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Putting corona into hedge fund managers' head

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Abstract

The paper discusses the sensitivity of hedge funds' risk of failure, attributed to Covid-19 outbreak using a non-linear threshold multivariate analysis. The empirical results indicate that hedge funds shift their attention more towards informative signals depicting the impact of the Covid-19 pandemic and less towards indicators that reflect market sentiment, volatility, and momentum. By understanding the behaviour of active managers and their risk perception in relation with the impact of Covid-19 outbreak, we gain insights into the extent to which certain factors continue to play key role in hedge funds' risk perception during exceptional times such as the post Covid-19 period.

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Special issue "In memory of Professor Michel Terraza"

1. Introduction

The Covid-19 outbreak has forced most economies to shut down and implement drastic lockdowns in the early months of 2020. As the world is now trying to deal with the continuous waves of the virus, it would be useful to learn as much as possible from the first wave. It is commonly accepted that the Covid-19 pandemic will have long-term effects on all sectors of social and economic life (Goodell, 2020), and the financial sector is no exception. For active investors, such as hedge funds (HFs), this can create an opportunity to reset and adapt their strategies to the new market environment.

This letter focuses on the following question: during exceptional times, such as the Covid-19 pandemic, are HFs able to exploit a different set of market opportunities through adjustments in their leverage, short-term funding, portfolio exposure and strategy? This can occur when following a decision-making process that might be based less on momentum and sentiment, but more on dynamic adjustments that account for HFs' own risk evaluations. In a global economy dominated by the Covid-19 uncertainty, HFs may be forced to reset and/or adjust their strategies to gain an edge ahead over other market participants. An important question then is to what extent HFs continue to base their strategies solely on market dynamics (including price volatility and trading patterns), or rather prefer to turn their attention to informative signals that might better capture the whole impact of the pandemic crisis. Drawing on the data collected during the first wave of the Covid-19 outbreak, this letter analyses how HFs' strategies alter due to a series of factors that might suddenly come to play a prominent role in HFs' risk perceptions and evaluations.

We employ a non-linear threshold vector autoregressive (TVAR) framework, focusing on intensity the HFs' risk of failure, which is conditional on the sudden changes of levered positions, liquidity, and risk perception, before and during the Covid-19 pandemic's first wave. We focus on the responses during the first 6-months of the Covid-19 outbreak and how HFs perceive risk, proxied by the conditional Value at Risk. We attempt to answer three research questions: (i) what the response of leverage is; (ii) how short-term funding impacts risk of failure, since leverage requires funding from prime brokers; (iii) how risk perceptions and HFs' strategies are related or else, how active players assess risk during exceptional periods, since risk is one of the most determinant factors that influence their ability to leverage.

The findings show that, because of Covid-19 pandemic, HFs shift their attention from market volatility and momentum to economic policy uncertainty, degree of levered positions and short-term funding. All these latter factors reflect either less accurate trading signals, which do not immediately allow for a precise market positioning, or extreme financial stress that restrain HFs' abilities to chase new market opportunities, also influencing their short-term strategies. We believe our insights might be useful to a larger body of research, when evaluating the impact of HFs' investment strategies in relation to some of their possible determinants, which were subject to major economic fluctuations during and after the Covid-19 pandemic.

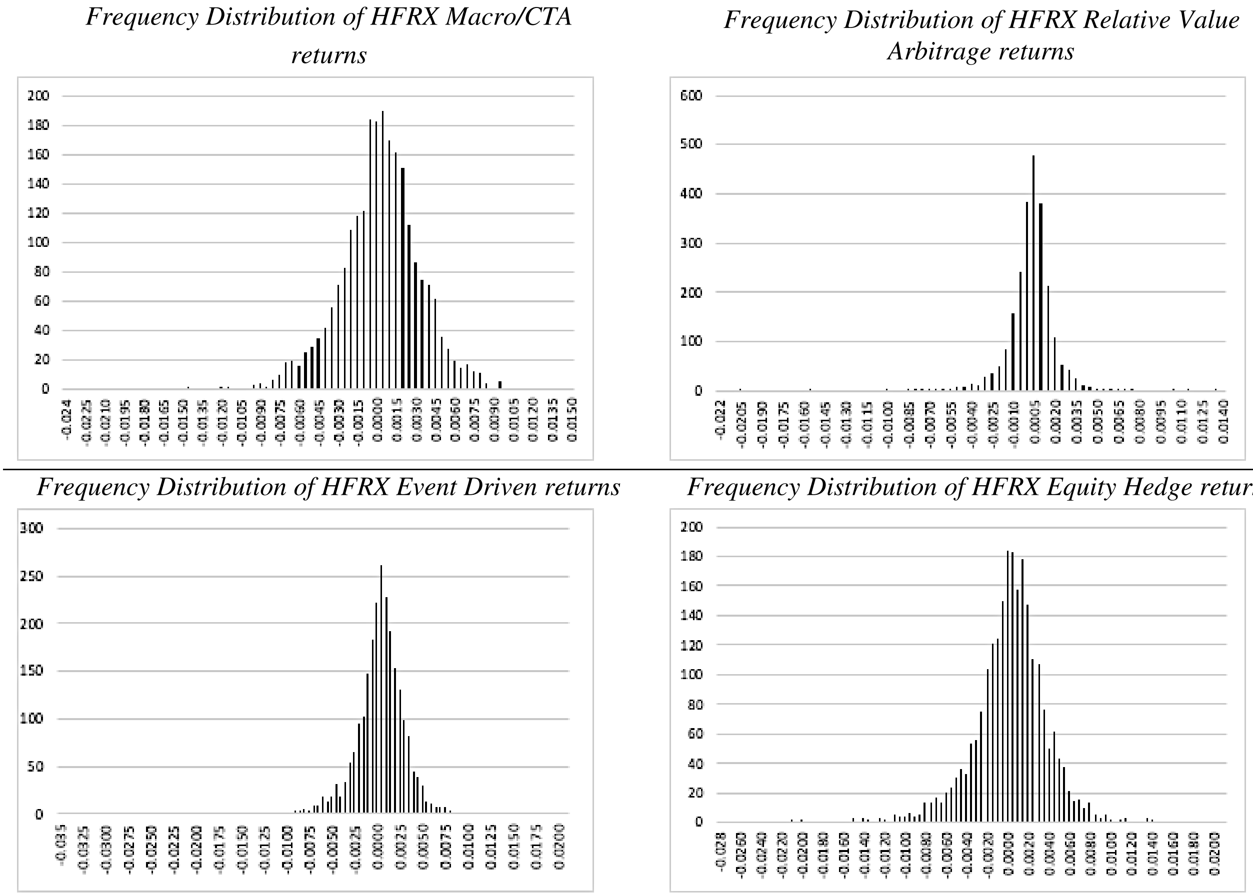
2. Data

Hedge funds' daily data come from the Hedge Fund Research (HFR) that constructs the HFRX Hedge Fund indices, which represent different hedge funds' investment strategies.[1] We focus on four main investable HFRX strategies, represented by the following indexes: (i) the *HFRX Event Driven* index; (ii) the *HFRX Equity Hedge* index; (iii) the *HFRX Macro/CTA* index; (iv) the *HFRX Relative Value Arbitrage* index. The period spans from the beginning of January 2011 until the end of July 2020, including significant worldwide economic and financial stress

[1] A detailed description of the HFRX strategies can be found in Table A1, in the Appendix. Source: https://www.hedgefundresearch.com/hfrx-index-characteristics. More information about the differences between the HFRX strategies can be found in Dragomirescu-Gaina *et al.* (2021).

events (e.g., the fall of oil prices 2014-2106, the trade war between USA and China, and so on), but also the first wave of the latest Covid-19 pandemic. We calculate the monthly Conditional Value at Risk (CVaR) for each HFRX strategy, using the Value at Risk under historical simulation with 95% level of confidence, to proxy the HFs' risk of failure.[2] CVaR is more sensitive to the shape of the tail of the loss (non-normal) distribution (Liang and Park, 2010; Limam *et al.*, 2017). Figure 1 reports the non-normal distribution of the HFRX indices' returns with fat left tails as evidence of higher risk of failure.

Figure 1. Distribution of HFRX strategies' returns



Notes: The figure illustrates the histogram for each HFRX strategy.

We consider five main factors that affect HFs' risk of failure.[3] First, we use the monthly (average) *volatility index* (*VIX*) provided by the Chicago Board Options Exchange. Volatility index is a good proxy for market sentiment, interpreted as the level of risk (Fassas and Siriopoulos, 2020). Higher levels of implied volatility refer to upcoming volatile periods even though implied volatility tends to overestimate future realized volatility. To capture systemic stress, we consider the Financial Stress Index (*FSI*) constructed by the St. Louis Fed for the US

[2] We calculated the Value at Risk (VaR) using both the variance-covariance (VCV) and the historical simulation (HS) methods, with 90%, 95% and 99% level of confidence. Thus, we computed the monthly CVaR derived from VCV and HS, using 22 working days of every month in our sample. Results are similar; however, it is up to analyst's decision.

[3] Data are available from Bloomberg.

market, available on monthly basis.[4] Periods of heightened financial stress and weak economic activity are episodic and generally coincide. We moreover consider the economic policy uncertainty (*EPU*) indicator (in log values) (Baker *et al*., 2016) to proxy for uncertainty based on (textual) information accessible through media coverage. EPU captures market agents' behaviour in relation to news, and other media-related factors, acting as a proxy for economic activity sentimental measure.

Next, we use the (log values of) Debt Margin Accounts (DMA) as a proxy for the degree of levered positions (Ang *et al*., 2011; Richardson *et al*., 2017), deriving the data from FINRA database.[5] The margin debt is the total amount (aggregate) of debit balances in customer securities margin accounts held by NYSE member firms. Finally, we take the Treasury Eurodollar spread (*TED spread*) which measures the tightness of the funding and funding liquidity (Agarwal *et al*., 2013; Richardson *et al*., 2017). The TED spread is a good proxy for the cost of short-term borrowing for prime brokers and therefore for leverage funding as it shows how prime brokers finance their hedge fund clients. Higher TED spreads can be seen as lower market liquidity because lenders require a higher rate of interest or are willing to accept lower returns on investments considered safe, such as T-bills.

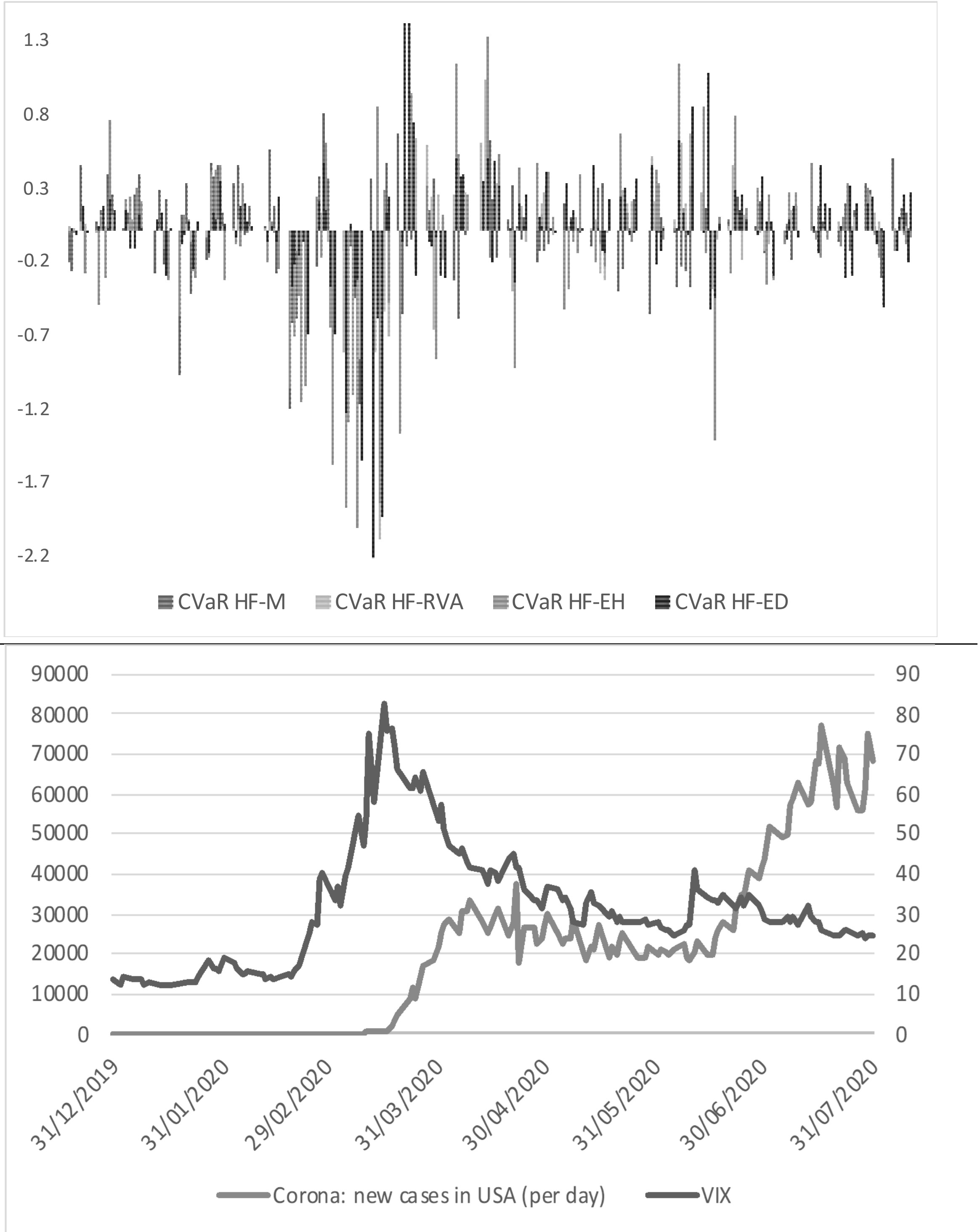
Results from a preliminary analysis for the HFRX CVaR strategies and the factors over the total sample period, before (pre-) and after (post-) the outbreak of Covid-19 pandemic are presented in Table A2 (Appendix). We observe that all the measures have high (absolute) values for skewness and kurtosis, illustrated also by their leptokurtic distributions with larger tails in returns (as we highlight in Figure 1), confirming a high sensitivity to stress events.[6] Correlations across the CVaRs are high, but low among the factors. Monthly averages and deviations of CVaR measures and market volatility (VIX) didn't change significantly during the Covid-19 pandemic. They initially followed an increasing momentum of high uncertainty but became rapidly smoothed afterwards, even when the number of new infected cases in USA was getting higher, as Figure 2 shows.

[4] The FSI is an equal-variance weighted average of eighteen explanatory variables, capturing various aspects of risk in different segments of the market.4 Three main categories of indicators are included: (a) interest rates (e.g., federal funds rates, short- and long-term Treasury rates, corporate bond yields, etc.); (b) yield spreads; and (c) other indicators (e.g., market volatility indices).

[5] Source: https://www.finra.org/investors/learn-to-invest/advanced-investing/margin-statistics.

[6] A detailed description of the preliminary analysis can be found in Table A2.

Figure 2. CVaR measures – New corona cases in the USA – VIX



Notes: The figure presents the daily CVaR measures (in bars, chart above), the new daily cases infected in the USA (grey line chart below) and the daily volatility index (VIX) values (black line chart below). The time period spans from the beginning of starting January 2020 to end of July 2020.

3. Empirical design

We design a two-step framework and apply it for two periods, the pre-Covid-19 period (until the end of 2019) and the overall sample including the Covid-19 outbreak (until July 2020).

In the first step, we specify a forward stepwise least square regression for the CVaR measure, of each HFRX strategy. This univariate regression model is used to obtain which factors have a greater impact on HFRX CVaR measures and to overcome any multicollinearity issues. We begin with no candidate variables in the model and at each step we add the candidate variable that increases R-squared the most and cannot be omitted afterwards. At the end, we stop adding variables when none of the remaining variables are significant, in terms of R-squared values.

In the second step, we estimate a non-linear threshold VAR model with five endogenous variables i.e., four CVaR measures (one for each HFRX strategy considered) and one factor as described in section 2. Non-linearity can address shocks' features such as differences with regards to their direction (positive vs. negative shocks), their size (small vs. large shocks), and differences in initial conditions (regime-dependencies). A threshold VAR (TVAR) model specification allows for a higher degree of nonlinearity in the parameters due to financial stress and violent changes in the economy, such as those generated by the Covid-19 pandemic. The threshold marks the triggering value of the factor and generates regime-switching behaviour. The TVAR can capture differences in initial conditions (regime dependencies),[7] whereby a shock would trigger disproportionate effects with different response magnitudes for the HFRX indices, depending on whether the shock is large or small and positive or negative, and time indifferent when the shock hits.

We use a "structural" threshold vector autoregression (TVAR) with one threshold (i.e., two regimes) and heteroscedasticity across the regimes (Balke, 2000; Afonso *et al.*, 2011), given without loss of generality as:

$$Y_t = A^1 Y_t + B^1(L)Y_{t-1} + (A^2 Y_t + B^2(L)Y_{t-1})I(z_{t-d} > \gamma) + U_t \tag{1}$$

where Y_t is a [5 x 1] vector containing the four indices of CVaR HFRX strategies, and a risk factor, as described in Section 2. $B^1(L)$ and $B^2(L)$ are the lag polynomial matrices while U_t are structural disturbances. z_{t-d} is the threshold variable (at lag order d, labelled as the delay parameter) that determines which regime the system is in, and $I(z_{t-d} > \gamma)$ the indicator function that equals one when $z_{t-d} > \gamma$ and zero otherwise. Because the threshold variable, z_{t-d}, is a function of risk factor's values (which in turn is an element in Y_t), the TVAR describes both the evolution of Y_t and the regimes. This implies that shocks to CVaR of the HFRX indices, as well as to risk factor can determine whether the system is in a tight stress regime. In addition to the lag polynomials changing across on regimes, contemporaneous relationships between variables may change as well. A^1 and A^2 reflect the "structural" contemporaneous relationships in the two regimes, respectively. The threshold is determined endogenously by a grid search over possible values of the triggered variable where the grid is trimmed at a lower and upper bound to ensure enough observations for the estimation in both regimes.[8] From the grid, the estimated threshold value corresponds to the model with the smallest determinant of the variance-covariance matrix of the estimated residuals, denoted as Ω_t:

$$\gamma^* = \underset{\gamma}{\operatorname{argmin}}\, log|\Omega_t(\gamma)| \tag{2}$$

We derive the main findings based on an analysis of generalised impulse response functions (GIRFs) to unexpected shocks in each factor (Koop *et al.*, 1996) in period k.

[7] The impact of the nature of shocks (their magnitude, direction, or both), materializes conditional on initial condition in which the shock hits. Initial conditions serve as an amplification (or attenuation) mechanism to the propagation of shocks. Consequently, initial conditions govern to what extent shocks of different size or direction generate nonlinearities.

[8] The level of trimming is chosen arbitrarily by the econometrician. No general guideline exists though 15% is very often used in the literature. The higher the number of data points, the less one is restricted in choosing extreme trimming values. For the present analysis, the data were trimmed to assure a minimum of 30% of the observations in each regime.

$$GIRF_y(k, u_t, \Omega_t) = E(Y_{t+k}|\Omega_{t-1}, u_t) - E(y_{t+k}|\Omega_{t-1}) \quad (3)$$

where Y_{t+k} is the vector of variables at horizon k.

4. Empirical results and interpretations

We start by setting up the TVAR specifications. To ensure that there is no serial correlation in the residuals, we use 1 to 3 lag lengths for the TVARs, based on the Akaike information criterion (AIC).[9] Table 1 summarizes the main results of the forward stepwise least square regression and reveals a consistent relationship between the HFRX strategies' risk of failure and the factors, both before and during the Covid-19 outbreak.[10] Tables 2 and 3 display the sign (direction of changes) and the horizon intervals for which the GIRFs are statistically significant in reaction to shocks in each factor considered.[11]

Table 1. Forward Stepwise Least Squares regression

Panel A: For the period until the end of 2019

CVaR HFRX	*constant*	*VIX*	*log(DMA)*	*TED spread*	*FSI*	*logEPU*
CVaR HFRX Macro/CTA	0.416	-0.038^{***} [R^2=0.21]	-	-	-	0.373^{*} [R^2=0.21]
CVaR HFRX Relative Value Arbitrage	-0.281^{*}	-0.027^{***} [R^2=0.11]	-	-0.08^{***} [R^2=0.12]	0.123^{***} [R^2=0.15]	0.225^{**} [R^2=0.19]
CVaR HFRX Event Driven	-0.612^{**}	-0.046^{***} [R^2=0.04]	-	-0.149^{***} [R^2=0.05]	0.23^{***} [R^2=0.09]	0.404^{*} [R^2=0.13]
CVaR HFRX Equity Hedge	-0.285	-0.047^{***} [R^2=0.12]	-	-	-	0.797^{*} [R^2=0.12]

Panel B: For the full period (until July 2020)

CVaR HFRX	*constant*	*VIX*	*log(DMA)*	*TED spread*	*FSI*	*logEPU*
CVaR HFRX Macro/CTA	0.55^{**}	-0.035^{***} [R^2=0.06]	2.02^{**} [R^2=0.10]	-0.04 [R^2=0.11]	-0.10- [R^2=0.14]	0.302^{**} [R^2=0.21]
CVaR HFRX Relative Value Arbitrage	0.385^{**}	-	1.66^{***} [R^2=0.081]	-	0.015^{**} [R^2=0.081]	-
CVaR HFRX Event Driven	-0.097	-	-	-	-	0.084^{*} [R^2=0.13]
CVaR HFRX Equity Hedge	0.232	-	-	-	-0.008^{*} [R^2=0.15]	0.327^{***} [R^2=0.15]

Notes: The table reports the estimated coefficients derived from the forward stepwise regression framework, for each CVaR HFRX strategy. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively. A dash indicates that the corresponding variable was not included in the regression. For every step, the corresponding R^2 is given in brackets.

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[9] More details about the optimal lag length criteria can be found in Table A4, in the Appendix.

[10] Stepwise regression allows some or all the variables in a standard linear multivariate regression to be chosen automatically, using various statistical criteria (p-value criterion in our analysis), from a set of variables (Hurvich and Tsai, 1990).

[11] We use a conservative interval of 95% for confidence bands and 1 standard deviation on either side of the median impulse responses. The graphical illustrations of some cited examples of the GIRFs are available at the accompanying online Supplement (Figures A and Figures S).

Table 2. TVARs: GIRFs to an unexpected shock in one factor for the period until the end of 2019

Significant GIRFs (horizon)	CVaR HFRX Macro/CTA Index	CVaR HFRX Relative Value Arbitrage Index	CVaR HFRX Event Driven Index	CVaR HFRX Equity Hedge Index
Regime 1 (positive)				
DMA (logs)	n.s.	n.s.	n.s.	n.s.
VIX	1-4 (+)	1-3 (+)	1-3 (+)	1-3 (+)
TED Spread	n.s.	n.s.	n.s.	n.s.
FSI	n.s.	n.s.	n.s.	n.s.
EPU	n.s.	n.s.	1-2 (+)	n.s.
Regime 2 (negative)				
DMA (logs)	n.s.	n.s.	1-2 (+)	n.s.
VIX	1-5 (+)	n.s.	n.s.	n.s.
TED Spread	1-2 (+)	n.s.	n.s.	n.s.
FSI	n.s.	n.s.	n.s.	n.s.
EPU (logs)	n.s.	n.s.	1-2 (+)	n.s.
Thresholds (until 12/2019)	$\hat{\gamma}_{VIX} = 0.1323$, $\hat{\gamma}_{TEDSPREAD} = 0.2235$, $\hat{\gamma}_{FSI} = -0.7430$, $\hat{\gamma}_{logEPU} = 2.5693$, $\hat{\gamma}_{logDMA} = 5.7755$			

Notes: Numbers displayed in the table denote the horizon intervals for which the GIRFs are statistically significant at +/- 1 standard deviations. The (-) or (+) denotes the sign or direction of the GIRFs in the specified interval. The label n.s. in the table means that, given the confidence bands, GIRFs are not significant for (at least) two consecutive observations. The threshold values are reported at the last raw of the table. The maximum horizon is truncated at 10 months. All the GIRFs figures are available at the online Supplement.

Table 3. GIRFs to an unexpected positive shock of one factor for the full period (until July 2020)

Significant GIRFs (horizon)	CVaR HFRX Macro/CTA	CVaR HFRX Relative Value Arbitrage	CVaR HFRX Event Driven	CVaR HFRX Equity Hedge
Regime 1 (positive)				
DMA (logs)	1-3 (+); 4-6 (-).	1-5 (-); 6-8 (+)	1-5 (-); 6-8 (+)	1-4 (-); 6-8 (+)
VIX	1-2 (+)	n.s.	n.s.	n.s.
TED Spread	1-3 (-)	1-6 (-)	1-3 (-)	1-3 (-)
FSI	n.s.	n.s.	n.s.	n.s.
EPU (logs)	1-4 (-)	1-9 (+)	1-9 (+)	1-6 (+)
Regime 2 (negative)				
DMA (logs)	n.s.	n.s.	n.s.	n.s.
VIX	1-4 (+)	n.s.	n.s.	n.s.
TED Spread	n.s.	1-2 (+)	1-2 (+)	n.s.
FSI	n.s.	n.s.	n.s.	n.s.
EPU (logs)	n.s.	n.s.	n.s.	n.s.
Thresholds (full period)	$\hat{\gamma}_{logDMA} = 5.5379$, $\hat{\gamma}_{VIX} = 0.1921$, $\hat{\gamma}_{TEDSPREAD} = 0.2122$, $\hat{\gamma}_{FSI} = -0.7372$, $\hat{\gamma}_{EPU}$ =2.1044			

Notes: Numbers displayed in the table denote the horizon intervals for which the GIRFs are statistically significant at +/- 1 standard deviations. The (-) or (+) denotes the sign or direction of the GIRFs in the specified interval. The label n.s. in the table means that, given the confidence bands, GIRFs are not significant for (at least) two consecutive observations. The threshold values are reported at the last raw of the table. The maximum horizon is truncated at 10 months. The corresponding GIRFs figures are available at the online Supplement.

There are some interesting findings derived from our framework. Until the end of 2019 (pre-Covid-19 period), we find evidence that HFs' managers were interested only in market volatility (VIX). Any VIX spikes were reflected in the CVaR measures of the four HFRX strategies. However, this behaviour changes after the Covid-19 outbreak. More specifically, levered positions (DMA), short-term funding (TED spread), financial stress (FSI) and economic uncertainty (EPU) all contribute to the risk of failure for all HFRX strategies with a mixed way, while market volatility (VIX) became less significant. This is also evident from the forward stepwise regression and can be illustrated by comparing GIRFs before and after the Covid-19 outbreak.

When addressing the relation between levered positions and HFs' risk, higher leverage leads to higher potential losses during the Covid-19 period, and excessive leverage leads to extremely large losses. In other words, exposing the direction of the underlying leverage in debt margin accounts seems less significant for stable periods, but becomes a significant factor on periods of high uncertainty for two HFRX strategies namely Macro/CTA and Relative Value Arbitrage.

Moreover, we find a statistically significant opposite movements between short-term funding and CVaR measures of HFRX Event Driven and Equity Hedge strategies before and, for Macro/CTA after the Covid-19 outbreak. When liquidity is abundant, HFs would not be impacted by margins and capital changes. During the Covid-19 pandemic instead, access to liquidity becomes difficult due to higher uncertainty and therefore, HFs intend to pay more attention on margin accounts. If liquidity suddenly dries-up, events such as flight to quality and margin/liquidity spiral may occur, which leads to further deterioration in the market equilibrium, impact on HFs capacity to lever their positions and their current leverage exposures and on their ability to meet margin calls.

The unidirectional influences from market volatility (VIX) on CVaRs became insignificant (except Macro/CTA strategy) when we make a comparison with the pre-pandemic period when it was the only significant factor. This indicates that market volatility is mostly a momentum factor for HFs, generating influences based on market pricing dynamics when no other major exogenous stress event occurs. Similar results can be found for the financial stress indicator, FSI.

Policy uncertainty (EPU) and financial stress (FSI) tend to become important during the pandemic. This supports the evidence of manager overconfidence observed before major financial crises (Malmendier *et al*., 2011). However, a misleading market risk assessment may lead to excessive use of leverage during the good times, resulting in higher levels of downside risk and higher losses during the bad times. We find positive and statistically significant effects of economic policy uncertainty and financial stress to the level of CVaRs, after the Covid-19 outbreak, thus confirming the HFs' pro-cyclical behaviour (Adrian and Shin, 2010; Dragomirescu-Gaina *et al*., 2021). These findings also challenge the convexity of the manager incentive option that would rather tend to encourage HFs on taking additional risk. However, the GIRFs seem to fade out rather fast, suggesting that managers are not keen to take an unbounded amount of risk because the fear of liquidation is stronger than a one-off extreme performance.

To conclude, our findings suggest that during exceptional times such as the current Covid-19 outbreak, HFs become less interested in indicators like market volatility that depict a momentum strategy. In contrast, they shift attention to indicators that are more informative about current market opportunities or to informative signals that are more directly related with the whole impact of Covid-19. As we observe from the GIRFs responses, they alter their strategies in short-term periods or during the peak of the outbreak, while paying higher attention to funding costs and leverage. The HF managers "felt" the high uncertainty as momentum for a short period during the Covid-19 outbreak and then they go back to "business as usual" strategies. Finally, our analysis also points to a relative significant effect of systemic stress events that works as a trade-off between accuracy and priority.

5. Conclusion

This bulletin uses a non-linear threshold VAR framework to expose how hedge funds' managers perceive risk during the Covid-19 outbreak. We estimate the direction and intensity of HFs' risk of failure responses to shocks in their levered positions and short-term funding. We find evidence that HFs are more likely to shift their focus on informative signals depicting the whole complex impact of the Covid-19 pandemic, and away from conventional volatility indicators that are more likely to reflect market sentiment and momentum. The nonlinear analysis is therefore strongly linked to the idea that the impact of certain shocks depends on initial conditions and is amplified (or attenuated) focusing on informative signals, whenever there is regime-switching from a favourable (no pandemic) to a non-favourable (high pandemic outbreak) regime. Notably, our implications are focused on the four HF styles, but we argue that many other market agents involved may be also part of the risk of financial sectors and markets across countries and therefore HFs are examined under the context of active investors and should be seen as small part of the aggregated global financial system under the Covid-19 outbreak.

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APPENDIX

Table A1. CVaR of HFRX strategies

Notes: The HFRX Hedge Fund (HFR) indices represent different focus on hedge funds' investment strategies. Every index represents eligible hedge fund strategies including convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, relative value arbitrage and so on. HFR utilises a methodology based on well-defined, predetermined rules and objective criteria to select and rebalance index components and maximise the representation of the HF investable universe. The construction of each index employs state-of-the-art quantitative techniques and qualitative analysis (i.e., multi-level screening, cluster analysis, Monte Carlo simulations, optimisation techniques, etc.), which ensure that each index is a pure representation of its corresponding HF investment style (Source: https://www.hedgefundresearch.com/hfrx-index-characteristics). More information about the differences between the HFRX strategies can be found in Dragomirescu-Gaina *et al*. (2021).

HF Investment strategy	Description
Event Driven	Event Driven managers maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments.
Equity Hedge	Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities and can range in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios.
Macro/CTA	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.
Relative Value Arbitrage	Relative Value investment managers maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities.

Additional notes:

[1] 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.

[2] Relative Value (RV) strategies, also called arbitrage strategies, are trading strategies that exploit mispricing in the financial markets among the same or related assets. Relative value trading is a popular investment strategy among many hedge fund managers who try to achieve high returns while minimizing risk. Note that Relative Value (RV) position may be involved in corporate transactions also, but as opposed to ED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

[3] Although main strategies employ RV techniques, Macro strategies are distinct from RV 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.

Table A2. Preliminary analysis

Notes: The table (panels A and B) reports the means, standard deviations (st. dev.), skewness (skew) and kurtosis (kurt.) for the CVaR HFRX strategies and factors over the sample period (N=117 obs.), before the outburst of corona virus pandemic (end of 2019 with N=110 obs.) and the 7-months period of corona virus effect (N=7 obs.).

Panel A. Descriptive statistics of the CVaR HFRX strategies

HFRX strategies	CVaR HFRX Macro/CTA	CVaR HFRX Relative Value Arbitrage	CVaR HFRX Event Driven	CVaR HFRX Equity Hedge
Mean: full sample	-0.0065	-0.0028	-0.0052	-0.0068
Mean: end at 12/2019	-0.0065	-0.0027	-0.0050	-0.0065
Mean: from 01 to 07 month of 2020	-0.0074	-0.0054	-0.0085	-0.0107
Standard deviation: full sample	0.0037	0.0028	0.0044	0.0045
Standard deviation: end at 12/2019	0.0037	0.0022	0.0036	0.0043
Standard deviation: from 01 to 07 month of 2020	0.0037	0.0072	0.0112	0.0071
Skewness: full sample	-1.8622	-3.5593	-3.3471	-1.9090
Skewness: end at 12/2019	-1.9709	-2.6377	-2.1521	-1.8971
Skewness: from 01 to 07 month of 2020	-0.2613	-2.1706	-2.5309	-1.4509
Kurtosis: full sample	4.5354	17.9169	16.5595	5.1559
Kurtosis: end at 12/2019	4.9958	10.6393	7.2725	5.6351
Kurtosis: from 01 to 07 month of 2020	-2.0390	5.0413	6.5307	2.1409

Panel B. Descriptive statistics of the factors

Factors	Debt Margin Accounts	VIX	TED SPREAD	FSI	EPU
Mean: full sample	491564.9138	17.1689	0.3092	-0.2819	165.3778
Mean: end at 12/2019	487702.3394	16.2383	0.3039	-0.3440	155.9210
Mean: from 01 to 07 month of 2020	551710.7143	31.6596	0.3929	0.6857	312.6338
Standard deviation: full sample	105370.6318	6.8066	0.1479	0.5707	64.4207
Standard deviation: end at 12/2019	107100.9696	4.8159	0.1116	0.3816	51.3886
Standard deviation: from 01 to 07 month of 2020	42945.7012	14.4841	0.4317	1.5678	71.3097
Skewness: full sample	-0.3675	2.9242	3.2544	3.6388	1.3278
Skewness: end at 12/2019	-0.2889	2.0284	0.8349	0.8666	0.9110
Skewness: from 01 to 07 month of 2020	-0.3631	0.8643	2.3305	1.5217	-0.4086
Kurtosis: full sample	-0.9563	11.9945	19.3814	21.2942	1.7552
Kurtosis: end at 12/2019	-1.0367	5.4567	-0.3033	0.3883	0.1197
Kurtosis: from 01 to 07 month of 2020	0.6532	0.8738	5.5478	1.4976	-0.6871

Table A3. Non-linearity test

Notes: The table presents standard inferences for testing a linear VAR against a threshold alternative to validate the choice of a TVAR model, derived from the test of Hansen (1996). All the results reject the null hypothesis of one state model.

	Log Likelihood	Likelihood Value	Likelihood Ratio
CVaR	38.7459	26.5756	12.1703
VIX	46.9434	23.6134	23.3299
Debt Margin Accounts	60.5996	42.8987	17.7008
TED spread	49.0165	26.9607	22.0558
(log) EPU	59.8286	41.5372	18.2914
FSI	53.4715	35.7368	17.7347

<u>*Reference*</u>

Hansen, B.E. (1996). "Inference when a nuisance parameter is not identified under the null hypothesis". *Econometrica* **64**, 413–430.

Table A4. Lag length criterion

Notes: The table presents the Akaike information criterion for optimal lag length structure in a standard VAR. The results show 1 lag up to 3 for the TEAD spread framework.

AIC (lags)	VIX	Debt Margin Accounts (logs)	TED spread	FSI	EPU (logs)
1	-41.301*	-41.319*	-23.980	-44.120*	-35.917*
2	-41.164	-41.100	-23.972	-44.088	-35.792
3	-40.842	-40.830	-24.042*	-44.078	-35.525

Table A5. TVAR coefficients (post Covid–19 pandemic outbreak)

Note: the table presents the coefficient (sensitivity) of the factor to the corresponding CVaR measure, for a TVAR specification, for each regime (taken from Eq. (1) the last row's coefficients of A_1 and A_2). A (*) denotes the statically significant coefficient (for a=0.95).

	CVaR HFRX Macro/CTA	CVaR HFRX Relative Value Arbitrage	CVaR HFRX Event Driven	CVaR HFRX Equity Hedge
Regime 1 (Matrix A_1)				
DMA (logs)	-0.00326*	-0.0053*	-0.0042*	-0.004*
VIX	0.00679*	0.00563	0.01237	0.00443
TED Spread	-0.06192*	-0.1350*	-0.08242*	-0.0497*
FSI	-0.2238	-1.1160	-0.3217	-0.4427
EPU (logs)	0.0690*	0.0553*	0.0201*	0.0152*
Regime 2 (Matrix A_2)				
DMA (logs)	-0.0020	-0.0065	-0.0038	-0.0014
VIX	0.01894*	0.08324	0.0190	0.0007
TED Spread	0.00427	0.00261*	0.0155*	-0.0035
FSI	0.5107	-0.3217	0.25387	-0.2774
EPU (logs)	0.00658	0.00031	0.0019	-0.0017