indicators, equity hedge benefits from turbulent market, while event-driven strategy takes advantage of the calm market. Macro strategy following its investing agenda, is hit most from international political and monetary instability.

The findings shed light on the role and performance of the HFs during the last decade, with special focus on the last five years. HFs as one of the least disclosed financial intermediaries have been under further activity monitoring, such as the Dodd-Frank act. For this reason, in this study we looked into their performance and reaction through different market conditions. Our results will give insightful outcomes to the Fed, market officials and regulators, and any investor interested in following HF strategies or their performance.

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Appendix A HFRX indices description.

	We use the hedgefundresearch (HFR) following 4 strategy indices. These indices are net of all fees. Indices are based on funds with an asset under management (AUM) of at least $50 million and a minimum of 24 months of performance history. These summaries were taken from the HFR website.
HFRXEH	Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. Equity Hedge managers would typically maintain at least 50%, and may in some cases be substantially entirely invested in equities, both long and short.
HFRXED	Event Driven Managers maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including but not limited to mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. Event Driven exposure includes a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure.
HFRXM	Macro strategy managers trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom-up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ Relative Value Arbitrage techniques, Macro strategies are distinct from Relative Value Arbitrage strategies in that the primary investment thesis is predicated on predicted or future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and Equity Hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposed to Equity Hedge, in which the fundamental characteristics on the company are the most significant and integral to investment thesis.
HFRXRVA	Relative Value (Relative Value Arbitrage Index) investment managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Managers employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. Fixed income strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. RVA position may be involved in corporate transactions also, but as opposed to HFRXED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction