SCUOLA DI DOTTORATO
UNIVERSITÀ DEGLI STUDI DI MILANO-BICOCCA

Department of Economics, Management, and Statistics (DEMS)

PhD program in Economics & Statistics Cycle: 34th

Curriculum in Economics

ESSAYS IN EMPIRICAL FINANCE

Surname: Noori Name: Mohammad

Registration number: 839391

Tutor: Claudio Morana

Supervisor: Asmerilda Hitaj

Coordinator: Matteo Manera

ACADEMIC YEAR 2022/2023

ESSAYS IN EMPIRICAL FINANCE

MOHAMMAD NOORI

A PhD dissertation submitted to
the University of Milano–Bicocca
in partial fulfillment of the requirements for the
PhD degree in Economics & Statistics

Spring 2023

Inspirational Quotes

"Everybody is a genius. But if you judge a fish by its ability to climb a tree, it will live its whole life believing that it is stupid."

Albert Eisntein, Physicist

"Business is business. I don't manufacture cars, but we do manufacture money."

Kenneth Griffin, Hedge fund manager

"Drink wine. This is life eternal. This is all that youth will give you. It is the season for wine, roses and drunken friends. Be happy for this moment. This moment is your life."

Omar Khayyam, Mathematician & Astronomer

"Science knows no country, because knowledge belongs to humanity, and is the torch which illuminates the world."

Louis Pasteur, Microbiologist

Acknowledgment

My doctoral studies started in November 2018 and ended in January 2023 at the University of Milano–Bicocca. During these years, I had so many wonderful moments, gained precious life experience in every aspect, and met many people across countries, cultures, and different social strata. Through these unique experiences, I was able to form a concrete perspective on living, and this gave me a deeper understanding of life, although scientifically specifically, following Bayes' rule, I keep updating my beliefs!.

First and foremost, I would like to thank my supervisor, Professor Asmerilda Hitaj, for her continuous support. We often had lengthy discussions about my ideas, which could last several hours a day, and I am grateful to her for listening to me and encouraging me to move forward. I also need to thank my fellow PhD students, Giorgio Massari, Marco Rispoli, Marco Membretti, and Marco Repetto. I must express my gratitude to Professor Matteo Manera for his support during my PhD studies.

During 2022, I was invited by Professor Vikas Agarwal, one of the world's leading scholars in the managed fund industry at the Robinson College of Business for a rather long academic visit to Georgia State University. Having this academic visit was very crucial to me, though it was not without its ups and downs. Academically, it was truly conducive, as the papers that I will write for several years after my PhD studies will be based on the ideas that I developed during this academic visit. It was there that I had the chance to benefit from research-related activities, including attending leading international conferences, brown bags and internal seminars, having access to rich data bases, etc., which really gave me a vision for cutting-edge level research. Thus, a sincere thanks to Professor Agarwal, and to the department of finance at Robinson College of Business for hosting me.

I am also grateful to the administrators and lecturers at the Stockholm School of Economics, the Swiss Finance Institute, and Georgia State University for letting me have the opportunity to participate in their research courses and internal research seminars/conferences.

Last but not least, my special thanks goes to my parents and siblings.

Abstract

All models are wrong but some are useful.

George P. E. Box

This PhD dissertation is comprised of two substantive chapters in different areas of empirical finance. In the first chapter which is published in the **International Review of Financial Analysis**, I dissect the investing style of different hedge fund strategies, while in the second chapter (under review at Oxford Bulletin of Economics and Statistics), I investigate the stock-oil conditional comoments, by employing a battery of modern econometric methods. The following paragraphs provide a summary for each chapter.

The first chapter, **"Dissecting Hedge Funds' Strategies"** (*joint with Asmerilda Hitaj*), dissects the dynamics of the hedge fund industry with four financial markets, including the equity market, commodities, currencies, and debt market by employing a large number of assets from these markets. We employ four main representative hedge fund strategy indices, and a cap-weighted global index to estimate an asymmetric dynamic conditional correlation (ADCC) GJR-GARCH model using daily data from April 2003 to May 2021. We break down the performance, riskiness, investing style, volatility, dynamic correlations, and shock transmissions of each hedge fund strategy thoroughly. Further, the impact of commodity futures basis on hedge funds' return is analyzed. Comparing the dynamic correlations during the 2008 global financial crisis (GFC) with COVID-19 pandemic reveals changing patterns in hedge funds' investing styles. There are strong and pervasive shock spillovers from hedge fund industry to other financial markets, especially to futures commodities. An increase in the futures basis of several commodities drives up hedge funds' performance. While hedge fund industry underperforms compared to equity market and commodities, the risk-reward measures show that hedge funds are superior to other markets, and safer than the bond market.

In regards to the first chapter, we would like to thank the participants at the Third Symposium of the Emerging Topics in Financial Economics at Linkoping University, the DATA21 Conference at University of Bahrain, and the ReLunch seminar at the University of Milano-Bicocca for helpful suggestions. We are grateful to four anonymous referees, Brian Lucey, and Hamid Beladi for their valuable comments and opinions.

The second chapter **"Stock-Oil Comovements Through Fear, Uncertainty, and Expectations: Evidence from Conditional Comoments"**, investigates the dependencies and comovements between the S&P 500 and WTI by means of time-varying conditional comoments from April 1983 to December 2021 at the daily level. The conditional comoments mark a new pattern between the two markets' dependencies since the 2008 global financial crisis (GFC). I employ three macroeconomic sentiment measures, including VIX (representing fear), economic policy uncertainty (representing uncertainty), and expected business condition index (representing expectation), to investigate the underlying mechanism for the new emerging stock-oil comovements, using the time-varying parameter vector autoregression (TVP-VAR) to investigate the time-varying impulse responses, and the nonlinear autoregressive distributed lag (NARDL) model to analyze the asymmetries in the short- and long-run effects of the sentiment indices for the pre- and post-GFC periods. The conditional comoments of both markets change direction since the GFC, with crude oil showing a stronger dependence on the S&P 500's return, skewness, and tail events than its counterpart. Overall, the time-varying impulse responses show heightened short-lived responses to the three sentiment indices after the 2008 GFC, with an asymmetric response from the conditional comoments of WTI (negative) and S&P 500 (positive) to the positive shocks in the fear index during the post-GFC period. The NARDL regression results prove that the explanatory power of the three sentiment indices increase largely after the GFC, pointing to the strong short-run asymmetries, and the ever-increasing effect of VIX. Further investigations reveal that oil-specific fear index (OVX) has weaker effect on stock-oil comoments than VIX.

In regards to the second chapter, I am grateful to the participants and chairs of the 8^{th} International Symposium on Environment and Energy Finance Issues, the 3^{rd} Financial Economics Meeting, the International Conference on Economic Modeling and Data Science, and the 39^{th} USAEE/IAEE North American Conference for their comments and opinions. I also need to thank two anonymous reviewers for their comments and suggestions.

Contents

List of Figures

List of Tables

Chapter 1

Dissecting Hedge Funds' Strategies

MOHAMMAD NOORI
ASMERILDA HITAJ

Published in the International Review of Financial Analysis
https://doi.org/10.1016/j.irfa.2022.102453

1.1 Introduction

This paper is motivated by Büyükşahin & Robe (2014), Singleton (2014), and Knittel & Pindyck (2016) , who blame Hedge Funds (HFs) for making noise, fluctuations, and price bubbles across different financial markets; and by another strand of literature which attributes the increased fluctuations in commodities to non-commercial players, including Chong & Miffre (2010) who argue the futures market has become an essential tool for strategic asset allocations; Tang & Xiong (2012), who find higher correlations among non-energy commodity prices; and Christoffersen et al. (2019) who argue the heightened volatility of commodity markets is linked to other markets' shock spillover. In this regard, we investigate the dynamics of the HFs with a large number of assets from four financial markets, including commodity futures, equities, currencies, and debt markets, with a special focus on futures contracts. We employ a variety of methods, including time-varying comovements and systemic shock transmission between HFs and other financial markets, to dissect the investing styles of different HF strategies. Then we calculate the futures basis, which is defined as the gap between futures and spot prices, for 13 commodities from the 5 primary categories of commodity futures (Gorton et al., 2013), which have the most liquid and active market in their own category[1] (Christoffersen et al., 2019) to figure out HFs' speculative behavior in commodities. Despite being inspired by Büyükşahin & Robe (2014), this study departs from their work in a number of ways. First, we only focus on modelling the dynamics of the HFs, and second, we use the return series to calculate the futures basis for each commodity to look into how HFs benefit from the increase in the gap between futures and spot prices (Section 1.3.2.2). In contrast, Büyükşahin & Robe (2014) model the equity-commodity return correlation and then regress this correlation on HFs' share of open interests in futures and options-on-futures total open interests, to inspect HFs' speculative behavior (among other intermediaries).

Understanding the volatility dynamics of HFs and unraveling their return generating process is crucial for two reasons: first, as a strategy formation for hedging, trading, or portfolio optimization; and second, in limiting their potential detrimental effect on financial markets[2]. In regards to the former, using several simple risk-reward measures, we find that the return delivered by HFs bears less risk than any asset class in our study, including the US 10-year Treasury note (T-note). In regards to the latter, we find that shocks to HFs propagate to many asset classes, especially futures market. Therefore, we provide insightful clues about HFs' trading strategy to any investor for asset and risk management and to policymakers for market intervention and regulations for better welfare objectives, especially after the two giant crashes, the GFC and COVID-19.

The literature[3] mainly focuses on modeling the entire HF industry's exposure to macroeconomic indicators like inflation, GDP, etc., in different business cycles (Roncalli & Weisang, 2009; Billio et al., 2012; Cai & Liang, 2012a,b; Jawadi & Khanniche, 2012; Patton & Ramadorai, 2013; Agarwal et al., 2017; Racicot & Théoret, 2019; Gregoriou et al., 2021). On the other hand, there are only a few studies analyzing HFs' dynamics with financial asset classes. For example, Li & Kazemi (2007) study the conditional proper-

[1] The reason is to avoid illiquid contracts, or those that have little market depth.

[2] Note that HFs do not disclose any information about their portfolio management, constituents, or trading.

[3] This work is distinct from another strand of literature studying HFs' flow-performance relationship, and return determinants (see Fung & Hsieh, 2001; Mitchell & Pulvino, 2001; Bali et al., 2017).

ties (by conditional density functions) of the HF indices with the S&P 500, the Lehman High Yield indices, and the Treasury bill. They find that the conditional correlations are symmetric and that there is no contagion between the HFs and other markets. On the other side, Elyasiani & Mansur (2017) find the opposite results. They use a univariate EGARCH, and claim that the volatility clusters of HFs affect those of S&P 500, real estate, and major bank indices. We contribute to this scant literature by studying HFs' volatility dynamics, time-varying comovements, and shock spillovers with a large number of assets using daily data[4], with special attention to the HF's impact on the futures market, by employing the asymmetric dynamic conditional correlation (ADCC) model (Cappiello et al., 2006), which is a promising model given HFs' dynamic asset management, their time-varying risk exposure to various asset classes, and their extensive usage of derivatives (which creates asymmetric responses to news), as demonstrated by the literature.

The ongoing COVID-19 pandemic has severely disrupted financial markets and the real economy worldwide, thus studying how HFs' dynamics changed in response to the recent COVID-19 pandemic is an important topic. In another novel contribution to the literature, we compare and study HFs' investing styles during the two giant crises, the GFC and COVID-19. The results show that, unlike the GFC, HFs do not decrease their exposure to equity markets during the COVID-19 crisis, but rather similar to the GFC, they increase their exposure to commodity futures as a buffer against the crisis in equity markets. This realignment of investment thesis might be a warning to policy writers, as it seems like HFs are focusing more on futures contracts than equities because the exposure to equities has decreased substantially across several HF strategies since the GFC.

In contrast to Li & Kazemi (2007) and Gregoriou et al. (2021), we find heterogeneity in the investing styles across the four HF strategies in our study, including Event Driven, Equity Hedge, Macro, and Relative Value Arbitrage. Only the Macro strategy seems to have market timing ability, and its time-varying correlations with different assets resemble option-like behavior, much like the Relative Value Arbitrage strategy. These two strategies underperform compared to the Event Driven and Equity Hedge strategies, which shows the adverse effect of intensive options trading.

The findings of this study make several contributions to the literature. First, we extend the scarce and dated literature on the dynamics of HFs with different financial markets,

[4]Previous papers use low-frequency data, such as seasonal or monthly data.

by employing data at higher frequency, that is daily data. Second, we study the systemic shock transmissions between HFs and other financial markets, both at micro (by strategies) and macro (by composite index) levels. In particular, corn and silver are the commodities heavily hit by almost all HF strategies' shocks, while E-mini contracts, gold futures, and USDJPY are the assets with widespread shock spillover across all HF strategies. Third, we compare the investing styles of different HF strategies during the two crises, the GFC and the COVID-19. Fourth, we find that HF strategies benefit from the increase in futures basis of different commodities, especially those with higher liquid markets and lower basis standard deviation (i.e., getting the highest return with the lowest risk) which is in line with the performance analysis in Section 1.2.1. Notably, Event Driven and Equity Hedge strategies exploit the increase in gold basis, while all strategies benefit from the increase in natural gas basis.

The paper is organized as follows: Section 1.2 contains the data with performance analysis (1.2.1), and the method (1.2.2). Section 1.3 discusses the results for the industry (1.3.1) and the strategies (3.2). Section 1.4 concludes.

1.2 Method & Data

1.2.1 Data

Our dataset spans from April 1, 2003 to April 29, 2021 for a total of 4546 daily observations. The continuous price indices for futures commodities are based on the nearest-to-maturity contracts. The data comes from Thomson Reuters EIKON/Datastream. We compute the daily return as $r_t = \ln(\frac{Price_t}{Price_{t-1}})$. More, all return series in this study are stationary[5] at 1% by augmented Dickey–Fuller (ADF) test. We employ hedgefundresearch[6] HFRX daily HF indices[7]. We use the HFRX UCITS[8] investable indices, including the cap-weighted composite global HF index (HFRXGL), Event Driven (HFRXED), Equity Hedge (HFRXEH), Macro (HFRXM), and Relative Value Arbitrage (HFRXRVA), with the last four representing HF strategies. As stated in many papers, HFR indices

[5] Test statistics are not reported due to space constraints.

[6] www.hfr.com

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

[8] 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.

are among the most reliable, accurate, and bias-free indices in the industry[9]. To the best of our knowledge, we are the first to use daily indices to investigate the dynamics of the HFs using a diverse set of assets across commodities, equities, forex, and bond markets. Tables 1.1 to 1.5 summarize the statistical characteristics of the assets under analysis. To conduct a performance analysis, we include measures like: the total return for the enitre sample period; a robust measure for skewness and kurtosis; historical conditional value at risk (CVaR[10]); and the maximum drawdown[11]. In addition to the Jarque-Bera test of normality, we employ both conventional and robust measures of higher moments to justify the use of the Student's t distribution in our study. While robust measures significantly reduce the impact of outliers, conventional measures of skewness and kurtosis significantly increase the impact of outliers. Additionally, robust measures can reveal the underlying riskiness of any asset (by tail events). We employ Groeneveld & Meeden (1984) robust measure for the third moment:

$$\text{Robust Skewness} = \frac{\mu - Q_2}{E|r_t - Q_2|} \tag{1.1}$$

Where μ is the sample mean, Q_2 is the second quantile, and r_t is the return observed at time t. The value is zero for symmetric distributions (Gaussian) and is bounded by -1 and +1. The advantage of this robust measure is that, unlike other robust measures for skewness, it does not completely ignore the impact of outliers (for more information, see Kim & White, 2004). Similar to skewness, we also report two measures for kurtosis. One is the conventional gross measure and the other is a quantile-based measure. Our choice of robust kurtosis is Crow & Siddiqui (1967) quantile-based kurtosis:

$$\text{Robust Kurtosis} = \frac{F^{-1}(0.975) - F^{-1}(0.025)}{F^{-1}(0.75) - F^{-1}(0.25)} \tag{1.2}$$

Note that for a Gaussian distribution, the value for conventional and robust kurtosis is 3 and 2.91 respectively.

Table 1.1 reports the descriptive statistics for the HF indices. The Event Driven strategy (HFRXED) outperforms other strategies in terms of return, with an average daily

[9]Stafylas et al., 2018 conduct an in-depth study on HFRX indices' methodology, and state that with HFRX algorithm, the return series has the maximum statistical likelihood of being accurately reflective of the HF industry.

[10]CVaR is the weighted average of the extreme losses in the tail of the distribution of returns, exceeding the VaR critical point.

[11]Maximum drawdown is the maximum observed loss from a peak to the trough of an index before a new peak is attained.

Table 1.1: Descriptive statistics for HFRX hedge fund indices.

	Mean return (in bps)	Total return (in %)	Standard deviation	Skewness	Robust skewness	Kurtosis	Robust kurtosis	CVaR (5%)	Max drawdown	Jarque–Beratest
HFRXGL	0.8	42	0.002	-1.25	-0.13	11.29	4.00	0.006	-0.27	FALSE
HFRXED	1.3	82	0.003	-1.30	-0.09	16.17	4.04	0.007	-0.28	FALSE
HFRXEH	0.8	41	0.004	-0.82	-0.10	8.43	4.09	0.010	-0.32	FALSE
HFRXM	0.5	25	0.003	-0.94	-0.06	9.57	3.87	0.009	-0.29	FALSE
HFRXRVA	0.7	35	0.002	-1.77	-0.10	45.78	5.06	0.006	-0.40	FALSE

return of 1.3 bps. It also has a comparably low maximum drawdown. The poorest performing strategy is the Macro (HFRXM), with a 0.5 bps average daily return. The riskiest strategy is the Equity Hedge (HFRXEH) with a 0.4% standard deviation. The conventional and robust measures of skewness both show evidence of likely frequent small gains (positive returns) and infrequent large losses (tail events) when the skewness is negative. The difference between conventional and robust measures of skewness and kurtosis indicates the impact of tail events. The robust kurtosis value across all HF indices shows that HFs are more likely to experience severe tail events. The Macro strategy has the lowest robust kurtosis (3.87). Equity Hedge (HFRXEH) is the strategy with the highest CVaR, and the highest standard deviation indicating the riskiest strategy. The Relative Value Arbitrage strategy (HFRXRVA) has the largest drawdown of 40% during the sample period. The Jarque-Bera test indicates the null hypothesis that the returns come from a normal distribution is rejected at the 1% significance level. Conventional and robust measures of skewness and kurtosis also support the non-normality of the return series. We employ the global HF index (representing the performance of the entire HF industry) when studying the dynamics of the HF industry with other markets' major indices in Section 1.3.1, while we employ HF strategies and 30 assets from different markets to dissect the investing styles in HF industry in Section 1.3.2. In regards to the equity market, we include all sectors of the S&P 500: information technology (abbreviated as SP InfoTech), healthcare (SP Health), consumer discretionary (SP ConsDis), telecom services (SP TeleCom), financials (SP Finance), industrials (SP Indust), consumer staples (SP ConsStap), utilities (SP Utilities), materials (SP Materials) and energy (SP Energy). We employ the Dow Jones (DJ) US real estate index instead of the S&P 500 real estate index. The reason for this is that the DJ real estate index is far more comprehensive than the S&P 500 real estate index and better represents the real estate giant market. We also include the S&P 100 representing the top 100 largest firms in the whole US economy representing 50% of the US stock market capital.

Table 1.2: Descriptive statistics for equity market indices.

	Mean return (in bps)	Total return (in %)	Standard deviation	Skewness	Robust skewness	Kurtosis	Robust kurtosis	CVaR (5%)	Max drawdown	Jarque–Bera test
S&P 100	3	340	0.012	-0.48	-0.04	17.21	4.89	0.03	-0.60	FALSE
S&P 500	3	391	0.012	-0.56	-0.05	17.41	4.95	0.03	-0.61	FALSE
VIX	-2	-38	0.056	–	–	–	–	–	–	FALSE
Nasdaq	5	944	0.013	-0.47	-0.07	11.93	4.40	0.03	-0.60	FALSE
SP InfoTech	5	1011	0.014	-0.30	-0.06	12.61	4.35	0.03	-0.59	FALSE
SP Health	3	358	0.011	-0.22	-0.04	14.04	4.11	0.03	-0.44	FALSE
SP ConsDis	4	684	0.013	-0.38	-0.06	13.34	4.54	0.03	-0.65	FALSE
SP TeleCom	2	175	0.013	0.02	-0.04	13.85	4.11	0.03	-0.57	FALSE
SP Fin	2	112	0.019	-0.25	-0.03	20.91	5.37	0.05	-0.89	FALSE
SP Indust	3	370	0.013	-0.53	-0.05	12.93	4.58	0.03	-0.69	FALSE
SP ConsStap	3	276	0.009	-0.17	-0.03	17.76	3.99	0.02	-0.38	FALSE
SP Utilities	3	257	0.012	0.03	-0.08	20.12	3.82	0.03	-0.53	FALSE
SP Materials	3	362	0.015	-0.50	-0.05	11.87	4.17	0.04	-0.67	FALSE
SP Energy	2	105	0.018	-0.70	-0.03	19.50	4.14	0.04	-0.84	FALSE
DJ Real estate	2	156	0.018	-0.21	-0.03	26.85	7.30	0.04	-0.84	FALSE
E.mini	3	391	0.012	-0.40	-0.06	19.42	4.85	0.03	-0.62	FALSE

The price index for the popular futures contracts on S&P 500 (E-mini) and the Nasdaq composite index, is also included in our study. Table 1.2 provides the descriptive statistics for the equity assets. In short, the best performing equity asset, in terms of return is the information technology (SP InfoTech) sector with a total return of 1011%, while the poorest performing sector is energy with negative total return (105%) over the whole period, although given other performance measures in Table 1.2, the financials sector is the poorest performing sector (112%, second lowest after the energy sector), which has the highest standard deviation (19%) among other sectors. This sector also has the highest CVaR (5%) and maximum drawdown (89%). Consumer staples on the other side, is the least risky sector with the lowest values for standard deviation (0.9%), CVaR (2%) and maximum drawdown (38%).

Table 1.3 reports the statistical characteristics of the commodity assets in our study. We have the Commodity Research Bureau (CRB) Index, gold and West Texas Intermediate (WTI) crude oil spot prices, in addition to the continuous time price index for 13 contracts from five different categories of futures market including metals, softs, grains, energy and live stocks (Gorton et al., 2013). Note that, these 13 commodities have the most liquid and active market in their own category (Christoffersen et al., 2019). Copper futures outperforms other commodities by a total return of 519% during the entire sample period. Gold futures is the least risky asset among all commodity assets with the lowest standard deviation (0.6%), CVaR (1%), and maximum drawdown (24%). On the other hand, WTI crude oil is the riskiest commodity by standard deviation ($\sim$3%),

Table 1.3: Descriptive statistics for commodities.

	Mean return (in bps)	Total return (in %)	Standard deviation	Skewness	Robust skewness	Kurtosis	Robust kurtosis	CVaR (5%)	Max drawdown	Jarque–Bera test
CRB	0	-1	0.011	-0.53	-0.06	8.71	3.71	0.03	-0.82	FALSE
Gold spot	3	429	0.010	-0.49	-0.01	12.46	5.38	0.03	-0.43	FALSE
WTI spot	2	118	0.027	-0.58	-0.02	22.83	3.90	0.06	-0.97	FALSE
WTI futures	2	118	0.027	-2.30	-0.04	62.17	3.86	0.06	-0.98	FALSE
Natural Gas Futures	0	-43	0.016	0.30	0.00	10.11	3.98	0.03	-0.71	FALSE
Heat oil futures	2	165	0.010	-0.19	0.02	9.11	4.03	0.02	-0.59	FALSE
Gold futures	2	428	0.006	-0.53	-0.03	10.50	4.43	0.01	-0.24	FALSE
Silver futures	2	487	0.010	-0.96	-0.05	15.48	4.59	0.03	-0.48	FALSE
Copper futures	3	519	0.008	-0.14	0.01	6.85	4.24	0.02	-0.40	FALSE
Soybean futures	3	162	0.011	-1.44	-0.01	24.20	5.40	0.03	-0.57	FALSE
Corn futures	2	171	0.011	0.44	0.03	7.81	4.33	0.02	-0.47	FALSE
Wheat futures	2	158	0.020	0.17	0.05	4.72	3.34	0.04	-0.82	FALSE
Sugar futures	1	123	0.009	0.09	0.01	6.17	3.69	0.02	-0.47	FALSE
Coffee futures	1	145	0.009	0.38	0.02	6.68	3.72	0.02	-0.45	FALSE
Cotton futures	1	50	0.008	-0.18	0.00	7.40	4.14	0.02	-0.50	FALSE
Cattle futures	1	52	0.008	-1.88	-0.02	24.59	5.23	0.02	-0.31	FALSE

CVaR (6%), and maximum drawdown ($\sim$100%). The large gaps between conventional and robust measures of skewness and kurtosis, suggest intrinsic risky nature of this fundamental commodity.

Table 1.4: Descriptive statistics for currencies and US 10-year Treasury note.

	Mean return (in bps)	Total return (in %)	Standard deviation	Skewness	Robust skewness	Kurtosis	Robust kurtosis	CVaR (5%)	Max drawdown	Jarque–Bera test
USDEUR	-0.05	-10	0.006	-0.03	0.02	5.10	3.58	0.01	-0.38	FALSE
USDGBP	-0.005	13	0.006	1.07	0.00	18.56	3.40	0.01	-0.30	FALSE
USDJPY	-0.02	-8	0.006	-0.13	0.00	7.99	3.75	0.01	-0.40	FALSE
10 year T-note	0.02	15	0.003	-0.05	0.01	8.54	4.62	0.01	-0.15	FALSE

Table 1.4 provides the descriptive statistics for the three currencies including US Dollar to European Euro (USDEUR), US Dollar to British Pound (USDGBP), US Dollar to Japanese Yen (USDJPY) and the US 10-year T-note. Except for the 10-year T-note, the three currencies have negative average returns, and similar to commodities, the currencies and the T-note seem to have symmetric distributions, evidenced by robust skewness. The distribution of the data is different from the Gaussian distribution based on the Jarque–Bera test at 1%.

Finally in Table 1.5, we provide the statistical characteristics of the futures basis for the 13 commodities. We compute futures basis as:

Table 1.5: Descriptive statistics for currencies and US 10-year Treasury note.

	WTI basis	Natural gas basis	Heat oil basis	Gold basis	Silver basis	Copper basis	Soybean basis	Corn basis	Wheat basis	Sugar basis	Coffee basis	Cotton basis	Live Cattle basis
Mean basis	0.001	0.021	0.006	0.002	0.001	-0.003	0.019	-0.001	0.041	-0.056	-0.153	0.041	-0.005
Standard Deviation	0.01	0.06	0.02	0.00	0.01	0.01	0.05	0.04	0.11	0.08	0.11	0.04	0.05

$$\text{The futures basis} = \ln\left(\frac{\text{futures price index}_t}{\text{spot price index}_t}\right) \tag{1.3}$$

Table 5 shows that most commodities have a positive basis, with cotton and wheat having the largest and sugar having the smallest. To conclude this section, note that none of the HF strategies outperform equity market sectors. A passive strategy in almost all equity sectors could yield more than twice of the HFs' total return during the sample period. But there is another facet: it seems that HFs are very safe investments. The standard deviation of all HF strategies is generally one tenth of almost all assets in the equity market or commodities. The CVaR of the HF industry is significantly lower (0.6% by HFRXGL) than that of the equity (3% by S&P 500) and commodity markets (2.7% by CRB). Further, the maximum drawdown of the HF industry (-27% by HFRXGL) is much lower than equity (-61% by S&P 500) and commodity (-82% by CRB) markets. HFs' returns seem to resemble a risk-free asset. Moreover, if we look at the 10-year T-note descriptive statistics in Table 1.4, the average return of this risk-free asset is 0.2 bps, with a standard deviation of 0.003, robust kurtosis of 4.6, CVaR of 1%, and with a maximum drawdown of -0.15, while HF's average return (by HFRXGL) is 0.8 bps, with a standard deviation of 0.002, robust kurtosis of 4, CVaR of 0.6%, and with a maximum drawdown of -0.27. These numbers clearly indicate that HFs are safer and more attractive than the 10-year T-note, to a risk-averse investor.

1.2.2 Method: Asymmetric dynamic conditional correlation (ADCC)

Unlike the constant conditional correlation (CCC), the dynamic conditional correlation (DCC) models the time-varying conditional correlations (R. Engle, 2002). The DCC is an intelligent response to the heteroscedasticity of the disturbances in multivariate models with the curse of dimensionality. Developed on the DCC, the ADCC[12](Cappiello

[12]Almost all other empirical studies (See Laurent et al., 2012; Santos et al., 2013; Santos et al., 2013; Hou & Li, 2016; Junttila et al., 2018; Bauwens & Xu, 2022) use the constrained version of the asymmetric generalized dynamic conditional correlation (AGDCC) model due to the dimensionality issues. Cappiello et al. (2006) state that, as the number of variables increases, AGDCC becomes infeasible and suggest restricted versions of the model.

et al., 2006) which has stronger statistical properties and the ability to capture the asymmetries in the dynamic correlations, is proven to outperform many competing models in empirical studies on financial markets (Cappiello et al., 2006; Laurent et al., 2012; Santos et al., 2013; Gjika & Horvath, 2013; Hou & Li, 2016; Junttila et al., 2018; Ameur et al., 2018; Samitas et al., 2020; Hoepner et al., 2021; Karkowska & Urjasz, 2021; Hachicha et al., 2022; Bauwens & Xu, 2022). This model not only outperforms DCC and CCC models, but also has an edge over vector error correction (VEC) and BEKK (Baba et al., 1990) models (Laurent et al., 2012). In the VEC and BEKK models, the conditional correlations are computed indirectly, unlike in ADCC. The existence of asymmetries between the comovements of HFs and other assets is supported both empirically (i.e., $H_0 : g = 0$ against $H_1 : g \neq 0$) as the asymmetry parameter in the model estimation) and by the previous studies in the literature[13]. Furthermore, it is essential to note that since our sample period is a long one with several minor or major financial crashes, and HFs' investing styles change (potentially asymmetric due to the use of call/put options) in response to these crashes, neglecting asymmetries in the dynamic correlations can lead to unreliable inference (Racicot & Théoret, 2019). Therefore, the ADCC is a perfect fit for studying HFs' time-varying and dynamic risk exposure to different financial assets and markets. The time-varying dynamic correlations also help in analyzing the reaction and the investing styles of HFs to the COVID-19 pandemic with regard to the GFC. The ADCC is generally estimated in two steps (Tsay, 2013); First we estimate the residuals using a multivariate VAR (1)[14] model as follows:

$$R_t = \Phi_0 + \Phi R_{t-1} + E_t \tag{1.4}$$

Where $R = (r_{1,t}, r_{2,t}, ..., r_{k,t})'$ is a $k-$dimensional vector of asset returns at time t, Φ_0 is a $k-$dimensional vector of intercepts, Φ is a $k \times k$ matrix containing the autoregressive coefficients, and $E = (e_{1,t}, e_{2,t}, ..., e_{k,t})'$ is the vector of error terms, which represents the part of R_t that is not linearly dependent on past observations. In this paper we assume that E_t given the information at time $t - 1(\Im_{t-1})$ is a sequence of serially uncorrelated random vectors with zero mean, covariance matrix H_t and ν degrees of freedom or $\mathbf{E}_t|\Im_{t-1} \sim Student - t(0, H_t, \nu)$. The reason for assuming a multivariate Student's t distribution for the error terms is based on the non-normality of the returns' series (by Jarque–Bera test and measures of higher moments), which is crucial in estimating the conditional variance-covariance matrix[15]. H_t can be decomposed as $H_t = D_t P_t D_t$

[13] Racicot & Théoret, 2019 witness the asymmetries in HFs' risk exposure to macroeconomic indicators. The existence of time-varying and asymmetric comovements across financial markets is also evidenced in several works (see, Junttila et al., 2018; Hu et al., 2020; Adams et al., 2021).

[14] Lag selection based on AIC.

[15] Several papers including Bollerslev (1987), Susmel & Engle (1994) or Baillie & Bollerslev (2002)

wherein P_t is the time-varying correlation matrix which contains the conditional correlations, and D_t is a diagonal $k \times k$ time-varying matrix of standard deviations, i.e., $D_t = \left[\sqrt{h_{i,t}^2}\right]_{k \times k}$, where $h_{i,t}^2$ is the conditional variance of the i^{th} return series estimated by a GARCH. We estimate the conditional variances by a GJR(1,1) of Glosten et al. (1993) which can capture the leverage effect[16]. GJR(1,1) reads as follows:

$$h_{i,t}^2 = \Omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1}^2 + \gamma_i e_{i,t-1}^2 I_{i,t-1} \qquad \text{for} \qquad i = 1, ..., k \tag{1.5}$$

where

$$I = \begin{cases} 1 & if\ e_{i,t-1} < 0 \\ 0 & Otherwise \end{cases} \tag{1.6}$$

with i referring to the i^{th} asset, Ω_i is a constant term, α_i measures the impact of the lagged shocks on the conditional variance (clusters or size of shocks), β_i measures the impact of lagged conditional variance (persistence of shocks), and γ_i captures asymmetries in the volatility (sign of shocks). At this point, we have estimated all the elements for D_t. In order to compute the components of the matrix P_t, we must first compute the standardized errors which are calculated as $\varepsilon_{i,t} = \frac{e_{i,t}}{\sqrt{h_{i,t}^2}}$ for $i = 1, ..., k$ then we calculate P_t as:

$$P_t = diag Q_t^{-1} Q_t diag Q_t \tag{1.7}$$

where:

$$Q_t = (1 - a - b)\bar{P} + a(\varepsilon_{t-1}\varepsilon_{t-1}') + bQ_{t-1} \tag{1.8}$$

and

$$diag Q_t^{-1} = \begin{bmatrix} \frac{1}{\sqrt{q_{11t}}} & \cdots & 0 \\ \vdots & \cdots & \vdots \\ 0 & \cdots & \frac{1}{\sqrt{q_{nnt}}} \end{bmatrix} \tag{1.9}$$

recommend the use of Student's t distribution in estimating models for financial time-series that are non-normally distributed and have excess kurtosis. Francq & Zakoian (2019) emphasize the benefits of employing GARCH processes with heavy-tailed distribution in capturing true data generating process over regime-switching models, for financial series.

[16] According to R. F. Engle & Ng (1993), ignoring asymmetries leads to model misspecification.

and $\bar{P} = E[\varepsilon_{t-1}\varepsilon'_{t-1}]$ is the unconditional correlation matrix of the standardized residuals. For mean reversion, the condition $a + b < 1$ must hold for the sum of two scalars a and b. Rewriting $P_t = diagQ_t^{-1}Q_t diagQ_t^{-1}$ we get the time-varying conditional correlation between assets i and j at time t as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{1.10}$$

where $q_{ij,t}$ is the conditional covariance between the returns of asset i^{th} and j^{th} at time t, and $q_{ii,t}$ and $q_{jj,t}$ are the diagonal elements of the covariance matrix Q_t, corresponding to the conditional variance estimates of the i^{th} and j^{th} assets at time t, respectively. We estimate the parameters by maximizing the log-likelihood of the probability density function of a multivariate Student's t distribution. Cappiello et al. (2006) state the dynamics of the Q_t for ADCC as follows with the three scalars a, b, g;

$$Q_t = (\bar{P} - a^2\bar{P} - b^2\bar{P} - g\bar{N}) + a^2(\varepsilon_{t-1}\varepsilon'_{t-1}) + g^2(n_{t-1}n'_{t-1}) + b^2Q_{t-1} \tag{1.11}$$

In eq. 1.11, the effect of negative shocks is absorbed by the variable n_t which can be exhibited as a Hadamard product of an indicator function and the standardized errors:

$$n_t = I[\varepsilon_{t-1}] \circ \varepsilon_{t-1} = \begin{cases} \varepsilon_t & \varepsilon_t < 0 \\ 0 & \varepsilon_t \geq 0 \end{cases} \tag{1.12}$$

where $I[\varepsilon_t]$ is a $K \times 1$ indicator function and $\bar{N} = E[n_{t-1}n'_{t-1}]$. The positive definiteness of Q_t can be guaranteed if $(a^2 + b^2 + wg^2) < 1$, where w is the maximum eigenvalue of the matrix $[\bar{P}^{\frac{-1}{2}}\bar{N}\bar{P}^{\frac{-1}{2}}]$. g^2 unveils whether conditional correlation between returns asymmetrically reacts to previous shocks. In the empirical part of this paper, we also report the shocks' half-life, which is another facet of volatility persistence and is computed as:

$$\text{half–life} = \frac{ln(0.5)}{ln(\alpha + \beta + (\frac{1}{2})\gamma)} \tag{1.13}$$

It indicates the time it takes for volatility to move half-way back to its unconditional mean.

1.3 Results

We start by discussing the dynamics of the entire HF industry (represented by the global index, HFRXGL) with other financial markets' major indices and fundamental macro variables in Section 1.3.1. It is important to emphasize that all previous studies employ HF strategies but not a representative composite index to study the dynamics of the entire HF industry. Systemic shock transmissions between HF industry and financial markets are discussed in Section 1.3.1.1, focusing on HF's effect. The investing style of each HF strategy is then covered in Section 1.3.2, and shock transmissions between HF strategies and various assets, as well as the effect of futures basis on the performance of the four HF strategies are examined in Sections 1.3.2.1 and 1.3.2.2, respectively.

1.3.1 The dynamics of HF industry

To study the dynamics of the entire HF industry with other asset classes, we employ eight major indices, including: S&P 100, S&P 500, Nasdaq, VIX, CRB, gold, WTI crude oil spot prices, and the 10-year T-note. Panel A of Table 1.6 shows that the HF industry's performance is Granger caused by all four equity indices (S&P 100, S&P 500, Nasdaq, and VIX) and the 10-year T-note, at 5% significance or below. This is in line with Patton & Ramadorai (2013), who find that the equity market is the primary source of risk for HFs at firm level. The opposite sign of the coefficients of S&P 100 and S&P 500 in HFRXGL's mean equation in the VAR model is interesting. The largest 100 firms in the US market are included in both the S&P 100 and the S&P 500 indices, though their effects on the HF industry differ. The top 100 largest firms in the US economy, which represent more than half of the US equity market capital, have a negative impact on the HF industry, while the remaining 400 top firms have a positive impact. We attribute the opposite signs to the fact that giant firms perform better during crises[17], while during calm periods they underperform compared to the other 400 firms in the S&P 500. There is a weak yet significant effect of VIX on HFs. In the literature, VIX is identified as a primary significant contributor to HF's systemic risk (see Gregoriou et al., 2021, or Racicot & Théoret, 2019), but we find a very weak effect from VIX on the HF industry. The S&P 100 has the greatest negative impact on the industry (-660 bps), followed by the S&P 500's positive impact. Furthermore, the results show a positive spillover effect of Nasdaq and US 10-year T-note with a similar magnitude on the HF industry (290 and 220 bps respectively). We can see that HFs affect equity market indices in the same way, as seen in panel A of Table 1.6. HFRXGL has a positive impact on S&P 100, while S&P 100 has a negative impact on HFRXGL. The equity market does not appear to have any significant effects on commodities.

[17]Based on our sample data, during the three economic crises: Dec 2007-Nov 2008 (GFC), US-China trade war in 2018, and Feb 2020-Jan 2021 (COVID-19), the total return of S&P 100 was -36.9%, -6.6%, and +17.3%, while the performance of S&P 500 was -40%, -7%, and +14.3%.

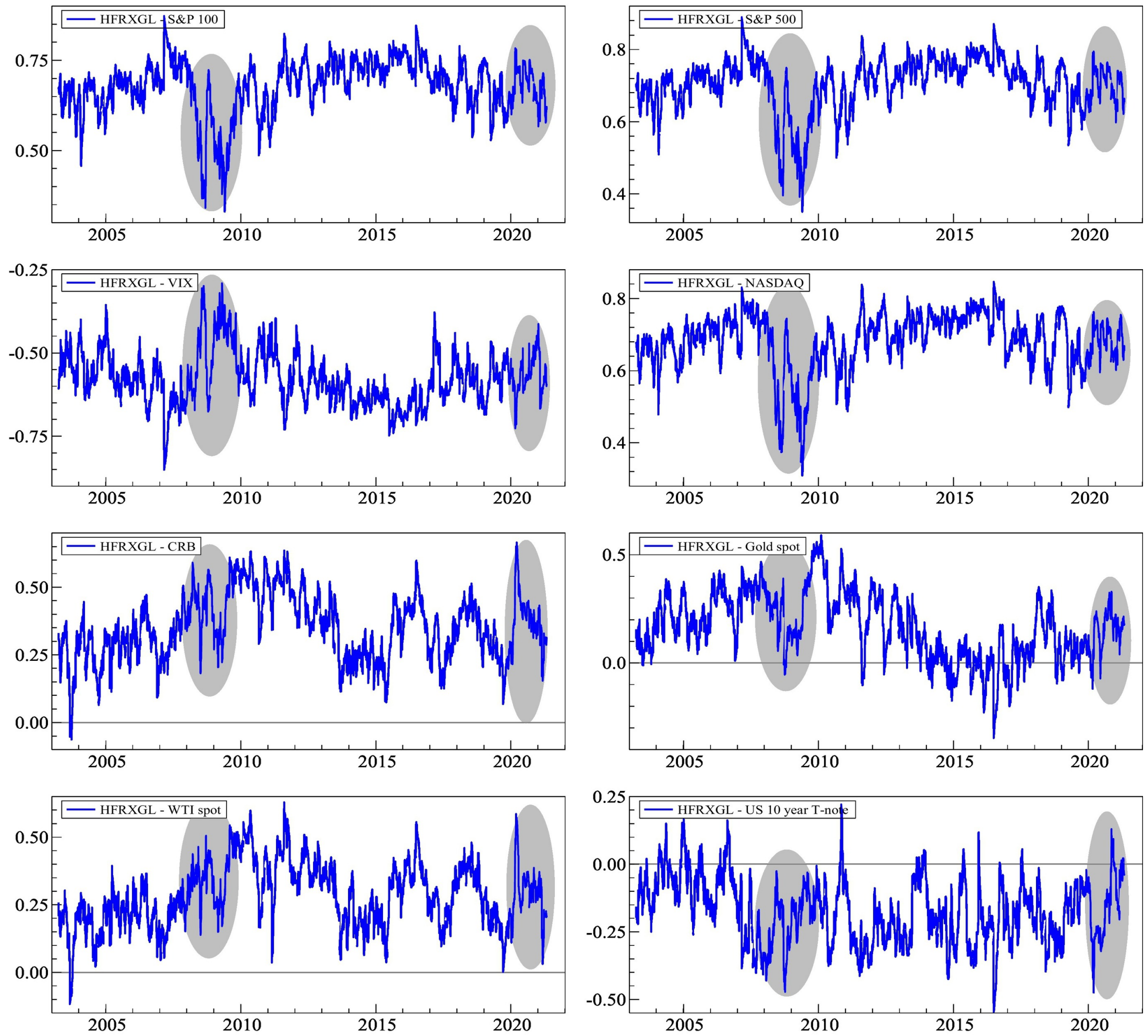


Figure 1.1: Dynamic correlations of HFRXGL.

The results demonstrate that the 10-year T-note Granger causes gold return significantly (by 15%). The S&P 100 and S&P 500 have asymmetric effects on the 10-year T-note. Empirically, during times of market turbulence, the bond market serves as a haven. This effect is due to the heterogeneous performance between the top 100 companies and the other 400 companies in the S&P 500, and is in line with the intuition that giant firms are safer investments during crises. The volatility equation parameters in panel B of Table 1.6 reveal that HFRXGL exhibits a substantial leverage effect, much like the S&P 100, S&P 500, and Nasdaq. The positive sign means that negative news (shocks) has a larger impact on volatility than positive news (shocks). Our results are in contrast with the findings of Elyasiani & Mansur (2017). According to them, positive news generates more volatility in HFs than negative news. They use monthly data, which could be the cause. That is, when low-frequency data is used in volatility models, information loss is substantially greater (Francq & Zakoian, 2019; Patton & Ramadorai, 2013). Furthermore, as pointed out earlier, GJR is shown to be more accurate in capturing asymmetry in volatility compared to EGARCH,

which is based on a log-transformation approximation. The CRB index and WTI spot price index exhibit leverage effects as well, though not to the same extent as the equity market indices. This could be related to lower fluctuations in commodities. Gold and VIX, on the other hand, fluctuate more when a positive shock hits the prices. The 10-year T-note has no leverage effect. The ARCH test refers to the Lagrange Multiplier test statistics for autoregressive conditional heteroscedasticity (ARCH) effects (R. Engle, 1982). The p-values strongly suggest the existence of nonlinear ARCH effects. Further information about the ADCC is provided at the bottom of Table 1.6.

The dynamic correlations of the global HF index (HFRXGL) with market indices and fundamental assets are depicted in Fig. 1.1. The two shaded ovals in each graph represent the GFC and COVID-19 crisis periods. The dynamic correlations of HFRXGL with the S&P 100, S&P 500, and Nasdaq are comparable and significantly stronger when compared to other markets, which is consistent with the previous section's VAR results. HFRXGL's dynamic correlation with VIX appears to be the inverse of that of three stock market indices. Fig. 1.1 shows several major widespread patterns across all dynamic correlations. When equity markets began to plummet in the early stages of the GFC, the dynamic correlation of HFRXGL with the three equity market indices and the gold price falls down. Simultaneously, the dynamic correlation of HFRXGL with the CRB commodity index and WTI initially increases, but then decreases in September 2008, when the crisis reaches a climax and Lehman Brothers declares bankruptcy. In September 2008, the dynamic correlation of HFRXGL with all of the three equity market indices, CRB, and WTI has dropped. The only increasing correlation is the one of gold. Then, from that time to mid-2009, all dynamic correlations with the three equity indices, plus CRB and WTI, experience a fast increase fol- lowed by a fast decline.

The second widespread pattern starts from 2011 up to 2015, contemporaneous with the zero-interest rate environment and European sovereign debt crisis. During this time, the dynamic correlation of HFRXGL with the three equity indices is steadily rising, while the dynamic correlations with CRB, WTI, and gold is gradually declining. Another main widespread pattern emerges in 2018 due to US-China trade war, which marks another switching position between the equity market and commodities by HFs. During that year, the dynamic correlations with the equity market decrease while they increase with commodities. Unlike the GFC, we do not witness declining correlations

Table 1.6: Model parameters for comprehensive indices.

Panel A: VAR coefficients

	$HFRXGL_t$	p-value	S&P 100_t	p-value	S&P 500_t	p-value	VIX_t	p-value	$Nasdaq_t$	p-value	CRB_t	p-value	Gold $cash_t$	p-value	WTI $cash_t$	p-value	US 10-year $T\text{-}note_t$	p-value
Constant	0.000	0.00	0.000	0.00	0.00	0.00	0.001	0.14	0.000	0.00	0.000	0.86	0.000	0.09	0.000	0.53	0.000	0.94
$HFRXGL_{t-1}$	0.132	0.00	0.188	0.06	0.182	0.08	-0.092	0.87	0.187	0.10	0.094	0.38	0.079	0.14	0.141	0.52	-0.003	0.89
S&P 100_{t-1}	-0.066	0.01	-0.274	0.05	-0.201	0.11	1.398	0.05	-0.264	0.12	-0.154	0.30	-0.141	0.08	-0.176	0.55	0.053	0.04
S&P 500_{t-1}	0.051	0.04	0.180	0.26	0.088	0.53	-0.860	0.23	0.105	0.58	0.223	0.15	0.093	0.24	0.292	0.35	-0.045	0.07
VIX_{t-1}	-0.002	0.01	-0.005	0.25	0.005	0.32	-0.074	0.01	-0.005	0.34	-0.006	0.20	-0.006	0.08	-0.005	0.55	0.000	0.91
$Nasdaq_{t-1}$	0.029	0.00	-0.036	0.35	-0.010	0.78	-0.275	0.17	0.044	0.37	-0.031	0.42	0.031	0.19	-0.085	0.34	-0.002	0.81
CRB_{t-1}	0.002	0.76	-0.018	0.48	-0.013	0.62	-0.081	0.60	-0.028	0.37	0.003	0.93	-0.020	0.17	0.149	0.04	-0.007	0.19
Gold $cash_{t-1}$	-0.001	0.76	-0.015	0.38	-0.011	0.55	0.143	0.21	-0.011	0.59	0.030	0.15	-0.027	0.14	0.011	0.79	0.005	0.36
WTI $cash_{t-1}$	0.000	0.94	0.004	0.66	0.003	0.79	0.033	0.48	0.011	0.41	-0.025	0.06	0.009	0.07	-0.116	0.00	0.001	0.41
US 10-year $T\text{-}note_t$	0.022	0.02	-0.049	0.24	-0.025	0.56	0.128	0.60	-0.009	0.86	0.088	0.12	0.147	0.00	-0.027	0.80	-0.039	0.02

Panel B: GJR(1,1) parameters

	$HFRXGL_t$	p-value	S&P 100_t	p-value	S&P 500_t	p-value	VIX_t	p-value	$Nasdaq_t$	p-value	CRB_t	p-value	Gold $cash_t$	p-value	WTI $cash_t$	p-value	US 10-year $T\text{-}note_t$	p-value
Ω	0.000	0.00	0.000	0.00	0.00	0.00	0.00	0.00	0.000	0.00	0.000	0.00	0.000	0.03	0.000	0.00	0.000	0.05
ARCH(α_1)	0.060	0.00	0.030	0.17	0.026	0.32	0.189	0.00	0.009	0.49	0.034	0.00	0.068	0.00	0.039	0.00	0.056	0.00
GARCH(β_1)	0.798	0.00	0.863	0.00	0.866	0.00	0.873	0.00	0.887	0.00	0.941	0.00	0.941	0.00	0.900	0.00	0.944	0.00
GJR(γ_1)	0.127	0.00	0.161	0.00	0.170	0.00	-0.166	0.00	0.147	0.00	0.036	0.00	-0.021	0.03	0.086	0.00	0.002	0.87
Log-likelihood	21974		15133		15075		7338		14166		14515		15900		11009		20540	
ARCH test	1132	0.00	1442	0.00	1457	0.00	394	0.00	1240	0.00	591	0.00	386	0.00	1055	0.00	636	0.00
ADCC parameters:			a^*	b^*	g^*	Log-likelihood	AIC	BIC	HQ	Degree of freedom								
*Significant at 1%:			0.022	0.959	0.002	159310	-70	-71	-70		8.6							

with equity market indices during the COVID-19 crisis. On the other hand, at the beginning of the pandemic in early 2020, we see transient jumps in the HFs' correlation with CRB, WTI, and gold. It is apparent that HFs are more focused on equity markets (Fig. 1.1). The average dynamic correlation of HFs with the S&P 100, S&P 500, and Nasdaq is 0.66, 0.70, and 0.67, respectively, compared to 0.32, 0.25, and 0.15 with the CRB, WTI, and gold, respectively. HFRXGL's average dynamic correlation with the 10-year T-note is -0.15. Our findings point to the evolving patterns in HF industry's investing strategy. Literature posits that HFs reduce their risk exposure to equity markets during market turmoil. According to Patton & Ramadorai (2013), HFs resort to cash at times of crises. While our findings suggest a significant drop in HF industry comovements with equity markets during the GFC, no such phenomenon is observed for the COVID-19 crisis.

1.3.1.1 Shock transmissions between HF industry and other markets

Using volatility clusters, we investigate the systemic shock transmissions between the HF industry and the financial markets discussed in Section 1.3.1. It is important to note that we only use the systemic shocks related to each index rather than using the conditional variance, which includes volatility clusters (systemic shocks), persistence (unsystemic shocks), and asymmetry. This way, we only focus on the systemic shocks between the markets, neglecting unsystemic shocks. In this regard, we compute the absolute value of the standardized errors $\left|\frac{e}{\sqrt{h^2}}\right| = \psi$ obtained from our estimations through the ADCC-GJR(1,1)-t and then use an OLS regression to model the shock transmissions between different markets. With an emphasis on HFs, we explore shock spillovers between markets and identify the systemic risk implications, as:

$$\psi_{i,t} = \theta_{i,0} + \sum_{j=1}^{8} \theta_j \psi_{j,t} + v_{i,t} \qquad i,j = 1,...,9 \quad \text{and} \quad i \neq j \tag{1.14}$$

where $\psi i, t$ and $v_{i,t}$ are the volatility cluster and error terms for each asset i at time t respectively, and $\theta_{i,0}$ is the constant term for the asset i. We report the results of the cluster interdependencies between major indices in Table 1.7. The second column of Table 1.7 reports the regression coefficients for HFRXGL cluster dependency equation. The shocks from the 10-year T-note, gold, WTI, CRB, Nasdaq, and VIX permeate the HF We discover that volatility cluster of WTI has no impact on those of S&P 100 and S&P 500, whereas gold volatility clusters do influence both of these equity indices. Another interesting result is the impact of the 10- year T-note. The volatility clusters of the 10-year T-note affect only the S&P 500 and has no effect on the S&P 100's giant companies. On the other hand, CRB only affects the S&P 100 and not the S&P 500. There are no shock transmissions between the CRB and VIX mutually. Among other results in Table 1.7, we note the strong bi-directional impact of the 10-year T-note and gold spot price volatility clusters on each other. Furthermore, WTI volatility clusters have the greatest impact on CRB volatility clustering, as expected. The HFs' volatility clusters affect the volatility clusters of the Nasdaq, CRB, gold, WTI, and 10-year T-note. This means that shocks to the HFs spread to other markets, which is consistent with the findings of dynamic correlations and shows that HFs exploit other markets during a crisis. Our paper suggests additional regulatory mandates are required to decrease HFs' detrimental effects on other markets.

1.3.2 The dynamics of HF strategies

In this section, we study the dynamics and investing styles of the four HF strategies, including Event Driven (HFRXED), Equity Hedge (HFRXEH), Macro (HFRXM), and Relative Value Arbitrage (HFRXRVA), with 30 liquid and major assets from four financial markets, including equities, commodity futures, currencies, and debt markets.
We consider all sectors in S&P 500 including: information technology (SP InfoTech), healthcare (SP Health), consumer discretionary (SP ConsDiscr), telecom services (SP TeleCom), financials (SP Finance), industrials (SP Indust), consumer staples (SP ConsStap), utilities (SP utilities), materials (SP materials), and energy (SP energy). As discussed in the data section, we prefer the Dow Jones (DJ) US real estate market index over the S&P 500 real estate index, because of its comprehensiveness. In addition, we consider the S&P 100, which includes the top 100 largest companies in the US and accounts for more than 50% of the US equity market cap. We also consider the E-mini contract (a popular futures contract on the S&P 500), which has a very deep and active market. Moreover, 13 commodity futures contracts reflecting 5 distinct categories of commodities are also considered. Among the commodities we consider in this section, are WTI crude oil (WTI F), natural gas (Gas F), and heating oil (Heat Oil F) as the three most traded energy futures contracts; gold (Gold F), silver (Silver F), and copper (Copper F) as the three most traded precious metals contracts; soybean (Soybean F), corn (Corn F), and wheat (Wheat F) as the three largest grain futures contracts; sugar (Sugar F), coffee (Coffee F), and cotton (Cotton F) as the three most traded soft futures contracts; and finally, the most liquid livestock futures contract, live cattle (Cattle F) from the Chicago Mercantile Exchange (CME). Given the crucial impact of debt securities in asset management, we consider the 10-year US T-note (10-year T-note). Finally, three heavily traded exchange rates from the forex market are included in our analysis: US-

Table 1.7: Cluster interdependencies between markets.

	HFRXGL		S&P 100		S&P 500		VIX		Nasdaq		CRB		Gold spot		WTI spot		US 10-year T-note	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Constant	0.49	0.00	0.41	0.00	0.39	0.00	0.35	0.00	0.53	0.00	0.51	0.00	0.44	0.00	0.49	0.00	0.54	0.00
HFRXGL			0.01	0.53	0.00	0.76	0.11	0.00	0.06	0.00	0.04	0.01	0.07	0.00	0.03	0.02	0.04	0.01
S&P 100	0.01	0.53			0.24	0.00	0.06	0.00	0.07	0.00	0.03	0.05	0.03	0.05	0.01	0.55	0.00	0.87
S&P 500	0.00	0.76	0.25	0.00			0.03	0.04	0.09	0.00	0.00	0.86	0.05	0.00	0.02	0.11	0.04	0.01
VIX	0.10	0.00	0.06	0.00	0.03	0.04			0.06	0.00	0.01	0.53	0.06	0.00	0.05	0.00	0.08	0.00
Nasdaq	0.06	0.00	0.08	0.00	0.10	0.00	0.07	0.00			0.04	0.01	0.05	0.00	0.17	0.00	-0.01	0.48
CRB	0.04	0.01	0.03	0.05	0.00	0.86	0.01	0.53	0.04	0.01			0.01	0.49	-0.02	0.33	0.00	0.79
Gold spot	0.07	0.00	0.03	0.05	0.04	0.00	0.06	0.00	0.01	0.49	0.04	0.00			0.03	0.03	0.10	0.00
WTI spot	0.03	0.02	0.01	0.55	0.02	0.11	0.05	0.00	-0.01	0.33	0.16	0.00	0.03	0.03			0.03	0.04
US 10-year T-note	0.04	0.01	0.00	0.87	0.04	0.01	0.09	0.00	0.00	0.79	-0.01	0.48	0.11	0.00	0.03	0.04		
F-Stat	18	0.00	49	0.00	50	0.00	26	0.00	19	0.00	22	0.00	20	0.00	23	0.00	17	0.00
R^2	0.03		0.08		0.08		0.04		0.03		0.04		0.03		0.04		0.03	

DEUR, USDGBP, and USDJPY.

Note that all of these assets are directly investable for any investor. Unlike previous studies, we focus on easily investable assets rather than including or constructing exotic portfolios. In studying HF strategies' investing styles, we only consider futures contracts rather than spot contracts because HFs cannot buy and store goods. As in HFR's defined formulaic methodology [18], any subscribed HF has to choose one of the following four main investing style categories initially: Event Driven, Equity Hedge, Macro, and Relative Value Arbitrage.

The literature analyzes HF strategies' dynamics with very broad economic indicators, from gold spot price, to inflation or GDP gap output. While there are potential relationships between those variables, we believe the 30 assets considered here are able to explain a large portion of the variation in volatility of the HFs, because HFs can invest in these assets, not in the GDP gap or inflation. Restating, the 30 assets are easily investible, heavily traded, and deep enough to include large groups of market players. As discussed in Section 1.2.1 (descriptive statistics), many of these assets had more than 200% return, during the whole sample period. Needless to mention that excessive derivatives trading generally leads to underperformance (Cici & Palacios, 2015). Table 1.8 shows the result of our estimation. We estimate the dynamic conditional correlations with the 30 assets for each HF strategy, avoiding spillovers between HF strategies. Panel A of Table 1.8 shows the result of the VAR(1) model for each HF strategy return equation. The constant terms show that Event Driven strategy generates 2 bps abnormal return (also referred to as manager's skill) during the entire sample period, outperforming other strategies. The HFRX*** coefficients represent the effect of the lagged return of each strategy on itself. In this regard, all strategies exhibit mean-reverting behavior. The S&P 100 has a severe negative impact on the Event Driven and Equity Hedge strategies.

Note that the two strategies are more focused on equity markets than other markets, based on their prospectuses. Looking at VAR results for Event Driven, we see a positive effect from the consumer discretionary sector. Amazon, McDonald's, Starbucks, and Walt Disney belong to this sector. Companies proved to be immune to market downsides, with steady yet slow growth. On the other hand, the consumer staples sector has a negative impact on the Event Driven strategy. The sector with businesses, less sensitive to economic cycles. The results also show that real estate market perfor-

[18]https://www.hfr.com/sites/default/files/pdf/HFRX_formulaic_methodol ogy.pdf

mance negatively affects Equity Hedge performance, although significant only at 10%. The widespread effect of the 10-year T-note is interesting. This bond, Granger causes the performance of three out of four HF strategies. This shows that HFs are active in the debt market as well. The performance of the Event Driven strategy can only be affected by two futures contracts: corn and live cattle, with the former having a positive effect and the latter having a negative effect.

The only strategy in our study that is significantly influenced by all four markets is the Equity Hedge, which is largely hit by the performance of the S&P 100. On the other hand, information technology, consumer discretionary, and financials sectors have a positive impact on this strategy. The real estate market has a negative impact on the Equity Hedge strategy, at 1% significance level. It is evident that the performance of E-mini positively influences the performance of Even Driven and Equity Hedge strategies. We also find that corn and cotton futures contracts Granger cause the Equity Hedge positively, while wheat has a negative impact on this strategy. Another positive effect comes from the currency market. We find a weak but positive relationship between the lagged return of the USDEUR and the Equity Hedge strategy performance. Moreover, the stronger the US Dollar against the European Euro (USDEUR), the higher returns for this HF strategy. This strategy is positively affected by silver futures contract, in addition to the comparably large influence from the 10-year T-note and information technology sector. There is a negative impact from the financials sector linked to this strategy, significant at 10%.

Finally, we witness the healthcare, consumer discretionary, and energy sectors, Granger cause the Relative Value Arbitrage strategy performance.

In Panel B of Table 1.8, we have the parameter estimates of the uni- variate GJR volatility model for each HF strategy. We can see significant parameters for volatility cluster (α_1), volatility persistence (β_1), and volatility asymmetry (γ_1) for all strategies. The persistence parameter explains a large amount of the conditional volatility in all HF strategies. The persistence (capturing the effect of the last period conditional variance) denoted by parameter β_1 is the largest in case of the Macro strategy (0.935) and smallest for the Equity Hedge (0.823) among the four strategies. The cluster effect α_1 refers to the impact of lagged shocks and ranges from 0.029 for the Equity Hedge, to 0.1 for the Relative Value Arbitrage. All strategies except the Macro, show significant and large leverage effect, which means negative news creates larger volatility than positive news. This result is in line with studies on stock market volatility modelling, poten-

Table 1.8: Model parameters for each HF strategy.

Panel A: VAR coefficients for each HF strategy mean equation with the p-value

	$HFRXED_t$		$HFRXEH_t$		$HFRXM_t$		$HFRXRVA_t$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	0.000	0.00	0.000	0.00	0.000	0.23	0.000	0.00
$HFRX{***}_{t-1}$	0.051	0.01	0.047	0.06	0.045	0.01	0.072	0.00
S&P 100_{t-1}	-0.048	0.06	-0.158	0.00	-0.014	0.73	-0.005	0.78
SP Information technology_{t-1}	0.007	0.45	0.034	0.01	0.022	0.09	0.003	0.65
SP Healthcare_{t-1}	-0.002	0.82	0.009	0.39	-0.001	0.96	0.009	0.03
SP Consumer $\text{discretionary}_{t-1}$	0.018	0.03	0.052	0.00	0.017	0.14	0.016	0.00
SP Telecom services_{t-1}	-0.001	0.79	-0.010	0.16	-0.005	0.47	-0.001	0.66
SP Financials_{t-1}	-0.004	0.50	0.015	0.09	-0.015	0.08	0.003	0.49
SP Industrials_{t-1}	0.001	0.92	-0.005	0.68	-0.003	0.78	-0.005	0.33
SP Consumer Staples $_{t-1}$	-0.019	0.04	0.005	0.68	-0.004	0.70	-0.003	0.50
SP Utilities_{t-1}	0.001	0.89	0.011	0.16	0.011	0.11	-0.004	0.21
SP Materials_{t-1}	0.003	0.60	0.007	0.44	-0.001	0.89	0.005	0.22
SP Energy_{t-1}	-0.003	0.44	0.009	0.20	0.007	0.21	0.006	0.01
DJ US Real estate_{t-1}	-0.007	0.10	-0.013	0.01	-0.008	0.13	0.005	0.17
US 10-year Treasury note_{t-1}	0.020	0.10	0.033	0.07	0.072	0.00	0.002	0.90
E.mini_{t-1}	0.071	0.00	0.082	0.00	0.026	0.20	0.009	0.45
WTI futures_{t-1}	-0.002	0.46	-0.001	0.75	0.002	0.42	0.001	0.68
Gas futures_{t-1}	0.002	0.35	-0.001	0.73	0.000	0.86	0.000	0.88
Heating oil futures_{t-1}	-0.001	0.87	-0.002	0.75	-0.009	0.20	-0.003	0.39
Gold futures_{t-1}	0.007	0.60	0.008	0.60	-0.019	0.20	0.003	0.66
Silver futures_{t-1}	0.001	0.85	-0.001	0.88	0.020	0.02	0.001	0.62
Copper futures_{t-1}	-0.007	0.21	0.012	0.13	-0.007	0.36	-0.004	0.22
Soybean futures_{t-1}	-0.001	0.83	0.001	0.90	0.004	0.41	-0.005	0.05
Corn futures_{t-1}	0.008	0.05	0.014	0.01	-0.005	0.47	0.005	0.07
Wheat futures_{t-1}	-0.003	0.19	-0.007	0.03	-0.001	0.82	-0.001	0.35
Sugar futures_{t-1}	0.005	0.14	0.005	0.35	0.000	0.95	0.002	0.38
Coffee futures_{t-1}	0.003	0.47	-0.001	0.90	-0.003	0.53	-0.002	0.25
Cotton futures_{t-1}	0.006	0.19	0.013	0.04	0.002	0.75	0.002	0.47
Live cattle futures_{t-1}	-0.008	0.07	-0.007	0.20	0.002	0.70	-0.002	0.51
USDEUR_{t-1}	-0.004	0.65	0.020	0.10	0.036	0.00	0.002	0.69
USDGBP_{t-1}	0.002	0.83	-0.012	0.32	-0.024	0.05	0.000	0.96
USDJPY_{t-1}	0.010	0.17	0.006	0.55	-0.013	0.19	-0.007	0.20

Panel B: Volatility equation GJR(1,1) parameters

Ω	0.000	0.00	0.000	0.00	0.000	0.02	0.000	0.01
ARCH(α_1)	0.056	0.00	0.029	0.05	0.094	0.00	0.092	0.00
GARCH(β_1)	0.837	0.00	0.823	0.00	0.935	0.00	0.870	0.00
GJR(γ_1)	0.126	0.00	0.178	0.00	-0.066	0.00	0.067	0.00
Half-life (in days)	16		11		174		288	
Log-likelihood	20860		19464		19374		23147	
ARCH test	1012	0.00	828	0.00	637	0.00	1078	0.00

Panel C: ADCC parameters

a^*	0.0051	0.00	0.0051	0.00	0.0065	0.00	0.0051	0.00
b^*	0.9903	0.00	0.9905	0.00	0.9868	0.00	0.9901	0.00
g^*	0.0003	0.00	0.0003	0.00	0.0005	0.00	0.0003	0.00
Log-likelihood	529032		528773		526870		530159	
AIC	-233		-233		-232		-233	
BIC	-233		-233		-232		-233	
HQ	-235		-234		-232		-234	

tially due to the large activity of HFs in equity markets. However, Elyasiani & Mansur (2017) find that positive news creates larger volatility compared to negative news in many HF strategies. As discussed earlier, one potential explanation for their result is the use of low-frequency monthly data. We also calculate the half-life volatility shock for each strategy, which states that when a shock permeates the conditional variance, how many days it takes for the volatility to get halfway back to its unconditional mean. While the Event Driven and Equity Hedge strategies have short-lived shock half-life ($\sim$ 2 weeks), shocks take 174 days, and 288 days to get back to their unconditional mean in the case of the Macro and Relative Value Arbitrage strategies, respectively. These results raise the possibility of a long-term shock spillover between these two strategies and their portfolio constituents. The Event Driven and Equity Hedge strategies seem to have more active asset management such that when a shock hits them, the shock is transient. On the other hand, when a shock spreads to the Macro or Relative Value Arbitrage strategies, it takes a long time to dissipate. This might be a sign of the semi-passive investing style of these two strategies. Finally, panel C of Table 1.8 reports the estimated parameters for the ADCC model.

Figs. 1.2–1.5 depict the dynamic correlations between HF strategies and each of the 30 assets. In Fig. 1.2, we have the dynamic correlations of the Event Driven strategy with the 30 assets. One can observe three ubiquitous patterns across many dynamic correlations: the first happens during the GFC, the second is the gradual decline across equity market assets that begins in early 2013, and the third one occurs during the COVID-19 pandemic. Prior to the GFC, the dynamic correlations are increasing across equity market sectors, but when the GFC hits the equity market at full strength in mid-2008, the Event Driven strategy decreases its exposure to nearly all equity market sectors except the utilities and energy. On the other hand, we witness jumps in the dynamic correlations of this strategy with commodities from mid-2008 to mid-2009, including those of WTI futures, natural gas, heating oil, soybean, wheat, corn, sugar, coffee, cotton, and cattle. The second ubiquitous pattern relates to the long-term gradual decline in dynamic correlations with equity market assets, which emerges in early 2013, after the low-interest environment of post-GFC. The second pattern seems to end just before the onset of the COVID-19. The third pattern that emerges during the COVID-19 also reveals a change in the investing style of this HF strategy. Similar to the GFC, the Event Driven strategy utilizes the futures contracts as a buffer against equity market turmoil at the beginning of the COVID-19 pandemic. This is evident by looking at the dynamic correlations with WTI, gas, heating oil, silver, soybean, and sugar, among other futures contracts. However, in contrast to the GFC, this time the dynamic correlations increased in several equity market assets. All in all, the dynamic correlations are very strong with equity market assets compared to other markets' assets, which means this strategy is concentrated on the equity market.

Fig. 1.3 shows the dynamic correlations between the 30 asset classes and the Equity Hedge strategy. It is evident that Equity Hedge strategy is highly focused on the equity market, similar to the Event Driven strategy. The dynamic correlations with equity market assets reach 80% in many cases, while in general the comovements of this HF strategy with currencies (except USDJPY) and the T-note are negative, especially during the GFC or Europe's sovereign debt crisis. Unlike the Event Driven strategy, the dynamic correlations of the Equity Hedge strategy with equities do not fall sharply during the GFC, and throughout the crisis, this strategy maintains or increases exposure to TeleCom, industrials, consumer staples, utilities, materials, energy, and real estate. On the other hand, by mid-2010, when the crisis has totally plagued the markets, the dynamic correlations with the S&P 100, InfoTech, Indust, and E-mini begin to fall. This is consistent with the fact that this strategy has the highest standard deviation, CVaR, and maximum drawdown when compared to the other HF strategies (Table 1.1).

This strategy is extremely vulnerable to crises due to a lack of market timing skill, and as a result, the increase in dynamic correlations with commodities only occurs after 2009. Futures contracts like WTI, silver, heating oil, copper, soybean, corn, wheat, and cotton are the ones with a pronounced increased correlation from 2009 to 2011. We observe a gradual decline in all equity market sector correlations during the COVID-19 pandemic period. In contrast, dynamic correlations with some futures contracts show a brief but significant surge in various contracts in early 2020. This trend is confirmed by the dynamic correlations of HFRXEH with gas, heating oil, sugar, cotton, and cattle.

As previously noted, the Macro strategy performed the worst among the HF strategies in terms of return in the whole sample period (Table 1.1). We do not notice a distinct difference in terms of investing style when examining its dynamic correlations with various asset classes from various markets (Fig. 1.4). A majority of dynamic correlations fluctuate between -10% and -50%. Consequently, this strategy is not focused on a particular market. When the equity markets were booming in early 2006, the dynamic correlations of the Macro strategy with those sectors swiftly increased. However, starting in mid-2007 (the start of the GFC), we observe the beginning of a sharp decline in the dynamic correlations, causing the correlations to turn negative. The dynamic correlations with commodity futures suggest this strategy too, exploits futures contracts,

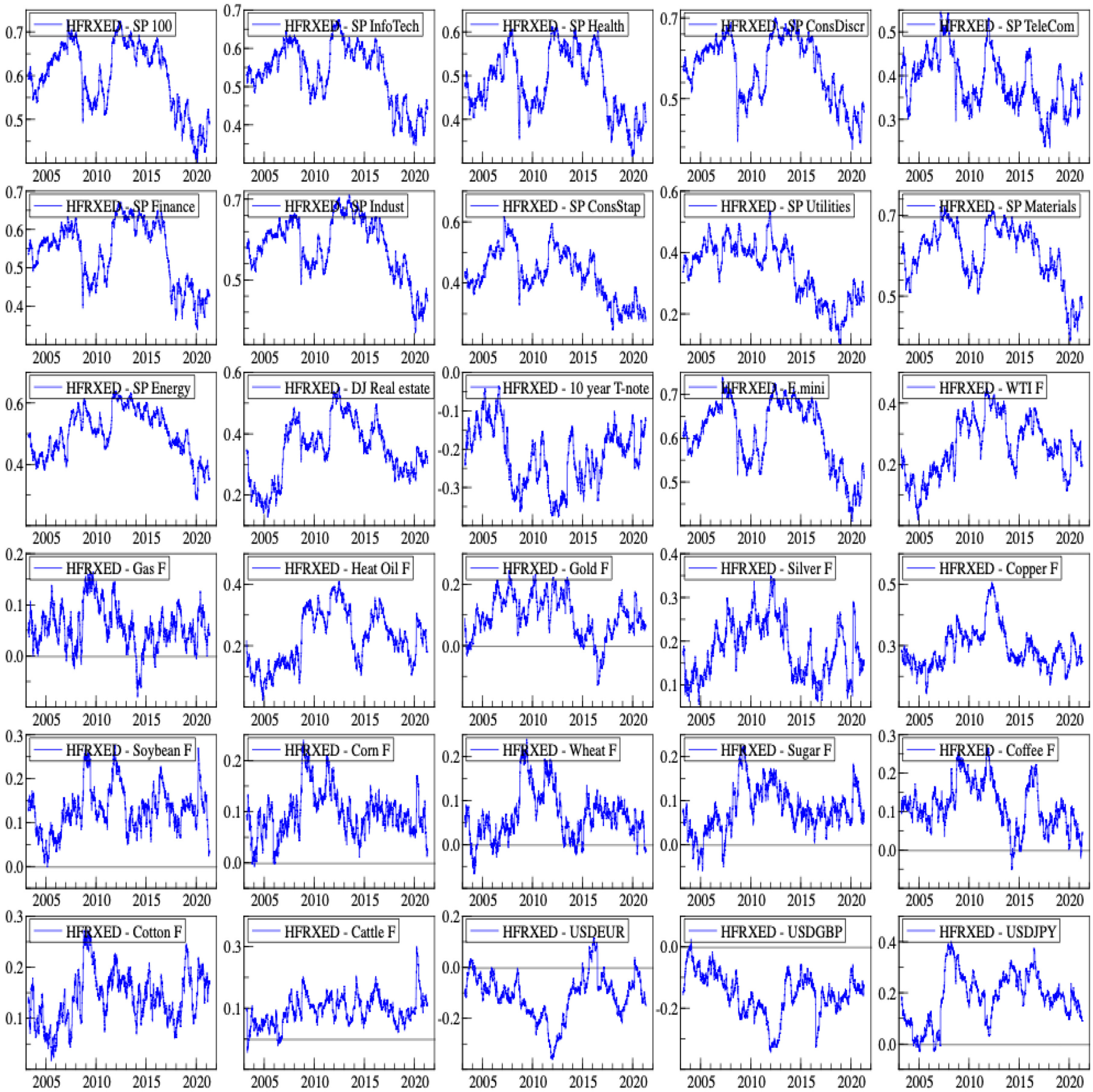


Figure 1.2: HFRXED (Event Driven strategy) dynamic correlations.

similar to the other HF strategies (2008–2010).

The jagged correlation lines across different markets and assets seem to resemble the extensive use of options by this HF strategy. During the COVID-19 period, the comovements of the Macro strategy in both equity and commodity assets show an increasing pattern, while the comovements with currencies are generally negative and decreasing. The dynamic correlation of the Macro strategy with the S&P 100, information technology, healthcare, consumer discretionary, telecommunications services, and materials all show rising trends. Similarly, WTI, gold, silver, copper, and cotton show a positive upward trend. This is the only HF strategy that has a positive correlation with the 10-year Treasury note, especially during crises. Patton & Ramadorai (2013) find that this strategy has the highest time-varying risk exposure compared to other strategies. Our results show that the Macro strategy seems to have good market timing skills (in line with Gregoriou et al., 2021) and is quick in switching between markets and assets to decrease the adverse effects of crashes, although this timing skill comes at the cost of underperformance.

Fig. 1.5 exhibits the dynamic correlations of Relative Value Arbitrage strategy with other assets across different financial markets. Similar to other strategies, the dynamic correlations with equity market assets show an upward trend since 2007, and then a downward trend in late 2008, falling to zero in early 2010, across all equity market sectors. Unlike other HF strategies, we do not find sharp increases or decreases in the dynamic correlations of this strategy with commodities in response to the GFC, although gradual rises in comovements with commodities exist across several futures contracts, including natural gas, wheat, cotton, and cattle. Relative Value Arbitrage appears to be an active speculator, much like the Macro strategy, based on the oscillations in its dynamic correlations, particularly with futures contracts.

Further support for the heavy usage of options can be seen in the statistical characteristics of this strategy's return. As in Table 1.1, among the four HF strategies, this strategy has the lowest standard deviation (0.2%) and smallest skewness (-1.77), but with the largest kurtosis (46) and maximum drawdown (-40%).

1.3.2.1 Shock transmissions between HF strategies and financial assets

To study the dynamics of the HF strategies in further detail, we analyze the (volatility) cluster dependency of each HF strategy on those of the 30 assets considered in the previous section. In this regard, and similar to Section 1.3.1.1, we employ the absolute

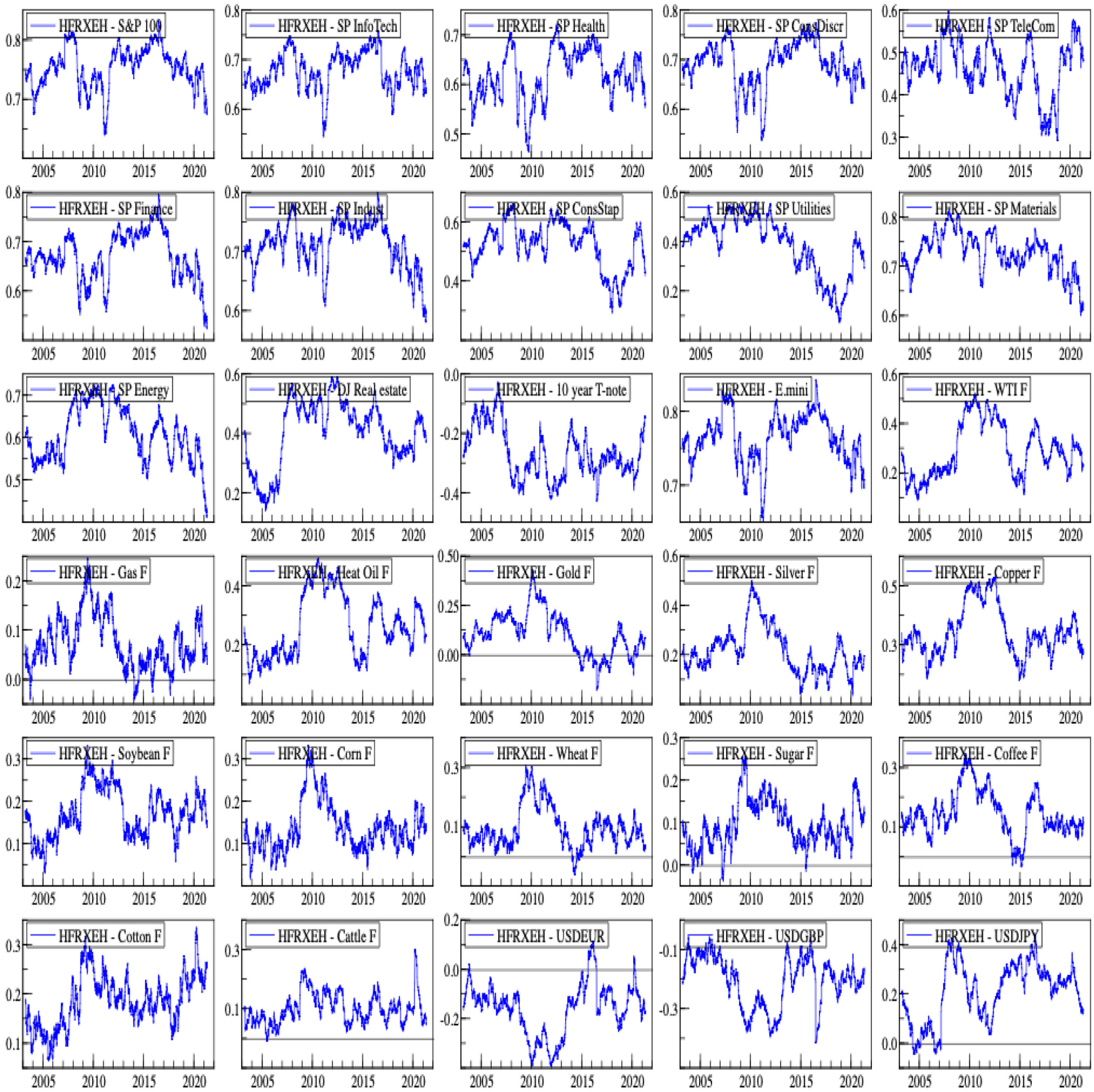


Figure 1.3: HFRXEH (Equity Hedge strategy) dynamic correlations.

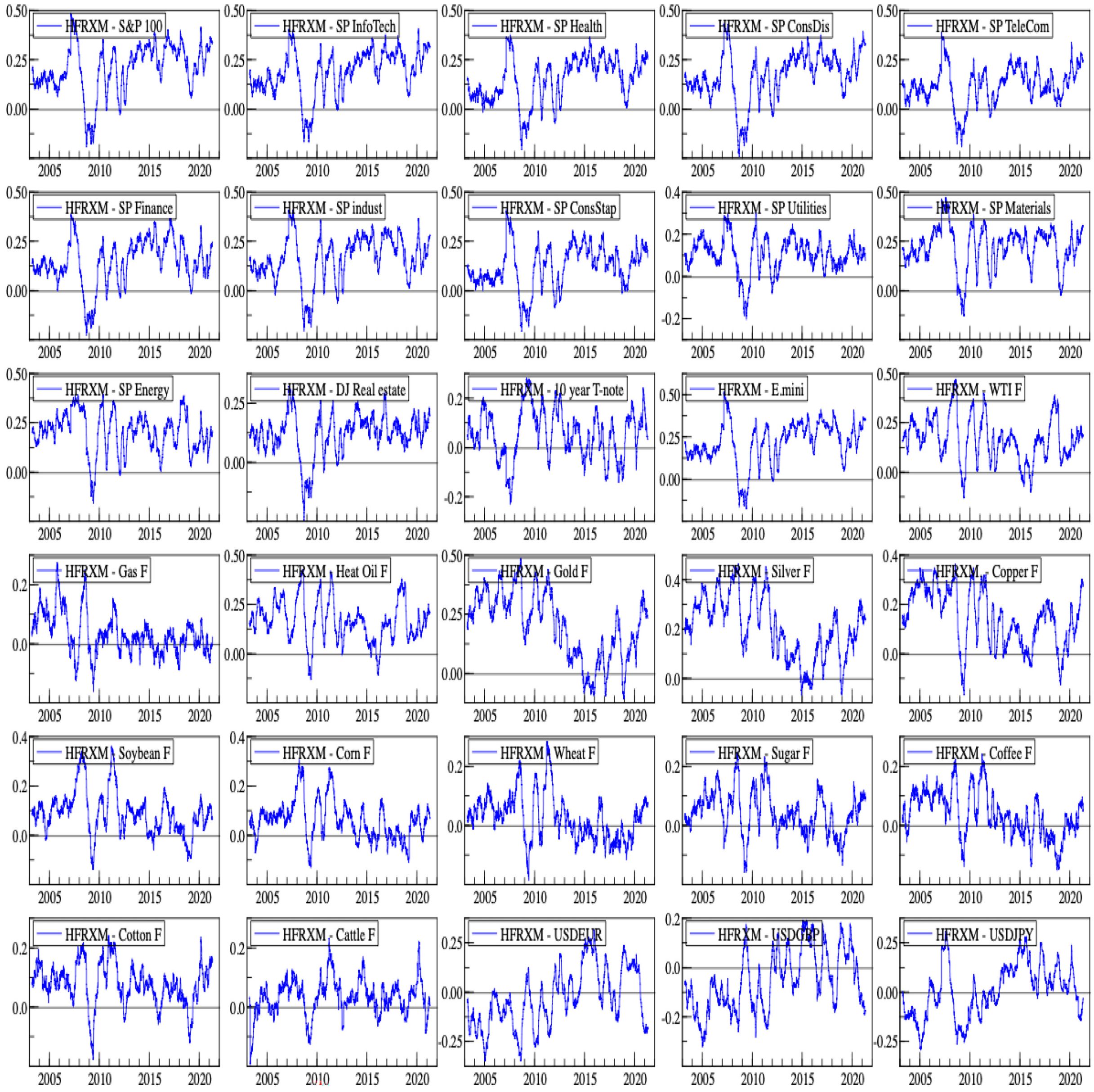


Figure 1.4: HFRXM (Macro strategy) dynamic correlations.

value of the standardized errors $\left|\frac{e'}{\sqrt{h'^2}}\right| = \kappa$ and regress the volatility cluster of each HF strategy on the volatility clusters of the 30 assets, with no spillover effect between HF strategies by an OLS regression. To that end, we investigate shock transmissions from those 30 assets on each of the four HF strategies in the following way:

$$\kappa_{i,t} = \eta_{i,0} + \sum_{j=1}^{30} \eta_j \kappa_{j,t} + \epsilon_{i,t} \qquad j = 1,2,3,...,30 \quad \text{and} \quad i \neq j \tag{1.15}$$

where $\kappa_{i,t}$ and $\kappa_{j,t}$ are the volatility clusters of HF strategy i ($i = 1,...,4$) and asset j ($j = 1,2,3,...,30$) at time t, respectively, $\eta_{i,0}$ is the constant term in HF i's cluster dependency regression, η_j refers to the estimated coefficients for each of the 30 assets, and $\epsilon_{i,t}$ are the error terms for HF strategy i at time t.

Table 1.9 shows the cluster dependencies of HF strategies. The results show that the volatility cluster of the Event Driven strategy is affected by the S&P 100, information technology, financials, consumer staples, materials, and E-mini volatility clusters heavily. Silver, live cattle, and USDJPY also have cluster spillover on this HF strategy. The volatility cluster of the Equity Hedge strategy is under the influence of four equity market assets' volatility clusters: consumer discretionary, consumer staples, materials, and the E-mini. Moreover, the two forex rates, USDGBP and USDJPY, also transmit shocks to this HF strategy. The volatility cluster of the Macro strategy is heavily influenced by the several assets from different markets. The volatility clusters of the S&P 100, health-care, consumer staples, utilities, energy, E-mini, the 10-year T-note, WTI, gold, silver, copper, soybean, coffee, and the three currencies all have significant spillover effect on the volatility clusters of Macro strategy. This might be the reason why the Macro strategy underperforms. The volatility cluster of the Relative Value Arbitrage strategy is affected by the volatility clusters of health- care and information technology sectors, the 10-year note, E-mini, gas, gold, and live cattle. Like other strategies, the volatility cluster of USDJPY has an impact on this HF strategy. Overall, consumer staples, E-mini, gold futures, and USDJPY are the assets with widespread cluster spillover across HF strategies in our work.

To see if the volatility clusters of HF strategies affect those of the 30 assets, we employ a Granger causality test. The Equity Hedge strategy influences 13 out of 30 assets in our study, as the most influential strategy. On the other hand, the volatility cluster of the Macro strategy, which is heavily influenced by the volatility clusters of the 30 assets, only Granger causes 5 assets' volatility clusters, as the least influential strategy

Table 1.9: HF strategies' cluster dependencies.

	$HFRXED_t$		$HFRXEH_t$		$HFRXM_t$		$HFRXRVA_t$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	0.432	0.00	0.448	0.00	0.296	0.00	0.432	0.00
S&P 100	0.045	0.00	0.017	0.26	-0.025	0.10	0.010	0.54
S&P Information technology	0.027	0.08	0.015	0.30	0.004	0.76	0.036	0.02
S&P Healthcare	0.008	0.59	0.008	0.60	0.026	0.07	0.046	0.00
S&P Consumer discretionary	0.017	0.27	0.041	0.01	-0.013	0.39	-0.021	0.18
S&P Telecom services	0.011	0.47	0.011	0.45	0.005	0.73	0.018	0.24
S&P Financials	0.026	0.10	0.011	0.46	0.006	0.71	0.008	0.63
S&P Industrials	-0.009	0.55	0.009	0.53	0.001	0.93	-0.012	0.44
S&P Consumer Staples	0.029	0.06	0.036	0.02	0.039	0.01	0.004	0.80
S&P Utilities	0.001	0.94	0.024	0.12	0.030	0.04	0.010	0.55
S&P Materials	0.041	0.01	0.026	0.08	0.013	0.36	0.004	0.78
S&P Energy	0.020	0.20	0.022	0.15	0.038	0.01	-0.009	0.59
DJ US Real estate	-0.002	0.92	-0.007	0.65	0.022	0.15	0.020	0.23
US 10-year Treasury note	0.013	0.40	0.005	0.76	0.037	0.01	0.031	0.05
E.mini	0.040	0.01	0.024	0.10	0.032	0.03	0.038	0.01
WTI futures	-0.008	0.59	0.015	0.33	0.060	0.00	0.021	0.19
Gas futures	0.016	0.29	0.021	0.16	-0.003	0.86	0.029	0.06
Heating oil futures	0.004	0.79	-0.015	0.32	-0.004	0.79	0.005	0.74
Gold futures	0.007	0.63	0.025	0.09	0.059	0.00	0.056	0.00
Silver futures	0.029	0.04	0.006	0.66	0.041	0.00	0.014	0.35
Copper futures	0.003	0.86	0.007	0.62	0.024	0.09	-0.003	0.82
Soybean futures	0.012	0.43	-0.017	0.23	0.003	0.81	0.009	0.57
Corn futures	0.012	0.42	0.020	0.17	0.020	0.13	0.005	0.74
Wheat futures	0.015	0.34	0.002	0.91	0.014	0.32	-0.009	0.56
Sugar futures	-0.006	0.68	0.015	0.31	0.015	0.27	-0.007	0.64
Coffee futures	0.006	0.67	0.019	0.19	0.030	0.03	0.019	0.22
Cotton futures	0.014	0.31	-0.008	0.56	-0.018	0.18	-0.010	0.50
Live cattle futures	0.034	0.01	0.012	0.35	0.000	0.98	0.043	0.00
USDEUR	0.000	0.99	0.013	0.40	0.068	0.00	0.026	0.11
USDGBP	0.010	0.49	0.027	0.06	0.027	0.06	0.019	0.22
USDJPY	0.030	0.05	0.036	0.01	0.031	0.03	0.036	0.02
R^2	0.021		0.012		0.041		0.023	
F-statistic	3.23	0.00	2.83	0.00	6.35	0.00	3.50	0.00

in our study (Table 1.10). It is intuitive to see that the Event Driven and Equity Hedge strategies, which are mainly focused on the equity market, Granger cause many assets' volatility clusters in this market.

The p-values in Table 1.10 show that the industrials, the 10-year T-note, and the futures contracts including WTI, natural gas, heating oil, copper, soybean and coffee are not under the influence of any of the HF strategies. It is interesting to see that USDJPY, whose volatility cluster influences all four HF strategies' volatility clusters, is not affected by any of the HF strategies' volatility clusters. Further, corn and silver are the futures contracts heavily hit by the volatility clusters of several HF strategies.

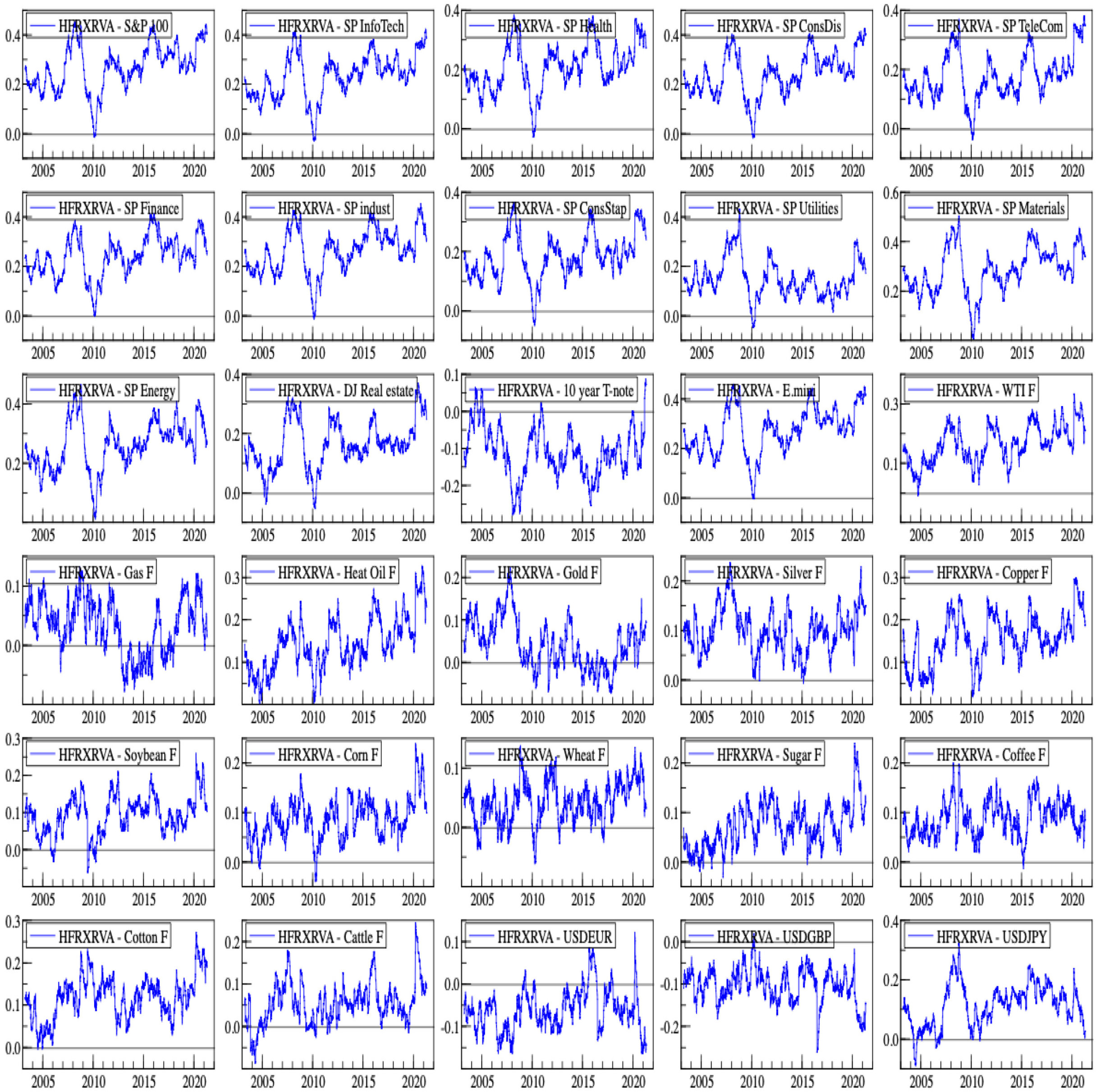


Figure 1.5: HFRXRVA (Relative Value Arbitrage strategy) dynamic correlations.

1.3.2.2 Futures basis and HFs' performance

The last section in our study, looks at the impact of the futures basis on HFs' performance. The theory of storage (Fama & French, 2016; Schwartz, 1997; Working, 1949) posits that, when the futures basis defined as the spread between the futures and spot prices of a commodity increases, the opportunity for arbitrage increases. Among our notable contributions to the literature, we examine whether the basis computed for the 13 commodities can explain HFs' performance to some degree. We do not find any previous study to examine this relationship.

As in theory of storage, the basis is defined as:

$$\text{The futures basis} = \ln\left(\frac{\text{futures price index}_t}{\text{spot price index}_t}\right) \tag{1.16}$$

When the gap between futures and spot prices of a commodity in- creases, the chance for opportunistic speculation increases. In this regard, we regress the returns of each HF strategy on the 13 bases computed on the commodities employed in our study. (Table 1.5)

$$r_{i,t} = m_{i,0} + \sum_{j=1}^{13} m_j b_{j,t} + \xi_{i,t}; \quad i = 1,..,4 \qquad j = 1,2,3,...,30 \quad \text{and} \quad i \neq j \tag{1.17}$$

In this regression equation, $r_{i,t}$ represents the return of the HF strategy $i(i = 1,...,4)$ at time t, $m_{i,0}$ is the constant term, m_j is the coefficient of the $j(j = 1,..,13)$ futures basis, $b_{j,t}$ is the basis for each commodity $j(j = 1,..,13)$ at time t, and $\xi_{i,t}$, t is the error term for HF strategy i at time t. The results are provided in Table 1.11. We find a generally mixed relationship between the bases and HFs' performance. The results show that there are positive relationships between all HF strategies' returns and natural gas basis, the largest of which belongs to the Equity Hedge strategy. The Macro is the only strategy that takes advantage of the basis of WTI. A 1% increase in the basis of WTI, increases the performance of Macro strategy by 88% bps. The large coefficients of gold basis in the regression equation of the Event Driven and Equity Hedge strategies, show that the two strategies benefit largely from the increased gap between gold's futures and spot prices. A 1% increase in gold's basis yields a 3 bps increase in the performance of the two strategies. Moreover, a 1% increase in silver's basis yields a 3.1 bps increase in the Relative Value Arbitrage's return, similarly a 1% increase in silver's basis creates approximately a 2 bps increase in the Macro's return. The relationship between cattle's basis and HFs' return is positive and significant, except for the Macro strategy. The Event Driven is the only strategy that benefits from cotton's basis, and the strategy that exploits the futures basis of more commodities than other strategies.

This evidence clearly shows the active presence of HFs in commodities with higher liquid market (like WTI, natural gas, silver, and gold), and lower basis standard deviation (gold, silver, and WTI) as in Table 1.5 which is in line with the performance analysis in Section 1.2.1, that is, delivering a higher return with the lowest risk.

1.4 Discussion & conclusion

Studies on HFs are scarce in comparison to other areas of the Finance literature. One particular reason is that this industry discloses the least amount of information possible. Almost all studies in the literature study HFs' performance utilize low-frequency data. The models and methods used to analyze HFs' performance are not totally suited to HFs' nature. To examine the anatomy of HFs, advanced models are necessary to account for their dynamic and time-varying investing styles across various financial markets and asset classes.

As a response, we apply ADCC-GJR-t to explore the dynamics of HFs with four financial markets: equities, commodity futures, debt, and currencies markets. We discover that, whereas HFs exploit the futures market as a hedge against financial crises and enjoy the equity market at other times, they do not have market timing overall. Furthermore, the dynamic correlations demonstrate that the reaction of HFs to the 2008 crisis differs from that of COVID-19 pandemic. During the current pandemic, HFs did not reduce their exposure to equity market (unlike the GFC), but instead increased their risk exposure to commodity futures (similar to the GFC).

Among the four HF strategies in our study, the Event Driven strategy outperforms the others, while the Macro strategy exhibits market timing. By investigating the volatility dynamics of HF strategies, we discovered significant heterogeneity in the shock lifetime of different HF strategies. The strategies that focus primarily on the equity markets (Event Driven and Equity Hedge) have a shock lifespan of less than a month. On the other hand, shocks take 174 days, and 288 days to get back to their conditional mean in the case of Macro and Relative Value Arbitrage strategies respectively.

Table 1.10: Granger causality test results.

	S&P 100	SP InfoTech	SP Health	SP ConsDis	SP TeleCom	SP Fin	SP indust	SP ConsStap	SP Utilities	SP Materials	SP Energy	DJ Real estate	10 year T-note	E.mini	WTI futures
HFRXED	0.00	0.02	0.00	0.00	0.09	0.51	0.36	0.23	0.00	0.11	0.82	0.37	0.29	0.21	0.73
HFRXEH	0.08	0.06	0.02	0.01	0.06	0.00	0.31	0.00	0.75	0.07	0.93	0.02	0.22	0.07	0.96
HFRXM	0.29	0.22	0.91	0.90	0.45	0.03	0.15	0.79	0.17	0.58	0.02	0.57	0.48	0.58	0.69
HFRXRVA	0.25	0.01	0.06	0.67	0.38	0.37	0.51	0.29	0.58	0.20	0.26	0.16	0.91	0.44	0.15

	Natural Gas Futures	Heating oil futures	Gold futures	Silver futures	Copper futures	Soybean futures	Corn futures	Wheat futures	Sugar futures	Coffee futures	Cotton futures	Cattle futures	USDEUR	USDGBP	USDJPY
HFRXED	0.79	0.93	0.64	0.24	0.95	0.25	0.04	0.88	0.83	0.38	0.13	0.41	0.22	0.02	0.44
HFRXEH	0.68	0.21	0.46	0.01	0.66	0.51	0.68	0.55	0.07	0.15	0.89	0.52	0.00	0.57	0.82
HFRXM	0.44	0.40	0.18	0.04	0.57	0.78	0.10	1.00	0.42	0.22	0.34	0.00	0.57	0.38	0.47
HFRXRVA	0.17	0.98	0.04	0.00	0.54	0.85	0.03	0.03	0.90	0.94	0.05	0.42	0.51	0.45	0.59

The reported p-values refer to the impact of the HF strategies on the 30 assets classes (lag = 1).

Additionally, we looked into the cluster interdependencies between 30 assets from different financial markets, and HF strategies. We detect numerous bidirectional cluster interdependencies. According to the findings of the Granger causality test, there are widespread shock transmissions between HF strategies and many assets in financial markets, especially those of commodity futures. In the final section of our study, we analyzed the effect of the futures basis on the performance of HF strategies. The results indicate that HFs benefited from the rise in the basis of many commodities.

In comparison to other financial markets, we find that HFs indeed performed poorly in terms of returns from April 2003 to May 2021. A passive strategy that tracks one or two equity market sectors can produce at least three times higher returns than the returns delivered by the top-performing HF strategy in our sample. However, when risk indicators like the standard deviation, CVaR, etc., are taken into account, the HF industry stands out as being safer than other markets, even the bond market.

This paper makes clear contributions to portfolio managers, investors, and hedgers with volatility sensitivity in their portfolio strategies, as well as policymakers seeking a better understanding of the links between HFs and other financial asset classes. The manipulative behavior of HFs in the futures market, which is a market for real production and hedging, creates increased market volatility in times of crisis. This is detrimental for the entire economy, such that when a crisis happens, in addition to job loss, unemployment, and market turmoil, the economy also has to deal with unrealistic surges in commodity prices, which are partially the result of the speculative behavior of HFs. This paper is a step forward in understanding the behavior of hedge funds across financial markets.

Table 1.11: OLS regression of the bases on HF strategies' performance.

	HFRXED		HFRXEH		HFRXM		HFRXRVA	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	0.0002	0.07	0.0003	0.03	0.0004	0.01	-0.0001	0.08
WTI basis	0.0020	0.56	0.0052	0.25	0.0088	0.05	-0.0011	0.69
Natural gas basis	0.0028	0.00	0.0032	0.00	0.0018	0.06	0.0023	0.00
Heating oil basis	-0.0001	0.98	0.0029	0.40	0.0007	0.84	0.0023	0.27
Gold basis	0.0338	0.02	0.0322	0.08	-0.0411	0.02	0.0118	0.32
Silver basis	-0.0125	0.16	-0.0412	0.00	0.0197	0.09	0.0313	0.00
Copper basis	0.0036	0.34	0.0078	0.12	0.0007	0.89	0.0014	0.65
Soybean basis	-0.0032	0.00	-0.0025	0.05	-0.0006	0.66	-0.0026	0.00
Corn basis	0.0008	0.53	0.0014	0.39	0.0011	0.53	0.0014	0.15
Wheat basis	-0.0029	0.00	-0.0030	0.00	-0.0011	0.06	-0.0015	0.00
Sugar basis	0.0012	0.05	0.0012	0.14	0.0005	0.48	0.0008	0.10
Coffee basis	-0.0001	0.76	0.0003	0.56	0.0016	0.00	-0.0018	0.00
Cotton basis	0.0023	0.08	0.0002	0.90	0.0015	0.39	-0.0004	0.72
Live cattle basis	0.0027	0.01	0.0038	0.00	0.0017	0.42	0.0022	0.00
R^2	0.015		0.012		0.006		0.024	
F-statistic	5.264	0.00	4.261	0.00	2.148	0.00	8.501	0.00
Degree of freedom	13		13		13		13	

Appendices

Appendix A

HFRX indices description.

	We use the hedgefundresearch https://www.hfr.com (HFR) database's following 5 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.
HFRXGL	The HFRX Global Hedge Fund Index is designed to be representative of the overall composition of the hedge fund universe. It is comprised of all eligible hedge fund strategies; including but not limited to Convertible Arbitrage, Distressed Securities, Equity Hedge, Equity Market Neutral, Event Driven, Macro, Merger Arbitrage, and Relative Value Arbitrage. The strategies are asset weighted based on the distribution of assets in the hedge fund industry.
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

Chapter 2

Stock-Oil Comovements Through Fear, Uncertainty, and Expectations: Evidence from Conditional Comoments

MOHAMMAD NOORI

2.1 Introduction

There is a rich literature studying the effect of oil price shocks on economic variables and systems, highlighting the importance and fundamental effect of oil price fluctuations in real economy[1]. As noted by the Energy Information Administration (EIA), in 2010, the expenditures on energy products, largely by petroleum category, accounted for 8.3% of the US GDP. However the deregulation of commodity markets in the early

[1]See Kilian (2014).

2000s opened the doors to non-commercial players looking for asset diversification and extra yields in other markets, especially in the crude oil futures contracts. Consequently, the tradings of these investors with diversified portfolios, create volatility spillover between commodities and equities. There are many papers (Tang & Xiong, 2012; Fattouh et al., 2013; Singleton, 2014; Christoffersen & Pan, 2018; Christoffersen et al., 2019 among others), evidencing that since 2004[2] the links between the equity markets and commodities have strengthened vastly. Christoffersen et al. (2019) find that commodity volatility correlations have set a new mean since that time and they are strongly related to stock market volatility (more than returns). They state that "the principal components in commodity futures volatility appear to be strongly related to volatility in other asset markets including the U.S. equity market". Christoffersen & Pan (2018) even find that oil shocks create funding constraints for financial intermediaries. Heath (2019) posits that the majority of the studies in the literature are conducted by linear, time-invariant, and model-free approaches, or via vector autoregression (VAR) models. He points to the fact that the previous models developed by VAR variants, neglect the apparent time variations in crude oil price risk, and emphasizes on time-varying and pro-cyclical nature of the oil price dynamics (Kilian, 2014; Hamilton & Wu, 2014).

Another strand of literature regarding the stock-oil relationship posits that since the GFC the correlation between the stock market's and crude oil's price has witnessed a structural change. A few papers have investigated this structural change, and attribute this nascent phenomenon to the aggregate growth shocks (Hitzemann, 2016), the slow down in global economic activity (Bernanke, 2016), the sovereign wealth funds speculative activity (Mohaddes & Pesaran, 2017), and the oil demand shocks (Ready, 2018). As stated by Heath (2019), these studies do not take into account the time-varying and pro-cyclical nature of the stock-oil comovements. Furthermore, all of these studies are primarily concerned with oil supply/demand shocks and are carried out at the macro level; thus the current paper differs from them and is carried out at the micro level using sentiment indicators. This is crucial as Kozlowski et al. (2015) posit, the persistence of the ex-ante quite unlikely 2008 GFC recession, has made market participants to update their prior beliefs about tail events in the markets, and accordingly when market participants face the challenge of accurately fathoming the probability distribution of the future economic development, ambiguity becomes more critical than risk in their decision making (Rossi et al., 2016).

[2] The period termed as "financialization" of commodity markets.

This paper aims at investigating the stock-oil comovements by means of conditional higher comoments focusing on the drivers of the post-GFC nascent stock-oil dynamic. Providing novel contributions to the literature, three time-varying conditional comoments (Fang & Lai, 1997) including beta, coskewness, and cokurtosis[3] are estimated for both crude oil and stock, which measure the sensitivity to the returns, skewness, and tail events in the counterpart market respectively, to investigate the interdependencies between the two markets from April 1983 to December 2021 using daily data. Then, given the observed structural changes in the conditional comoments after the GFC, we analyze the effect of the three macroeconomic sentiment indicators including the CBOE VIX representing fear, the Baker et al. (2016) economic policy uncertainty (EPU) which represents uncertainty, and the thorough Aruoba et al. (2009) index for expectation of real economic condition (ADS henceforth), on the conditional comoments[4] using the time-varying parameter vector autoregression (TVP-VAR) developed by Primiceri (2005) to analyze the time-varying impulse responses of the conditional comoments to shocks in the aforementioned sentiment indices. This is to learn if the recent elevated conditional comoments (post-GFC) relate to the macroeconomic sentiments. Whether macroeconomic upturns and downturns can have asymmetric impact on stock-oil comovements is another topic that hasn't been addressed in the literature. This becomes more important, especially when these asymmetries might persist in the long-run. For this inquiry, a nonlinear autoregressive distributed lag (NARDL) model (Shin et al., 2014) is employed to observe if the positive and negative movements in macroeconomic sentiment indicators influence the conditional comovements asymmetrically.

The time-varying conditional comoments estimated by the asymmetric dynamic conditional correlation (ADCC) GJR-GARCH (Glosten et al., 1993; R. Engle, 2002; Cappiello et al., 2006) show that, in this dual relationship between stock and oil, it is the crude oil which is heavily dependent on stock's performance, skewness, and tail events, with the COVID-19 marking the pinnacle of this dependency. Since the GFC, the increased mutual exposure of the two markets means a decreased opportunity for the portfolio managers, speculators, and hedgers to benefit from diversification between these giant markets. The time-varying impulse response analyses declare that since the GFC, shocks to the sentiment indices (fear, uncertainty, and expectation) create unprecedented strong responses in the stock-oil comovements, especially in the long-run. In

[3] Dittmar (2002) argues that kurtosis measures the likelihood of extreme values while cokurtosis captures the sensitivity of asset returns to extreme market return realizations.

[4] We highlight the three macroeconomic indicators' distinctive feature of having higher frequency daily data, a characteristic that is both uncommon in macroeconomic variables and crucial in studies on volatility modeling.

particular, shocks to the fear index create an asymmetric response in stock (positive) and oil (negative) markets. Given the asymmetric responses in the time-varying impulse response, we examine whether there are asymmetries in the explanatory power of the macroeconomic indices, that is, if positive and negative movements have asymmetric effects on the conditional comoments. The NARDL regression results support the findings of the time-varying impulse responses by showing strong short-run asymmetric effects, especially after the GFC. Similar to the time-varying impulse responses, NARDL regression estimates show that the explanatory power of the three sentiment indices increase vastly for the post-GFC period. In particular, the effect of fear index on WTI conditional beta changes from positive in the pre-GFC period to negative in the post-GFC period. Lastly, in a further inquiry we reestimate the NARDL regressions for the post-GFC period, accommodating the oil-specific fear index (OVX) effect in the models. Interestingly, we find that the effect of the VIX fear index is greater than oil-specific fear index, even for WTI conditional beta. Overall, the results shed light on the alarming and ever-increasing effect of VIX on the stock-oil dependencies.

To summarize, this paper is the first in the literature to: study stock-oil dependencies using time-varying conditional comoments; analyze the time-varying impulse responses to identify the primary macro sentiment shock sources on the stock-oil comoments; investigate the asymmetric effects of macroeconomic sentiment indices on the stock-oil comoments in both the short- and long-run; and identify the major source of the nascent post-GFC dynamics in stock-oil comovements.

The paper is organized as follows. Section 2.2 describes the data, elaborates the estimation procedure of conditional comoments, and presents the theoretical TVP-VAR, with Section 2.3 discussing the estimated conditional comoments and the time-varying impulse responses. Section 2.4 then investigates the asymmetric effects of macroeconomic indicators on the conditional comoments using the NARDL, with the empirical results discussed in Section 2.5. Section 2.6 concludes.

Table 2.1: Descriptive statistics of the dataset

	Mean	SD	Skewness	Kurtosis	Expected Shortfall (5%)	Jarque-Bera (1%)	ADF†	ARCH(1)
S&P500	0.00035	0.011	-1.22	30	0.027	FALSE	-17.5	2527
WTI Futures	0.00010	0.024	-1.90	50.6	0.056	FALSE	-17.8	442

†ADF test with constant, linear and quadratic trend.

2.2 Method & data

In our empirical analysis, we model the conditional comoments between WTI continuous time futures[5] price index[6], and S&P 500 index from April 1983 to December 2021 using daily data. Table 2.1 reports the descriptive statistics of the dataset. In this table, expected shortfall refers to the historical conditional value at risk, Jarque-Bera tests the normality of returns (False in this case, denotes the non-normality of returns), ADF refers to augmented Dickey–Fuller test stat on unit root test at 1% significance level, and finally ARCH(1) is the Lagrange Multiplier test statistics for autoregressive conditional heteroscedasticity (ARCH) effect (R. Engle, 1982) with the values significant at 1%. We calculate the daily changes as $r_t = Ln(\frac{P_t}{P_{t-1}})$ where P_t refers to index price at time t. Note that, only the daily changes of the WTI and S&P 500 are in excess of the one-month TBill rate.

We employ three important macroeconomic indices including CBOE VIX representing fear, Baker et al. (2016) EPU representing uncertainty, and Aruoba et al. (2009) real business conditions index as macroeconomic expectations in the economy[7]. The EPU uncertainty index[8] developed by Baker et al. (2016) is truly an uncertainty measure. This news-based index uses newspaper archives from the Access World News Bank service on words related and/or associated with the word "uncertainty". Several studies find significant relationship between EPU index with many macroeconomic and financial variables (see Al-Thaqeb & Algharabali (2019) for a comprehensive review). The Aruoba et al. (2009) ADS daily index[9] is an indicator for expectation on real business conditions which is computed on economic variables including: weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly real personal income less transfer payments, monthly real manufacturing and

[5]Fattouh et al. (2013), Hamilton & Wu (2014), Heath (2019) emphasize the advantage of employing oil futures price in capturing all types of demands, from speculators and arbitrageurs to true hedgers, i.e. oil futures price is truly representative of all oil market participants. It is a stylized fact that futures market (especially for crude oil) is deeper than spot market and its time-varying term structure helps in forecasting spot prices (Heath, 2019).

[6]Based on nearest-to-maturity price.

[7]We also compute the daily log changes for the three sentiment indices. All the three macro indices' series, are stationary by ADF test.

[8]The data is available at federal reserve bank of Saint Louis.

[9]The data is available at federal reserve bank of Philadelphia.

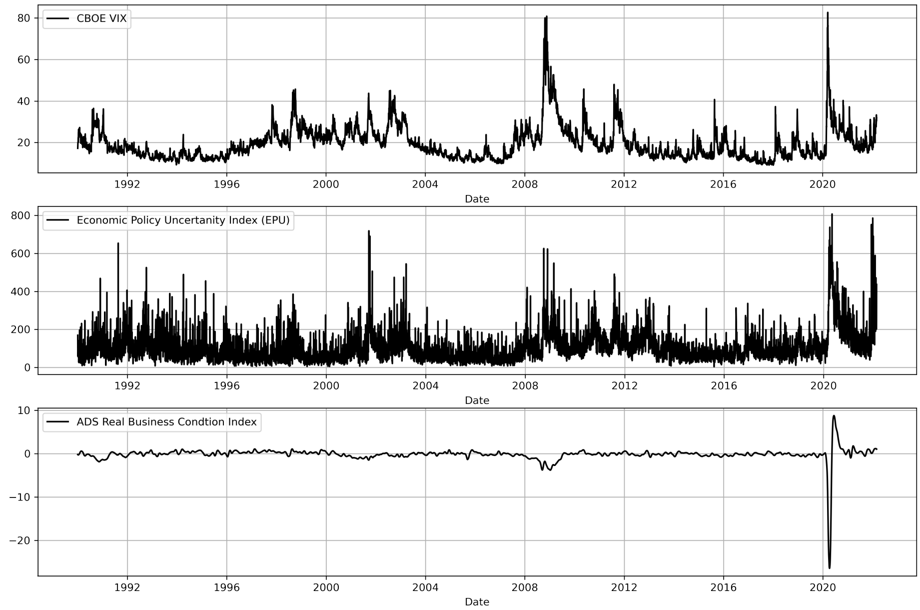


Figure 2.1: Macroeconomic indices

trade sales, and quarterly real GDP. This index has a zero mean, with positive values as progressively better-than-average conditions, and negative values as progressively worse-than-average conditions. Figure 2.1 depicts the three macroeconomic time series. Note that in studying the impact of macroeconomic indicators on the conditional comoments, the empirical analyses are conducted from the year 1990, due to the availability of the macroeconomic variables.

2.2.1 Conditional comoments

The importance of higher moments in asset pricing models was primarily initiated by Samuelson (1975), and Rubinstein (1973), although only later finds place in asset pricing models proposed by Kraus & Litzenberger (1976), Fang & Lai (1997), and Harvey & Siddique (2000). CAPM a two-moment (mean-variance) asset pricing model states that, given the risk free rate r_f, the expected gross return $R_{i,t}$ of asset i at time t is generated by the expected market premium (or excess return) $R_{m,t}$ through asset i's conditional covariance with the market scaled by the market's variance $\sigma^2_{m,t}$ that is :

$$E(R_i) - r_f = \frac{Cov(R_m, R_i)}{Var(R_m)} E_t(R_m) \tag{2.1}$$

Note that the covariance $Cov(R_m, R_i)$ is equal to $E[(R_i - \bar{R}_i)(R_m - \bar{R}_m)]$ with $\bar{R}_i$ and $\bar{R}_m$ referring to the mean return of the asset i and market respectively. Quite often $\frac{Cov(R_m, R_i)}{Var(R_m)}$ is defined as the conditional $\beta_{i,t}$ of the asset i with the market. Now let's provide a broader view of the CAPM foundations. In the absence of arbitrage, given the available information set Ω_t and asset i's gross return $R_{i,t+1}$, the stochastic discount factor m_{t+1} is defined as (Cochrane, 2009):

$$E[m_{t+1}R_{i,t+1} \mid \Omega_t] = 1 \tag{2.2}$$

If the canonical assumptions of CAPM are met including Gaussian distribution of returns, or quadratic utility function for an investor (among other assumptions), then the stochastic discount factor (SDF) m_{t+1} can be formulated as a linear function of market return, or:

$$m_{t+1} = \delta_1 + \delta_{2,t}R_{m,t+1} \tag{2.3}$$

However, given the evident failure of the CAPM's assumptions including the Gaussian distribution of the returns, and the quadratic utility function[10], the SDF has a nonlinear relationship with the market return $R_{m,t+1}$, and can be specified with a third-order polynomial of market return as:

$$m_{t+1} = \delta_1 + \delta_{2,t}R_{m,t+1} + \delta_{3,t}R^2_{m,t+1} + \delta_{4,t}R^3_{m,t+1} \tag{2.4}$$

with the δ_1 as the constant term and $\delta_{2,t}, \delta_{3,t}$, and $\delta_{4,t}$ as the coefficients. Following Fang & Lai (1997), CAPM is extended to account for the coskewness and cokurtosis in a four-moment pricing model:

$$E(R_i) - r_f = \zeta_1 Cov(R_m, R_i) + \zeta_2 Cov(R^2_m, R_i) + \zeta_3 Cov(R^3_m, R_i) \tag{2.5}$$

Where $Cov(R_m, R_i)$, $Cov(R^2_m, R_i)$, and $Cov(R^3_m, R_i)$ are the time-varying conditional beta, coskewness, and cokurtosis respectively, with the associated coefficients ζ_1, ζ_2, and ζ_3. It is evident that in equation 5, the conditional comoments are not scaled, so in order to arrive at a correct inference, we must scale these covariances. In this regard we have that:

$$Beta_i(\beta_i) = \frac{Cov(R_m, R_i)}{Var(R_m)} \quad Coskewness_i(\Gamma_i) = \frac{Cov(R^2_m, R_i)}{[Var(R_m)]^{1.5}} \quad Cokurtosis_i(\Lambda_i) = \frac{Cov(R^3_m, R_i)}{[Var(R_m)]^2} \tag{2.6}$$

[10]Quadratic utility requires investors to have increasing absolute risk aversion, which is counter intuitive.

Now after scaling the covariances we arrive at the following model which is the starting point of our empirical investigation:

$$E(R_i) - r_f = \zeta_1'\beta_{i,t} + \zeta_2'\Gamma_{i,t} + \zeta_3'\Lambda_{i,t} \tag{2.7}$$

In the empirical analysis, we get WTI's conditional β after dividing the $Cov(R_{sp}, R_{wti})$ by the S&P 500's variance $Var(R_{sp})$, and the conditional coskewness and cokurtosis of WTI, dividing $Cov(R_{sp}^2, R_{wti})$ and $Cov(R_{sp}^3, R_{wti})$, by $[Var(R_{sp})]^{1.5}$ and $[Var(R_{sp})]^2$ respectively. Similarly, the conditional beta, coskewness, and cokurtosis of S&P 500 can be calculated dividing the $Cov(R_{sp}, R_{wti})$, $Cov(R_{sp}, R_{wti}^2)$, and $Cov(R_{sp}, R_{wti}^3)$, by $[Var(R_{wti})]$, $[Var(R_{wti})]^{1.5}$, and $[Var(R_{wti})]^2$ in turn.

Unlike the literature (Guidolin & Timmermann, 2008; Yang et al., 2010; Chiang, 2016; Chan et al., 2018), we employ a multivariate GARCH model which is superior to the typically used regime switching model where the correlations and covariances are time invariant in each regime. Francq & Zakoian (2019) state that while Markov switching regime models are flexible, they are only an approximation of the data generating process. Additionally in our empirical model, we consider the role of asymmetries (leverage effect) within and in-between the assets[11]. None of the above studies address those issues in their work. The method used in this paper is also superior to rolling regression, in that we take into account the stochastic nature of the conditional comovements in the time-varying covariances, and there is no arbitrary choice of an interval, nor neglecting some part of the data as in rolling regression methods.
We estimate the $Cov(R_{sp}, R_{wti})$ by the following multivariate GARCH model, specified as below:

$$R_{wti,t} = \phi_{wti} + \epsilon_{wti,t} \tag{2.8}$$

$$R_{sp,t} = \phi_{sp} + \epsilon_{sp,t} \tag{2.9}$$

Where ϕ_{wti} and ϕ_{sp} are the relevant constants and $\epsilon_{wti,t}$ and $\epsilon_{sp,t}$ are the relevant innovations. Then to compute the $Cov(R_{sp}^2, R_{wti})$ and $Cov(R_{sp}^3, R_{wti})$, we substitute R_{sp}^2 and R_{sp}^3 in equation 2.9 respectively. We scale these estimated conditional covariances by the conditional variance of the S&P 500 using a univariate GJR(1,1)[12] as explained

[11]Francq & Zakoian (2019) encourage the use of heavy-tailed marginal distributions when estimating long return series with GARCH processes, to avoid a possible spurious strong volatility persistence

[12]To obtain the conditional comoments for S&P 500, we repeat the same procedure by substituting R_{wti}^2 and R_{wti}^3 in equation 2.8 to get $Cov(R_{sp}, R_{wti}^2)$ and $Cov(R_{sp}, R_{wti}^3)$, and then divide the covariances by the WTI's conditional variance.

earlier. To estimate the time-varying covariances, we employ $ADCC - GJR - t$. The ADCC model (Cappiello et al., 2006) is built on the DCC model of R. Engle (2002). Dynamic conditional correlation models, are an intelligent response to the heteroscedasticity of the disturbances with the highest parsimony in estimating the parameters. The ADCC can capture the potential asymmetries between comovements of the assets, in addition to having stronger statistical properties. The GJR(1,1) process of Glosten et al. (1993) reads as:

$$h_{i,t}^2 = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i' h_{i,t-1}^2 + \gamma_i e_{i,t-1}^2 I_{i,t-1} \qquad i = S\&P\,500, WTI \tag{2.10}$$

$$where \qquad I = \begin{cases} 1 & if\ e_{i,t-1} < 0 \\ 0 & Otherwise \end{cases} \tag{2.11}$$

In equation 2.10, $h_{i,t}^2$ refers to asset i's conditional variance, ω_i is a constant term in asset i's conditional variance, α_i measures the impact of the lagged shocks to the conditional variance (known as clusters or size of shocks), β_i' measures the impact of the lagged conditional variance (known as persistence of shocks) and γ_i captures asymmetries in the volatility (sign of shocks). Now that we have computed the conditional variances in the previous step, we need to compute the standardized errors by $\varepsilon_{i,t} = \frac{\epsilon_{i,t}}{h_{i,t}}$ and the time-varying covariance matrix H_t afterwards. We posit that the vector of time-varying innovations ($\mathbf{E}_t = [\epsilon_{wti,t}, \epsilon_{sp,t}]'$) follows $\mathbf{E}_t \mid \Delta_{t-1} \sim Student's\ t(0, H_t, v)$ where the time-varying covariance matrix $H_t = D_t P_t D_t$ consists of the time-varying correlation matrix P_t and the time-varying diagonal matrix of the standard deviations D_t. The time-varying correlation matrix P_t reads as:

$$P_t = diagQ_t^{-1} Q_t diagQ_t^{-1} \tag{2.12}$$

where:

$$Q_t = (\bar{P} - a^2\bar{P} - d^2\bar{P} - g\bar{N}) + a^2(\varepsilon_{t-1}\varepsilon_{t-1}') + g^2(n_{t-1}n_{t-1}') + d^2 Q_{t-1} \tag{2.13}$$

and $\bar{P} = E[\varepsilon_{t-1}\varepsilon_{t-1}']$ is the unconditional correlation matrix of the standardized errors, with $\bar{N} = E[n_{t-1}n_{t-1}']$ and the scalars a, d, and g. Further the effect of negative shock is absorbed by the variable n_t which can be expressed as a Hadamard product with the following characteristics:

$$n_t = I[\varepsilon_{t-1}] \circ \varepsilon_{t-1} = \begin{cases} \varepsilon_t & \varepsilon_t < 0 \\ 0 & \varepsilon_t \geq 0 \end{cases} \tag{2.14}$$

Where $I[\varepsilon_{t-1}]$ is a $K \times 1$ indicator function. The positive definiteness of the Q_t is guaranteed only if $(a^2 + d^2 + \frac{1}{2}g^2) \leq 1$. We employ a multivariate Student's t to estimate the parameters of the time-varying correlation matrix Q_t. Table 2.2 summarizes the estimated parameters of a GJR(1,1) process for each of the parameters.

Table 2.2: Volatility equation parameters

	S&P500	*p-value*	WTI futures	*p-value*	$S\&P500^2$	*p-value*	$S\&P500^3$	*p-value*	WTI^2 futures	*p-value*	WTI^3 futures	*p-value*
$\phi * 10^4$	0.02	0.00	0.00	0.57	0.10	0.89	0.1	0.13	1.9	0.14	0.4	0.51
$\omega * 10^4$	0.02	0.00	0.02	0.31	0.02	0.00	0.3	0.01	0.6	0.00	144	0.00
$ARCH\ (\alpha)$	0.015	0.03	0.062	0.00	0.057	0.00	0.027	0.20	0.070	0.00	0.068	0.00
$GARCH\ (\beta')$	0.896	0.00	0.911	0.00	0.920	0.00	0.891	0.00	0.924	0.00	0.826	0.00
$GJR\ (\gamma)$	0.131	0.00	0.047	0.00	-0.004	0.79	0.148	0.00	-0.039	0.49	0.167	0.00

2.2.2 Fear, uncertainty, and expectations: TVP-VAR with stochastic volatility

In order to study the impact of the three daily macroeconomic variables on conditional comoments, the TVP-VAR (Primiceri, 2005, Del Negro & Primiceri, 2015) is employed. Categorized in non-linear VAR class (Primiceri, 2005; Kilian & Lütkepohl, 2017), TVP-VAR is able to identify 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. More importantly, this model is developed to provide time-varying VAR coefficients (based on some stochastic process) and impulse response functions (IRFs) which is suitable to our analysis of the conditional comoments that encompasses several decades of different economic policies and boom/bust. The evident existence of the different economic regimes, and changes in the conditional volatility of both oil and stock market (Figure 2.2) all refer to the smooth structural changes (Primiceri, 2005; Nakajima et al., 2011 ; Del Negro & Primiceri, 2015; Kilian & Lütkepohl, 2017). Following Primiceri (2005) the TVP-VAR model is derived from structural VAR model, and reads as follows for a multivariate case:

$$\boldsymbol{Y}_t = c_t + A_{1,t}\boldsymbol{Y}_{t-1} + \cdots + A_{p,t}\boldsymbol{Y}_{t-p} + u_t \qquad t = 1, ..., T \tag{2.15}$$

Where $\boldsymbol{Y}$ is a $n \times 1$ vector of endogenous variables, c_t is an $n \times 1$ vector of constant terms' coefficient, and the coefficients $A_{i,t}$ with $i = 1, ..., p$ are $n \times n$ time dependent matrices. The heteroscedastic unobservable shocks 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 innovations' covariance is decomposed to:

$$\Sigma_{u,t} = B_t^{-1} \Sigma_{w,t} B_t^{'-1} \tag{2.16}$$

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

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

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:

$$\boldsymbol{Y}_t = c_t + A_{1,t}\boldsymbol{Y}_{t-1} + ... + A_{p,t}\boldsymbol{Y}_{t-p} + B_t^{-1} w_t \tag{2.17}$$

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 $b_t = [b_{21,t}, b_{31,t}, b_{32,t}, \cdots, b_{k1,t}, \cdots, b_{kk-1,t}]'$ 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:

$$\alpha_t = \alpha_{t-1} + \eta_t^{\alpha} \tag{2.18}$$

$$b_t = b_{t-1} + \eta_t^{b} \tag{2.19}$$

$$log\sigma_t = log\sigma_{t-1} + \eta_t^{\sigma} \tag{2.20}$$

Summing up, the covariance matrix shock 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 shock terms are independent of one another with:

$$\alpha_t \sim \mathcal{N}(\mu_\alpha, \Sigma_\alpha) \qquad b_t \sim \mathcal{N}(\mu_b, \Sigma_b) \qquad \sigma_t \sim \mathcal{N}(\mu_\sigma, \Sigma_\sigma) \tag{2.21}$$

Assuming $Z_{t-1} \equiv (1, \boldsymbol{Y}_t, \cdots, \boldsymbol{Y}_{t-p})'$ the initial VAR in equation 2.15 becomes:

$$\boldsymbol{Y}_t = (Z'_{t-1} \otimes I_k)\alpha_t + u_t \tag{2.22}$$

With the symbol $\otimes$ referring to Kronecker product. Equation 2.22 and the random walk process of α_t (Eq. 2.18) are basically a state-space model with measurement equation (Eq. 2.21) and transition equation (Eq. 2.18). Generally there are two ways to estimate this model, one is maximum likelihood estimation, and the other, 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 use one lag, further we follow Primiceri (2005) regarding priors and distributions of parameters as follows[13]:

$$(\Sigma_\alpha)_i^{-2} \sim Gamma(20, 0.01) \qquad (\Sigma_b)_i^{-2} \sim Gamma(2, 0.01) \qquad (\Sigma_\sigma)_i^{-2} \sim Gamma(2, 0.01) \tag{2.23}$$

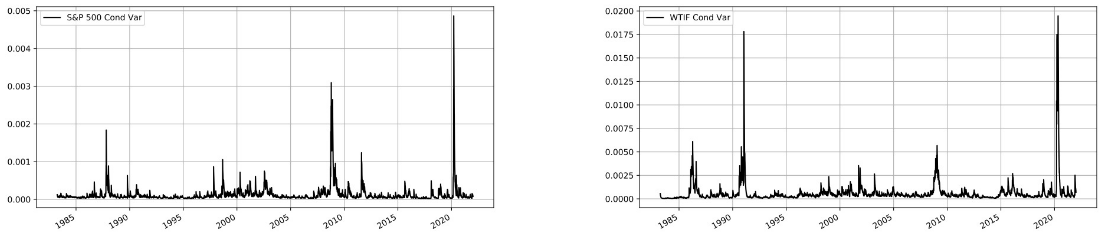
Where i refers to the i^{th} element of the matrices. We also picked the first 1000 data points corresponding to nearly 4 years of data for calibration of the prior distributions.

2.3 Empirical results part A: Conditional comoments & time-varying impulse responses

Figure 2.2 depicts the conditional variances for S&P 500 and WTI futures. The giant impact of the ongoing COVID-19 pandemic is greater than any crisis during the last four decades. While COVID-19 effect on WTI's conditional variance is comparable to the Iraq-Kuwait war in early 1990s[14], stock's response to crises seem to follow a worrisome upward trend. Moreover, WTI shows greater fluctuations than its counterpart during the sample period.

[13]Note that due to the data daily frequency, long sample period, and the complexity of the model, including the number of observations required for initialization of the priors, calculating the impulse response for each comoment might take several hours to days.

[14]For a comprehensive review of civil conflicts and geopolitical risks effects on oil price refer to Noguera-Santaella (2016).



(a) S&P 500 (b) WTI futures

Figure 2.2: Conditional variances 1983-2021

Figures 2.3 and 2.4 exhibit the time-varying conditional comoments of S&P 500 and WTI futures respectively. Figure 2.4 shows that from 1983 to 2008, WTI's conditional beta had a zero mean with two salient negative spikes around the 1987 black Monday crisis, and Iraq-Kuwait war, while after GFC, the sensitivity of the WTI to the stock market performance finds a new positive mean, restating the fact that the two market are getting more connected than before[15]. Similarly, the S&P 500 beta has found a new mean since GFC, although the late 2002 spike could have been an early signal for the beginning of a new stock-oil comovement era. S&P 500 coskewness and cokurtosis show an emerging pattern since GFC too. Figure 2.3 clearly illustrates a visible pattern happening between 2008-2014[16], which relates to zero-interest rate period, starting in the aftermath of GFC, and ending in late 2014 when the US economy fully recovered from GFC crash. The conditional coskewness of both markets (Figures 2.3 and 2.4), illustrate that the two markets were sensitive to each others' skewness since 1997, even crude oil were already sensitive to stock, beginning 1983. The oil's coskewness suggests that whenever the stock's skewness gets more positive (stock market performs bad for some period), WTI return decreases. Similarly, WTI cokurtosis shows that oil's response to stock's tail events is getting more extreme, with COVID-19 stock market crash on February 2020, as the pinnacle. In the beginning of COVID-19 pandemic (early March to early May 2020) WTI futures contracts experienced an unprecedented stressful period for several weeks, such that on April 20, 2022 even the delivery price of May contracts which would expire in less than hours, turned to negative. Two consecutive major events including worldwide travel restrictions to limit COVID spread, and the Saudi-Russian oil price war were largely responsible for the event. This is reflected in the coskewness of both S&P 500, which is novel since 1980s oil glut. Over-

[15] Macroeconomic literature attributed the emerging phenomenon to aggregate growth shocks (Hitzemann, 2016), slow down in global economic activity (Bernanke, 2016), the sovereign wealth funds speculative activity (Mohaddes & Pesaran, 2017), or oil demand shocks (Ready, 2018).

[16] With a pause in early 2011, when the oil price increased for a short while due to the Arab Spring.

all, these evidences denote that the new phase of stock-oil comovement since GFC, is a source of concern for investors who used to benefit from diversification between the two markets, and for policy makers since speculators might turn to another fundamental market(s) in search of better diversification, thus contributing to fragility of financial systems (Lagunoff & Schreft, 2001). It is noteworthy that, oil's comoments are greater than stock's, meaning that oil is more sensitive to stock condition than the other way around, contributing to oil's already high fluctuations (Figure 2.2, panel b).

Figures 2.5 to 2.7 present the time-varying impulse responses of S&P 500's (panel a) and WTI futures' (panel b) conditional comoments to a +1% permanent increase to fear (VIX), uncertainty (EPU), and expectation (ADS) indices. There are three time intervals, a 6-day response by blue line (short-lived response), a 12-day response by purple line, and a 24-day[17] response (long-lasting response) by green line [18]. All impulse responses show time-varying and asymmetric patterns during our long sample period. Also, comparing panels a and b in Figures 2.5 to 2.7, we realize that the response of oil's comoments to shocks in the three sentiment indicators are much more intense than those of stock's (for instance in case of WTI's cokurtosis, the responses to macro indices are roughly ten times greater than the response of stock's cokurtosis). Figure 2.5, shows the response of conditional beta of both market to the shocks in the macro indices. It is evident that since GFC, the responses of both WTI (panel b) and S&P 500 (panel a) are much stronger to fear, and uncertainty than before. As in top graphs in panel a and b of the Figure 2.5, the positive response of S&P 500 beta to a shock in fear index (more fearful market) translates to an increase in the exposure to crude oil market, while on the other side, the response of WTI beta is negative, which means decrease in the exposure to stock market performance. We witness the same asymmetric pattern by looking at Figures 2.6 and 2.7, regarding the asymmetric response of conditional coskewness and cokurtosis to shocks in the fear index. It is intuitive to see the persistence of macro shocks on WTI's cokurtosis (Figure 2.7, panel b) denoting the strong dependence of oil to stock tail events. Figure 2.7, also shows that macroeconomic shocks have much more long-lasting effects on cokurtosis than beta or coskewness, emphasizing the fact that tail events have long-lasting impact on stock-oil dynamics. Overall, responses to shocks in macro expectations are much stronger, gradual, long-lasting, and more asymmetric than the responses to shocks in fear or uncertainty indices, while on the other hand uncertainty has the weakest effect on the

[17]Response after 6, 12, and 24 days.

[18]Note that, in experimenting with longer time intervals for the impulse responses, the responses were negligible to nonexistent above 50 days, which is inline with the nature of our study.

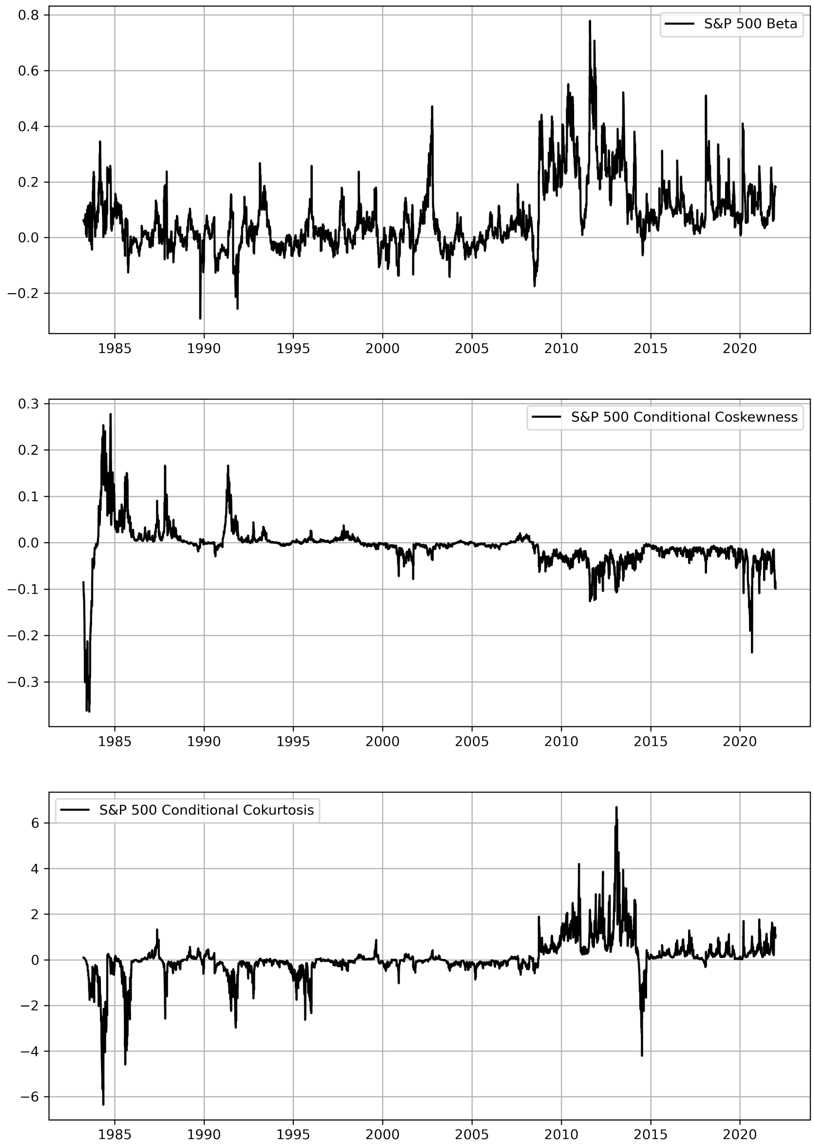


Figure 2.3: Conditional comoments of S&P 500

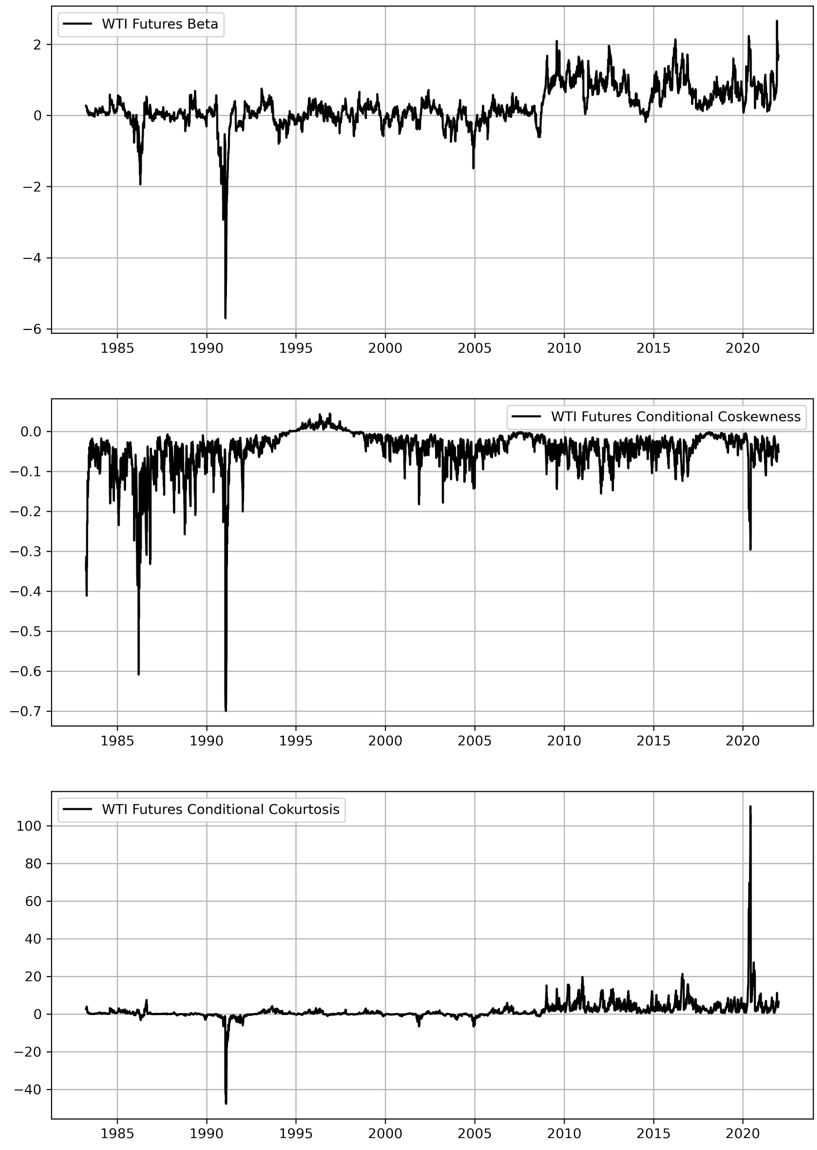


Figure 2.4: Conditional comoments of WTI Futures

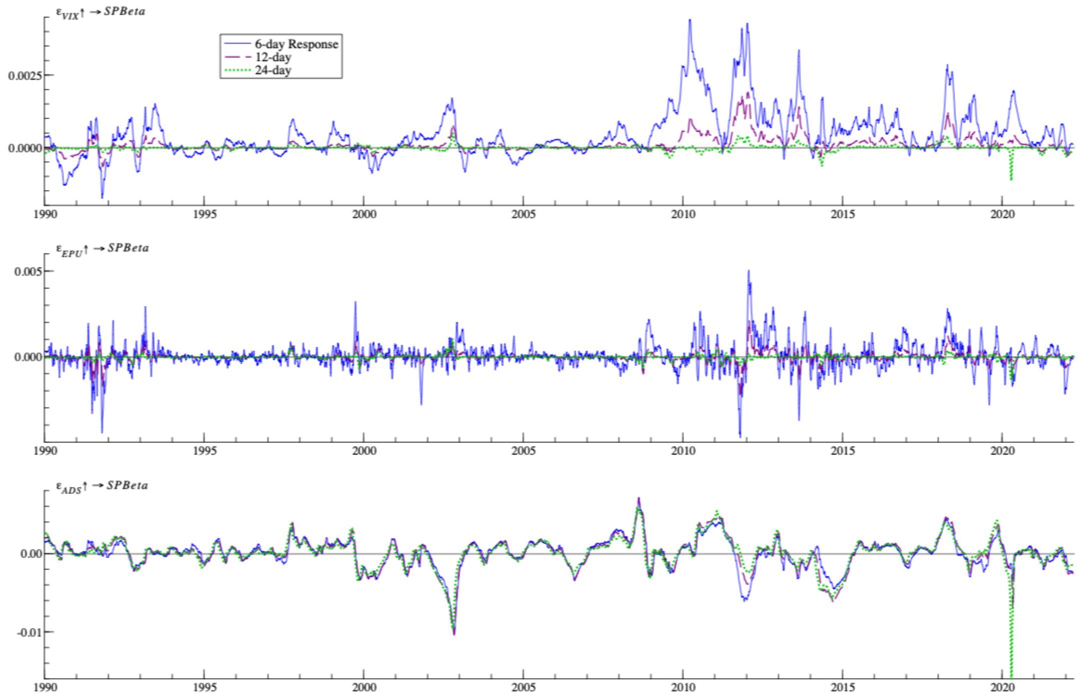
conditional comoments. These findings are in line with Kozlowski et al. (2015) who state that ex-ante the 2008 GFC was deemed unlikely by markets participants, and in this regard the recession caused by GFC was quite long, which led to economic agents updating their beliefs about the macroeconomic risk, creating long-lasting effects on investment among other economic realities[19].

2.4 The asymmetric responses to macroeconomic indicators: A NARDL approach

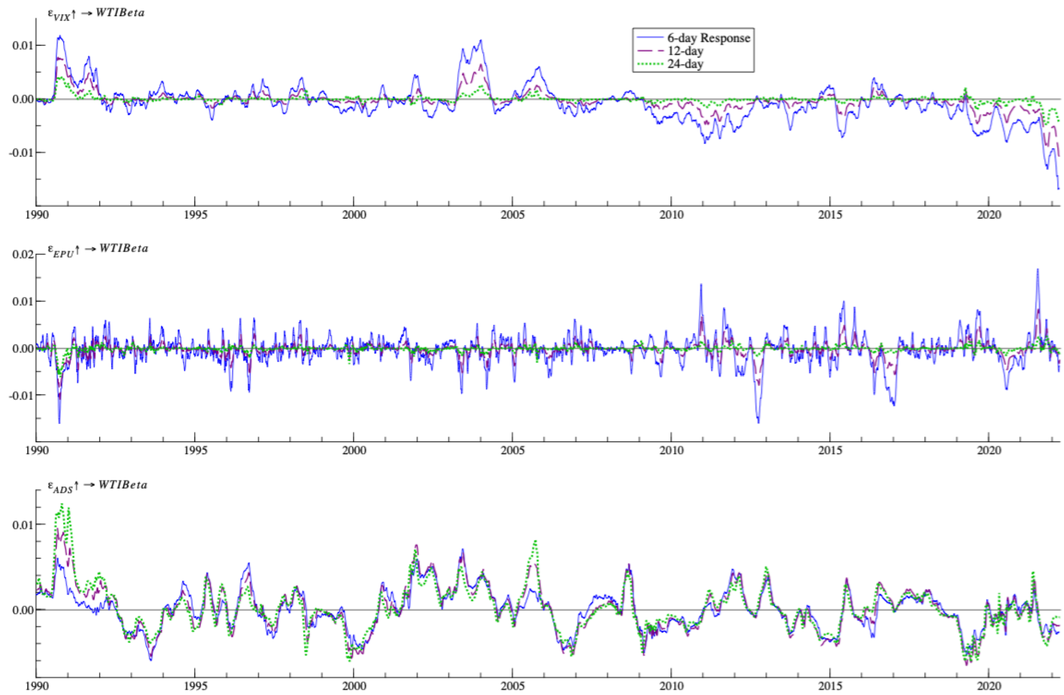
In this section, we investigate the effect of the three macro sentiment indicators in explaining the variations of conditional betas[20]. In this regard, we employ the nonlinear autoregressive distributed lag (NARDL) model of Shin et al. (2014) which separates the asymmetric nonlinear responses based on the positive and negative sums of the movements in explanatory variables. Moreover the model reveals the short-run and long-run dynamics between the dependent and independent variables. This method is particularly suitable to our study, since the conditional comoments are nonlinear with great fluctuations through time. Shin et al. (2014) derive the dynamic conditional error correction representation associated with the asymmetric long-run cointegrating regression, resulting in the NARDL model. NARDL is an extension to the original autoregressive distributed lag (ARDL) model of Pesaran et al. (1995) and is capable of producing consistent and unbiased estimators in the presence of $I(0)$ and $I(1)$ regressors. Another advantage of this model is to reveal the responses to positive and negative changes in the independent variables both at short- and long-run based on partial sum of positive and negative changes. In addition, bounds test (Pesaran et al., 2001) stats are employed to test the existence of long-run cointegration.
Following Shin et al. (2014) a NARDL(p,q) can be represented by its asymmetric conditional error correction form as follows:

[19]There are three strands of literature regarding the effect of sentiment on economy: i) animal spirit followers who believe that all economic booms and busts are due to optimism and pessimism of economic agents; ii) another large strand, points to the self-fulfilling beliefs, stating that sunspot-driven waves create macroeconomic fluctuations; iii) news and noise advocators who suggest that economic booms (short-term busts) emerge when economic agents have the correct (false) signal about the future growth in the economy ex-ante (Nowzohour & Stracca, 2020).

[20]NARDL results for conditional coskewness and cokurtosis are provided in appendix B.

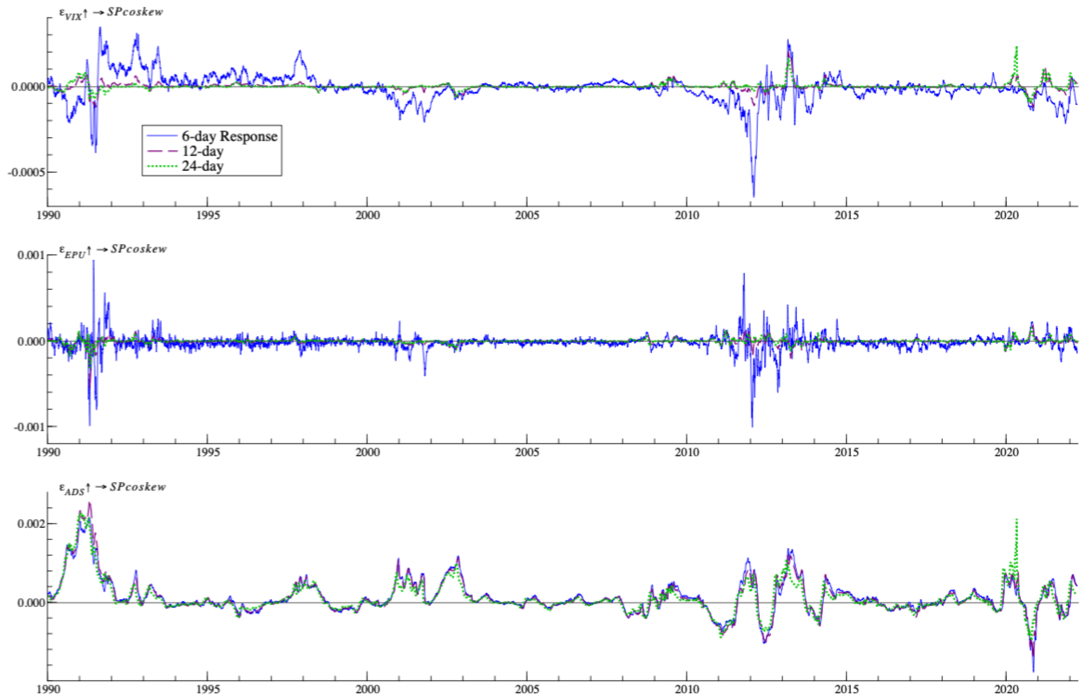


(a) S&P 500 beta impulse responses

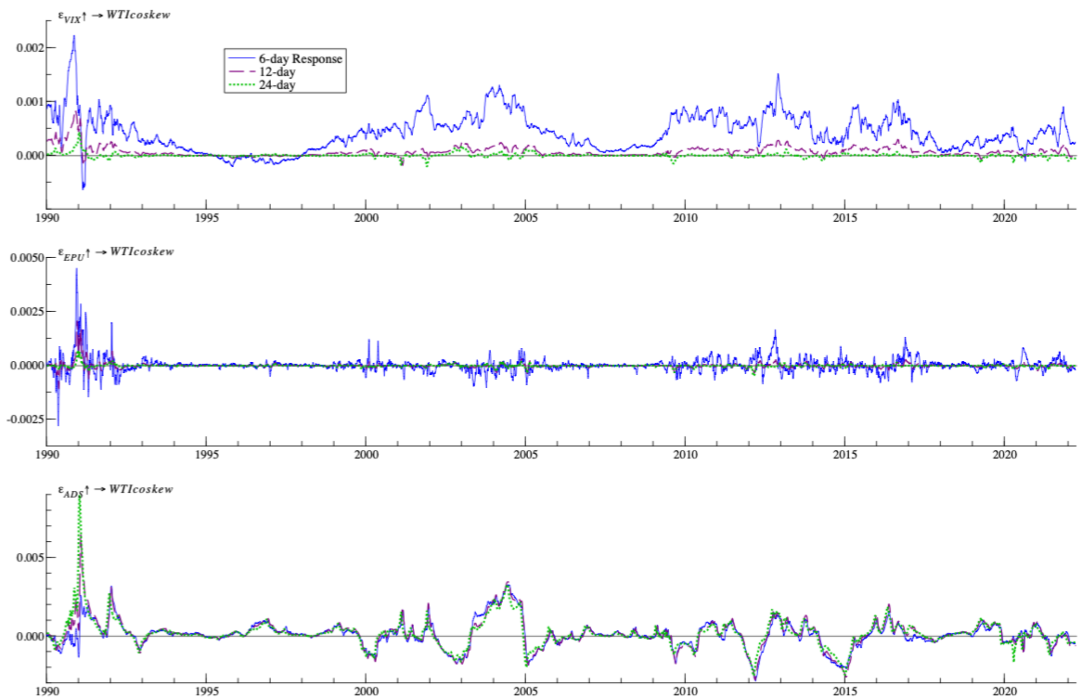


(b) WTI futures beta impulse responses

Figure 2.5: Time-varying impulse responses for beta Jan 1990 - Dec 2021

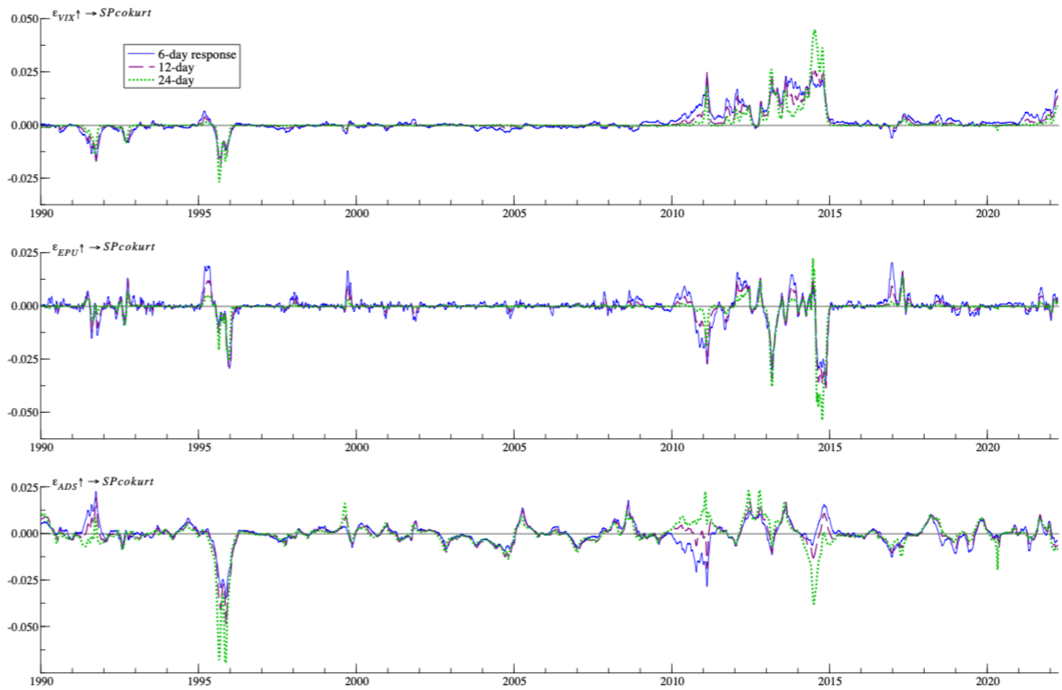


(a) S&P 500 cond. coskewness impulse responses

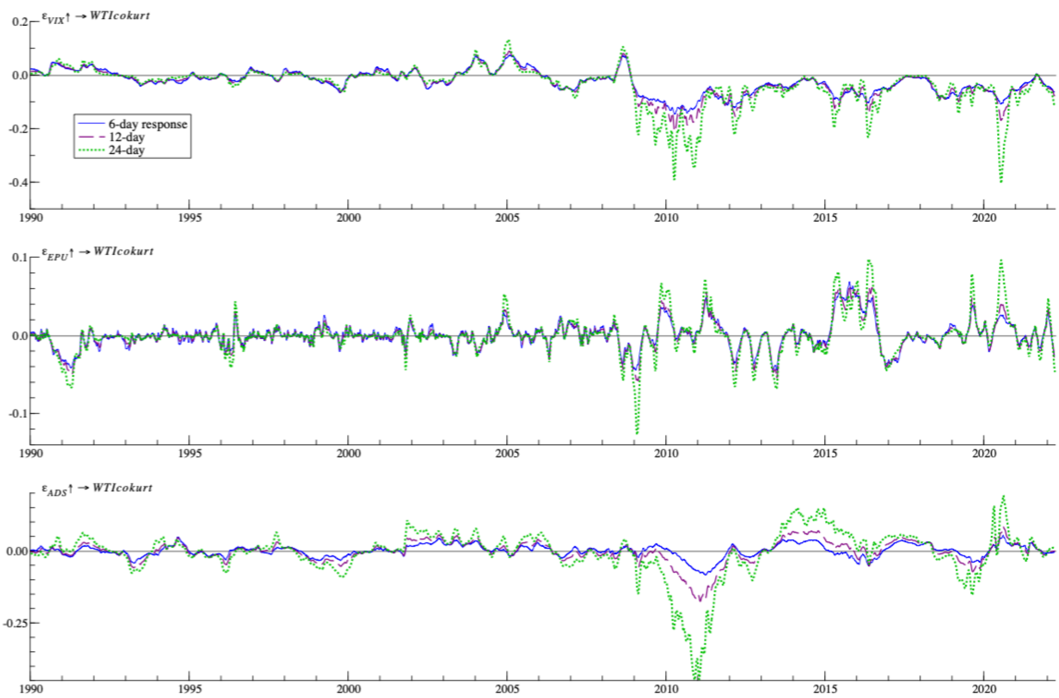


(b) WTI futures cond. coskewness impulse responses

Figure 2.6: Time-varying impulse responses of cond. coskewness Jan 1990 - Dec 2021



(a) S&P 500 cond. cokurtosis impulse responses



(b) WTI futures cond. cokurtosis impulse responses

Figure 2.7: Time-varying impulse responses of cond. cokurtosis Jan 1990 - Dec 2021

$$\triangle y_{i,t} = \mu_i + \overbrace{\rho_i y_{i,t-1} + \theta_l^+ x_{l,t-1}^+ + \theta_l^- x_{l,t-1}^-}^{\text{Long-run dynamics}} + \overbrace{\sum_{j=1}^{p-1} \psi_{i,j} \triangle y_{i,t-j} + \sum_{j=0}^{q-1} (\pi_{l,j}^+ \triangle x_{l,t-j}^+ + \pi_{l,j}^- \triangle x_{l,j-t}^-)}^{\text{Short-run dynamics}} + \epsilon_i' \tag{2.24}$$

where $x_{l,t-j}^+$ and negative $x_{l,t-j}^-$ are respectively $l \times 1$ vectors of the positive and negative partial sums of the explanatory variables $l = \{\text{VIX, EPU, ADS}\}$ calculated as follows:

$$x_{l,t-j}^+ = \sum_{j=1}^{t} \triangle x_{l,t}^+ = \sum_{j=1}^{t} max(\triangle x_{l,j}, 0) \qquad x_{l,t-j}^- = \sum_{j=1}^{t} \triangle x_{l,t}^- = \sum_{j=1}^{t} min(\triangle x_{l,j}, 0) \tag{2.25}$$

Note that in equation 2.24, $y_{i,t}$ is the dependent variable $i = \{\text{SPBeta, WTIBeta}\}$ at time t, $\triangle$ is the first difference operator, μ_i is the intercept, θ_l^+ (θ_l^-)[21] is the parameter that measures the long-run adjustment to the positive changes (negative changes) in the explanatory variable l while ρ_i is the autoregressive parameter, the parameters for short-run/shocks dynamics include $\psi_{i,j}$ for the dependent variable i and $\pi_{l,j}^+$ $(\pi_{l,j}^-)$ for the positive (negative) changes in the explanatory variable l, p and q refer to the respective lag orders for the dependent variable i and explanatory variable l, and ϵ_i' are an IID process with zero mean and finite variance. It is evident that NARDL corrects for residual autocorrelation (by use of lag order), the possible endogeneity in the regressors[22], the omitted variable bias, and the reverse causality (Harris & Sollis, 2003). Finally, the long-run asymmetry parameters are computed as $\frac{-\theta_l^+}{\rho_i}$ for positive changes and $\frac{-\theta_l^-}{\rho_i}$ for the negative changes.

2.5 Empirical results part B: NARDL regression

We start by dividing the sample into two periods, pre-GFC (1990-2008) and post-GFC (2009-2021) since the conditional comoments evolve after the GFC. To check whether the conditional comments are not integrated of order two or more (i.e. $I(2)$) we perform the standard Augmented Dickey-Fuller (ADF) and find that both conditional betas (dependent variables) and the macro indices (independent variables) are $I(0)$[23]. Our goal is twofold, first to study whether the effect of the three sentiment indicators

[21] Also known as asymmetric distributed lags parameters.

[22] For further information about the mathematical derivation of NARDL, refer to the original paper by Shin et al. (2014).

[23] Results are not reported due to space constraints.

on the conditional betas at the short-and long-run are asymmetric regarding the positive and negative movements in the independent variables, and second, to investigate how the NARDL regression parameters (if any) change from pre- to post-GFC.

Tables 2.3 and 2.4 report the results of the NARDL regressions for the two betas (S&P 500 and WTI respectively), in the pre- and post-GFC periods. The choice of lags in each NARDL regression are based on AIC. The panels that report short- and long-run symmetry tests in each table, are based on the following hypotheses tested by a two-tailed F-test:

$$\text{Long-run symmetry } H_0: \theta_l^+ = \theta_l^- \quad \text{against} \quad H_1: \theta_l^+ \neq \theta_l^-$$

$$\text{Short-run symmetry } H_0: \begin{cases} \pi_{l,j}^- = \pi_{l,j}^+ \quad \text{for each } l \text{ and } j \\ \\ \text{or} \\ \\ \sum_{l=1}^{q} \pi_l^- = \sum_{l=1}^{q} \pi_l^+ \end{cases}$$

$$\text{Short-run symmetry } H_1: \begin{cases} \pi_{l,j}^- \neq \pi_{l,j}^+ \quad \text{for each } l \text{ and } j \\ \\ \text{or} \\ \\ \sum_{j=1}^{q} \pi_l^- \neq \sum_{j=1}^{q} \pi_l^+ \end{cases}$$

In reporting the NARDL regression parameters, if a variable enters the model with zero-lag, the short-run symmetry test cannot be tested. In addition to the bounds test stats (by two-tailed F-stat and t-stat) related to long-run cointegration ($H_0 : \rho_i = \theta_l^+ = \theta_l^- = 0$), we also conduct a Wald test to rule out degenerate cointegration, which is a joint test of parameter significance on all coefficients associated with distributed lag variables at the levels ($H_0 : \theta_l^+ = \theta_l^- = 0$). Two test stats for residuals diagnostics including Breusch-Godfrey serial correlation test (H_0 : residuals are serially uncorrelated) and Breusch-Pagan-Godfrey heteroscedasticity test (H_0 : residuals are homoscedastic) are reported in the diagnostics and stats panels. Since our data is at daily level, and the null hypothesis that residuals are homoscedastic is rejected, the covariance matrix is estimated by White (1980) heteroscedasticity-consistent estimator.

Table 2.3: NARDL regression results – S&P 500 Beta

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	0.0001	Const.	-0.0012
$SPBeta_{t-1}$	-0.0175^{***}	$SPBeta_{t-1}$	-0.0215^{***}
VIX^+_{t-1}	0.0166^{***}	VIX^+_{t-1}	0.1128^{***}
VIX^-_{t-1}	0.0167^{***}	VIX^-_{t-1}	0.1128^{***}
EPU^+_t	0.0000	EPU^+_t	0.0004
EPU^-_t	0.0000	EPU^-_t	0.0004
ADS^+_t	0.0000	ADS^+_{t-1}	0.0001
ADS^-_t	-0.0009^{*}	ADS^-_{t-1}	0.0000
$\triangle SPBeta_{t-1}$	-0.0423^{***}	$\triangle SPBeta_{t-1}$	-0.0547^{***}
$\triangle SPBeta_{t-2}$	0.0227	$\triangle VIX^+_t$	0.0315^{***}
$\triangle VIX^+_t$	0.0072	$\triangle VIX^-_t$	-0.0570^{***}
$\triangle VIX^-_t$	-0.0006	$\triangle VIX^+_{t-1}$	0.0271^{***}
		$\triangle VIX^-_{t-1}$	-0.0640^{***}
		$\triangle VIX^+_{t-2}$	-0.0433^{***}
		$\triangle VIX^-_{t-2}$	-0.0048
		$\triangle VIX^+_{t-3}$	-0.0134^{**}
		$\triangle VIX^-_{t-3}$	-0.0142^{***}
		$\triangle ADS^+_t$	-0.0004
		$\triangle ADS^-_t$	0.0109^{***}
Long-run parameters			
VIX^+_{t-1}	0.9499^{***}	VIX^+_{t-1}	5.2471^{***}
VIX^-_{t-1}	0.9539^{***}	VIX^-_{t-1}	5.2467^{***}
EPU^+_t	0.0027	EPU^+_t	0.0198
EPU^-_t	0.0033	EPU^-_t	0.0202
ADS^+_t	-0.0047	ADS^+_{t-1}	0.0060
ADS^-_t	-0.0514^{*}	ADS^-_{t-1}	0.0026
Long-run coefficient symmetry F-test			
ADS	3.1^{*}	ADS	1.9
EPU	1.5	EPU	0.1
VIX	0.3	VIX	0.1
Short-run coefficient symmetry F-test			
ADS	NA	ADS	6.1^{***}
EPU	NA	EPU	NA
VIX	1.3	VIX	119.3^{***}
Diagnostics and stats			
R^2	0.01	R^2	0.30
Log likelihood	13700	Log likelihood	8505
F-stat	6.6^{***}	F-stat	77^{***}
AIC	-5.7	AIC	-5.2
Bounds F-stat	7.5^{***}	Bounds F-stat	23.3^{***}
Bounds t-stat	-6.4^{***}	Bounds t-stat	-6.6^{***}
Wald test	2.7^{***}	Wald test	21.8^{***}
Serial Correlation Test	0.6	Serial Correlation Test	1.3
Heteroscedasticity Test	47.6^{***}	Heteroscedasticity Test	36.4^{***}

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table 2.4: NARDL regression results – WTI futures Beta

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	-0.0005	Const.	0.0346***
$WTIBeta_{t-1}$	-0.0253^{***}	$WTIBeta_{t-1}$	-0.0247^{***}
VIX^{+}_{t-1}	0.1487***	VIX^{+}_{t-1}	-0.2523^{***}
VIX^{-}_{t-1}	0.1486***	VIX^{-}_{t-1}	-0.2527^{***}
EPU^{+}_{t}	-0.0002	EPU^{+}_{t-1}	-0.0030
EPU^{-}_{t}	-0.0001	EPU^{-}_{t-1}	-0.0030
ADS^{+}_{t}	0.0062***	ADS^{+}_{t-1}	-0.0009
ADS^{-}_{t}	-0.0007	ADS^{-}_{t-1}	-0.0010
$\triangle WTIBeta_{t-1}$	0.0216	$\triangle WTIBeta_{t-1}$	-0.0318^{*}
$\triangle WTIBeta_{t-2}$	0.0179	$\triangle VIX^{+}_{t}$	-0.0184
$\triangle WTIBeta_{t-3}$	0.0422***	$\triangle VIX^{-}_{t}$	0.0602**
$\triangle VIX^{+}_{t}$	-0.0186	$\triangle VIX^{+}_{t-1}$	-0.0656^{**}
$\triangle VIX^{-}_{t}$	0.0683**	$\triangle VIX^{-}_{t-1}$	0.0657***
$\triangle VIX^{+}_{t-1}$	-0.0814^{***}	$\triangle EPU^{+}_{t}$	0.0037
$\triangle VIX^{-}_{t-1}$	-0.0100	$\triangle EPU^{-}_{t}$	-0.0083^{*}
		$\triangle ADS^{+}_{t}$	-0.0262^{*}
		$\triangle ADS^{-}_{t}$	0.0068
		$\triangle ADS^{+}_{t-1}$	0.0520***
		$\triangle ADS^{-}_{t-1}$	0.0543***
Long-run parameters			
VIX^{+}_{t-1}	5.8694***	VIX^{+}_{t-1}	-10.1995^{***}
VIX^{-}_{t-1}	5.8668***	VIX^{-}_{t-1}	-10.2154^{***}
EPU^{+}_{t}	-0.0116	EPU^{+}_{t-1}	-0.1237
EPU^{-}_{t}	-0.0066	EPU^{-}_{t-1}	-0.1213
ADS^{+}_{t}	0.2478***	ADS^{+}_{t-1}	-0.0382
ADS^{-}_{t}	-0.0196	ADS^{-}_{t-1}	-0.0416
Long-run coefficient symmetry F-test			
ADS	4.8**	ADS	0.1
EPU	5**	EPU	0.2
VIX	0.0	VIX	0.1
Short-run coefficient symmetry F-test			
ADS	NA	ADS	8.4***
EPU	NA	EPU	4.4**
VIX	7.6***	VIX	19.3***
Diagnostics and stats			
R^2	0.02	R^2	0.09
Log likelihood	4520	Log likelihood	3388
F-stat	6.3***	F-stat	17.8***
AIC	-1.8	AIC	-2.06
Bounds F-stat	10.6***	Bounds F-stat	12.8***
Bounds t-stat	-7.9^{***}	Bounds t-stat	-6.4^{***}
Wald test	3.7***	Wald test	8.1***
Serial Correlation Test	0.5	Serial Correlation Test	0.9
Heteroscedasticity Test	2.7***	Heteroscedasticity Test	11.9***

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table 2.3 presents the results of NARDL regression for S&P 500 beta for pre- and post-GFC periods. In both periods, bounds test stats firmly verify the existence of long-run cointegration, and the Wald test stat reject any degenerate cointegration. The R^2 declares that the explanatory power of the model increases vastly from pre- (0.01) to post-GFC (0.30) periods. Similarly, the NARDL regression parameters increase in size. In particular the long-run parameters of VIX get roughly 5 times greater (from approximately 0.9 to 5.2 in both positive and negative parameters). We witness the same pattern in all other parameters generally. The symmetry coefficient test stats show that while in the pre-GFC period there are some instance of long-run parameter asymmetry, no such asymmetry exists post-GFC era. On the other hand, there is a strong statistically significant asymmetry in the short-run parameter for both VIX and ADS parameters only in the post-GFC period. The contemporaneous short-run parameters of VIX ($\triangle VIX_t^+$ and $\triangle VIX_t^-$) and ADS ($\triangle ADS_t^+$ and $\triangle ADS_t^-$) show that any positive or negative shocks in the stock market fear index (the expectation index) leads to increased (decreased) exposure of S&P 500 performance to WTI. These homogeneous responses in the short-run are in contrast to those of the long-run parameters.

The result of the NARDL regression for WTI is summarized in Table 2.4. In this regard, uncertainty and expectation are not significant factors on WTI beta fluctuations in the long-run in both sample periods (except positive movements in uncertainty). On the other hand, there are evidences of strong asymmetry effects in the short-run (shocks) in post-GFC period. In addition, compared to the pre-GFC period, in the post-GFC period, nearly all regression parameters including R^2 increase largely in WTI beta NARDL regression similar to that of the S&P 500. The results in the Table 2.4, indicate that the direction of the WTI beta to positive and negative changes in the contemporaneous short-run parameter of VIX, EPU, and ADS is homogeneous in contrast to that of the long-run parameters. While responding the question about why the conditional betas respond homogeneously to the contemporaneous short-run movements (i.e. shocks), remains a question for studies in the future, nonetheless we attribute it to the disposition effect (Shefrin & Statman, 1985) which is the tendency of investors to ride losses and realize gains, leading to underreaction to the news in the short-run.

Table 2.4, also reveals that the response of the WTI beta to the positive and negative movements (both long-run and short-run) in the fear index VIX, is the opposite of those of the S&P 500 beta. [24] This becomes more surprising when we realize that the

[24]Note that the time-varying impulse responses supported this result for the post-GFC period in section 2.4.

long-run VIX coefficients in the S&P 500 and WTI NARDL regressions have the same sign during the pre-GFC period, but in the post-GFC period, that sign changes to negative for the WTI NARDL regression. This is a clear evidence that the external shocks in WTI, most likely stem from the speculators' activities in the stock market. There is another evidence to back up our claim, which is the fact that the long-run parameters of VIX in the WTI beta NARDL regression are twice larger than those of the S&P 500. Among the three sentiment indices in our studies, the fear index VIX has the strongest effect on the stock-oil conditional beta both at short- and long-run, by far.

2.5.1 VIX versus OVX

The CBOE oil volatility index (OVX) which was developed only after 2007, measures the fear index in the crude oil market. OVX is based on the United States Oil Fund (USO) options, which is a commodity Exchange-Traded Fund (ETF) designed to replicate the returns of the WTI price through the use of futures contracts. Because OVX only covers a small part of our sample period (1990-2021), we can only reestimate the NARDL regressions for the post-GFC period to see how OVX's impact on conditional betas compares to VIX's. This inquiry stems from our findings that WTI responds more strongly to fluctuations in the S&P 500 and VIX. As in Table 2.5, the inclusion of OVX in the NARDL regressions increases the explanatory power of the estimated earlier NARDL regressions (Tables 2.3 and 2.4, post-GFC) for both the S&P 500 beta and WTI beta. In comparison to the Table 2.3 (Post-GFC) the R^2 increases from 0.30 to 0.33 in the S&P 500 beta NARDL regression, and in case of the WTI (Table 2.4, post-GFC) it doubles (from 0.09 to 0.18). The jump in the R^2 of WTI is intuitive since OVX measures fear exclusively for crude oil market participants.

Table 2.5 indicates that the impact of oil fear on the S&P 500 beta is negative; that is, when the tensions in the crude oil market are high, the performance of the S&P 500 is less exposed to the crude oil return decreases, while when the oil market is at peace (low fear), the comovement of S&P 500 return with the crude oil return increases. Based on the coefficient symmetry tests, in the long-run there is no asymmetric effect between positive and negative movements in the crude oil fear index on S&P 500 beta, but the short-run coefficients are asymmetric and significant. The long-run parameters show that a 1% increase in VIX leads to roughly 7% increase in S&P 500 beta while a 1% increase in OVX creates approximately 4.2% decrease in S&P 500 beta. On the other hand, when the oil fear index increases, the exposure of WTI return to S&P 500 market return increases. Interestingly, the long-run parameters suggest that the fear in the stock market has a stronger effect on WTI' beta than WTI's own fear index. This result is in line with the previous findings in our paper that, crude oil market acts as a safe haven for stock market participants' sudden whims. Similar to the previous section, we find that the response of the conditional betas to short-run contemporaneous parameters is homogeneous.

2.6 Conclusion

This paper conducts an empirical analysis to disentangle the stock-oil comovements using a battery of econometrics methods including the ADCC, TVP-VAR, and NARDL. The conditional comoments mark a strong structural break in stock-oil comoments during the 2008 GFC, and to investigate the underlying patterns for this structural change, we utilize three fundamental macroeconomic indices which measure investors' behavior including VIX, EPU, and ADS representing fear, uncertainty, and expectations in the economy, respectively. The results of the time-varying impulse responses show that shocks to these sentiment indices create much stronger responses in the conditional comoments since the GFC, with long-lived responses in case of cokurtosis, and short-lived responses in beta. More importantly, there is an unprecedented asymmetric response between the S&P 500 and WTI to the shocks in the fear index VIX.

To examine whether the sentiment indices have an asymmetric effect on the conditional comoments in the short- and long-run, this paper employs the NARDL model. The results suggest that there are strong asymmetries associated with the effect of all three sentiment indices on the conditional comoments, only in the short-run and after the GFC. In particular, the change in the sign of the fear effect on WTI conditional beta that happens after the GFC should increase alarms for policymakers. This phenomenon gets more worrisome when we realize that the conditional comoments of WTI respond several times stronger to fluctuations in VIX than those of the S&P 500, especially after the 2008 GFC. Finally, we turn to the oil-specific fear index (OVX) to determine if it has stronger effect on WTI conditional beta than VIX, and realize that, surprisingly, the effect of VIX is greater than OVX.

The findings of this paper should alarm policymakers since the effects of financialization are changing the natural dynamics of crude oil fluctuation much faster than before. Previous studies have identified aggregate growth shocks, a slowdown in global economic activity, oil demand shocks, or speculative activity by sovereign wealth funds as

Table 2.5: Post-GFC NARDL regression results with OVX

S&P 500 Beta		WTI Beta	
Asymmetric conditional error correction			
Const.	-0.0003	Const.	0.0232***
$SPBeta_{t-1}$	−0.0206***	$WTIBeta_{t-1}$	−0.0214***
VIX^{+}_{t-1}	0.1469***	VIX^{+}_{t-1}	−0.4043***
VIX^{-}_{t-1}	0.1465***	VIX^{-}_{t-1}	−0.4047***
OVX^{+}_{t-1}	−0.0888***	OVX^{+}_{t-1}	0.4022***
OVX^{-}_{t-1}	−0.0884***	OVX^{-}_{t-1}	0.4026***
EPU^{+}_{t}	0.0003	EPU^{+}_{t-1}	-0.0035
EPU^{-}_{t}	0.0003	EPU^{-}_{t-1}	-0.0034
ADS^{+}_{t-1}	0.0000	ADS^{+}_{t-1}	-0.0001
ADS^{-}_{t-1}	-0.0000	ADS^{-}_{t-1}	-0.0001
$\triangle SPBeta_{t-1}$	−0.0655***	$\triangle WTIBeta_{t-1}$	−0.0557***
$\triangle VIX^{+}_{t}$	0.0395***	$\triangle VIX^{+}_{t}$	−0.0624***
$\triangle VIX^{-}_{t}$	−0.0583***	$\triangle VIX^{-}_{t}$	0.1046***
$\triangle VIX^{+}_{t-1}$	0.0171	$\triangle VIX^{+}_{t-1}$	−0.0574*
$\triangle VIX^{-}_{t-1}$	−0.0828***	$\triangle VIX^{-}_{t-1}$	0.1303***
$\triangle VIX^{+}_{t-2}$	−0.0528***	$\triangle OVX^{+}_{t}$	0.1328***
$\triangle VIX^{-}_{t-2}$	-0.0111	$\triangle OVX^{-}_{t}$	−0.1466***
$\triangle VIX^{+}_{t-3}$	−0.0174***	$\triangle OVX^{+}_{t-1}$	0.1655***
$\triangle VIX^{-}_{t-3}$	−0.0164***	$\triangle OVX^{-}_{t-1}$	−0.2841***
$\triangle OVX^{+}_{t}$	−0.0176***	$\triangle OVX^{+}_{t-2}$	−0.1704***
$\triangle OVX^{-}_{t}$	-0.0021	$\triangle OVX^{-}_{t-2}$	0.1181***
$\triangle OVX^{+}_{t-1}$	0.0015	$\triangle EPU^{+}_{t}$	0.0043
$\triangle OVX^{-}_{t-1}$	0.0591**	$\triangle EPU^{-}_{t}$	−0.0075*
$\triangle OVX^{+}_{t-2}$	0.0346***	$\triangle ADS^{+}_{t}$	-0.0193
$\triangle OVX^{-}_{t-2}$	0.0101	$\triangle ADS^{-}_{t}$	0.0196
$\triangle OVX^{+}_{t-3}$	0.0220***	$\triangle ADS^{+}_{t-1}$	0.0270*
$\triangle OVX^{-}_{t-3}$	0.0035	$\triangle ADS^{-}_{t-1}$	−0.0427**
$\triangle ADS^{+}_{t}$	0.0027		
$\triangle ADS^{-}_{t}$	0.0125***		
$\triangle ADS^{+}_{t-1}$	-0.0008		
$\triangle ADS^{-}_{t-1}$	-0.0070		
$\triangle ADS^{+}_{t-2}$	-0.0025		
$\triangle ADS^{-}_{t-2}$	−0.0092**		
$\triangle ADS^{+}_{t-3}$	0.0023		
$\triangle ADS^{-}_{t-3}$	0.0106**		
Long-run parameters			
VIX^{+}_{t-1}	7.0988***	VIX^{+}_{t-1}	−18.8851***
VIX^{-}_{t-1}	7.0820***	VIX^{-}_{t-1}	−18.9026***
OVX^{+}_{t-1}	−4.2956***	OVX^{+}_{t-1}	18.7869***
OVX^{-}_{t-1}	−4.2732***	OVX^{-}_{t-1}	18.8047***
EPU^{+}_{t}	0.0152	EPU^{+}_{t-1}	-0.1618
EPU^{-}_{t}	0.0161	EPU^{-}_{t-1}	-0.1605
ADS^{+}_{t-1}	0.0037	ADS^{+}_{t-1}	-0.0053
ADS^{-}_{t-1}	-0.0030	ADS^{-}_{t-1}	-0.0063
Long-run coefficient symmetry F-test			
ADS	2.7*	ADS	0.0
EPU	0.3	EPU	0.0
OVX	0.7	OVX	0.0
VIX	0.5	VIX	0.0
Short-run coefficient symmetry F-test			
ADS	2.9*	ADS	1.6
EPU	NA	EPU	4.7**
OVX	3.5*	OVX	43.0***
VIX	138.3***	VIX	58.0***
Diagnostics and stats			
R^2	0.33	R^2	0.18
Log likelihood	8575	Log likelihood	3570
F-stat	46.9***	F-stat	28.6***
AIC	-5.2	AIC	-2.01
Bounds F-stat	22.3***	Bounds F-stat	17.5***
Bounds t-stat	−6.3***	Bounds t-stat	−5.7***
Wald test	21.1***	Wald test	14.4***
Serial Correlation Test	2.1	Serial Correlation Test	0.7
Heteroscedasticity Test	21.1***	Heteroscedasticity Test	24.6***

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

potential macro sources of the new stock-oil comovements. However, the findings of this study indicate that market sentiment is among the main drivers of this emerging pattern. Asset managers, speculators, and other non-commercial parties in the crude oil market shall not benefit from the diversification between the two markets, and this could potentially lead them to migrate to another fundamental market, creating bubbles in other sections of the economy. The higher the dependencies between different markets, the greater the fragility of financial systems. The conclusions of this research take our understanding of stock-oil comovements one step further.

Appendices

Appendix B

: NARDL regression results for conditional coskewness and cokurtosis

Table B.1: NARDL regression results – S&P 500 Coskewness

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	0.0000	Const.	0.0000
$SPCoskew_{t-1}$	-0.0173^{***}	$SPCoskew_{t-1}$	-0.0372^{***}
VIX^{+}_{t-1}	-0.0016	VIX^{+}_{t-1}	-0.0048^{*}
VIX^{-}_{t-1}	-0.0016	VIX^{-}_{t-1}	-0.0047
EPU^{+}_{t-1}	0.0000	EPU^{+}_{t}	0.0000
EPU^{-}_{t-1}	0.0000	EPU^{-}_{t}	0.0000
ADS^{+}_{t-1}	-0.0001	ADS^{+}_{t-1}	-0.0002^{***}
ADS^{-}_{t-1}	-0.0002	ADS^{-}_{t-1}	-0.0001^{***}
$\triangle SPCoskew_{t-1}$	-0.1931^{***}	$\triangle SPCoskew_{t-1}$	-0.1990^{***}
$\triangle SPCoskew_{t-2}$	-0.0638^{***}	$\triangle VIX^{+}_{t}$	-0.0041^{**}
$\triangle SPCoskew_{t-3}$	0.0617^{***}	$\triangle VIX^{-}_{t}$	0.0114^{***}
$\triangle VIX^{+}_{t}$	0.0001	$\triangle VIX^{+}_{t-1}$	-0.0102^{***}
$\triangle VIX^{-}_{t}$	0.0021	$\triangle VIX^{-}_{t-1}$	0.0026
$\triangle EPU^{+}_{t}$	0.0000	$\triangle VIX^{+}_{t-2}$	0.0017
$\triangle EPU^{-}_{t}$	0.0001	$\triangle VIX^{-}_{t-2}$	-0.0063^{***}
$\triangle ADS^{+}_{t}$	0.0038	$\triangle ADS^{+}_{t}$	-0.0011
$\triangle ADS^{-}_{t}$	0.0006	$\triangle ADS^{-}_{t}$	0.0020
		$\triangle ADS^{+}_{t-1}$	0.0007
		$\triangle ADS^{-}_{t-1}$	0.0045^{***}
		$\triangle ADS^{+}_{t-2}$	-0.0000
		$\triangle ADS^{-}_{t-2}$	0.0028^{**}
		$\triangle ADS^{+}_{t-3}$	0.0001
		$\triangle ADS^{-}_{t-3}$	-0.0055^{***}
Long-run parameters			
VIX^{+}_{t-1}	-0.0937	VIX^{+}_{t-1}	-0.1313
VIX^{-}_{t-1}	-0.0957	VIX^{-}_{t-1}	-0.1265
EPU^{+}_{t-1}	0.0036	EPU^{+}_{t}	0.0018
EPU^{-}_{t-1}	0.0037	EPU^{-}_{t}	0.0012
ADS^{+}_{t-1}	-0.0064	ADS^{+}_{t-1}	-0.0048^{***}
ADS^{-}_{t-1}	0.0099	ADS^{-}_{t-1}	-0.0044^{***}
Long-run coefficient symmetry F-test			
ADS	0.3	ADS	0.65
EPU	0.3	EPU	5.9^{***}
VIX	1.3	VIX	4.8^{**}
Short-run coefficient symmetry F-test			
ADS	0.6	ADS	5.0^{**}
EPU	1.2	EPU	NA
VIX	0.4	VIX	32.2^{***}
Diagnostics and stats			
R^2	0.05	R^2	0.13
Log likelihood	20841	Log likelihood	12275
F-stat	17.9^{***}	F-stat	22.9^{***}
AIC	-8.7	AIC	-7.5
Bounds F-stat	5.1^{***}	Bounds F-stat	8.9^{***}
Bounds t-stat	-5.7^{***}	Bounds t-stat	-7.2^{***}
Wald test	1.8^{*}	Wald test	5.5^{***}
Serial Correlation Test	1.2	Serial Correlation Test	0.6
Heteroscedasticity Test	20.7^{***}	Heteroscedasticity Test	14.3^{***}

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table B.2: NARDL regression results – WTI futures Coskewness

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	0.0000	Const.	0.0003
$WTICoskew_{t-1}$	-0.0367^{***}	$WTICoskew_{t-1}$	-0.0571^{***}
VIX^{+}_{t-1}	0.0598^{***}	VIX^{+}_{t-1}	0.0398^{***}
VIX^{-}_{t-1}	0.0598^{***}	VIX^{-}_{t-1}	0.0400^{***}
EPU^{+}_{t}	-0.0004^{*}	EPU^{+}_{t-1}	0.0002
EPU^{-}_{t}	-0.0004^{*}	EPU^{-}_{t-1}	0.0002
ADS^{+}_{t-1}	0.0016^{***}	ADS^{+}_{t-1}	-0.0000
ADS^{-}_{t-1}	-0.0007^{*}	ADS^{-}_{t-1}	-0.0000
$\triangle WTICoskew_{t-1}$	0.0008	$\triangle WTICoskew_{t-1}$	0.0048
$\triangle WTICoskew_{t-2}$	0.0494^{***}	$\triangle WTICoskew_{t-2}$	0.0491^{***}
$\triangle WTICoskew_{t-3}$	-0.0286^{**}	$\triangle WTICoskew_{t-3}$	0.0269^{*}
$\triangle WTICoskew_{t-4}$	0.0220	$\triangle WTICoskew_{t-4}$	0.0135
$\triangle VIX^{+}_{t}$	0.0081^{**}	$\triangle WTICoskew_{t-5}$	-0.0003
$\triangle VIX^{-}_{t}$	-0.0009	$\triangle WTICoskew_{t-6}$	-0.0258^{*}
$\triangle VIX^{+}_{t-1}$	-0.0030	$\triangle VIX^{+}_{t}$	0.0077^{***}
$\triangle VIX^{-}_{t-1}$	-0.0138^{***}	$\triangle VIX^{-}_{t}$	-0.0193^{***}
$\triangle ADS^{+}_{t}$	0.0151	$\triangle VIX^{+}_{t-1}$	0.0113^{***}
$\triangle ADS^{-}_{t}$	-0.0160	$\triangle VIX^{-}_{t-1}$	-0.0118^{***}
$\triangle ADS^{+}_{t-1}$	-0.0255^{**}	$\triangle EPU^{+}_{t}$	-0.0001
$\triangle ADS^{-}_{t-1}$	0.0249^{**}	$\triangle EPU^{-}_{t}$	0.0003
		$\triangle EPU^{+}_{t-1}$	-0.0005
		$\triangle EPU^{-}_{t-1}$	-0.0000
		$\triangle ADS^{+}_{t}$	0.0018
		$\triangle ADS^{-}_{t}$	-0.0014
		$\triangle ADS^{+}_{t-1}$	-0.0105^{***}
		$\triangle ADS^{-}_{t-1}$	0.0065^{***}
Long-run parameters			
VIX^{+}_{t-1}	1.6300^{***}	VIX^{+}_{t-1}	0.6962^{***}
VIX^{-}_{t-1}	1.6288^{***}	VIX^{-}_{t-1}	0.7002^{***}
EPU^{+}_{t}	-0.0117^{*}	EPU^{+}_{t-1}	0.0043
EPU^{-}_{t}	-0.0111^{*}	EPU^{-}_{t-1}	0.0037
ADS^{+}_{t-1}	0.0440^{***}	ADS^{+}_{t-1}	-0.0006
ADS^{-}_{t-1}	0.0190^{*}	ADS^{-}_{t-1}	-0.0007
Long-run coefficient symmetry F-test			
ADS	5.0^{**}	ADS	0.0
EPU	6.9^{***}	EPU	6.6^{***}
VIX	0.2	VIX	5.5^{***}
Short-run coefficient symmetry F-test			
ADS	1.1	ADS	40.2^{***}
EPU	NA	EPU	3.5^{*}
VIX	7.8^{***}	VIX	149^{***}
Diagnostics and stats			
R^2	0.08	R^2	0.30
Log likelihood	14483	Log likelihood	11454
F-stat	21.2^{***}	F-stat	54.4^{***}
AIC	-6.0	AIC	-7.0
Bounds F-stat	29.7^{***}	Bounds F-stat	12.8^{***}
Bounds t-stat	-9.7^{***}	Bounds t-stat	-6.4^{***}
Wald test	3.7^{***}	Wald test	27.2^{***}
Serial Correlation Test	1.5	Serial Correlation Test	0.5
Heteroscedasticity Test	2.2^{***}	Heteroscedasticity Test	12.8^{***}

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table B.3: NARDL regression results – S&P 500 Cokurtosis

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	-0.0148^{***}	Const.	0.0188^{*}
$SPCokurt_{t-1}$	-0.0290^{***}	$SPCokurt_{t-1}$	-0.0290^{***}
VIX^{+}_{t-1}	-0.0956^{***}	VIX^{+}_{t-1}	0.2040^{***}
VIX^{-}_{t-1}	-0.0939^{***}	VIX^{-}_{t-1}	0.1972^{***}
EPU^{+}_{t}	0.0011	EPU^{+}_{t}	-0.0101
EPU^{-}_{t}	0.0010	EPU^{-}_{t}	-0.0092
ADS^{+}_{t-1}	-0.0037^{*}	ADS^{+}_{t}	0.0005
ADS^{-}_{t-1}	-0.0072^{***}	ADS^{-}_{t}	0.0010
$\triangle SPCokurt_{t-1}$	-0.0247^{*}	$\triangle SPCokurt_{t-1}$	-0.0298^{*}
$\triangle VIX^{+}_{t}$	-0.0441^{*}	$\triangle SPCokurt_{t-2}$	0.0606^{***}
$\triangle VIX^{-}_{t}$	-0.0437	$\triangle SPCokurt_{t-3}$	-0.0451^{***}
$\triangle ADS^{+}_{t}$	-0.1631^{**}	$\triangle VIX^{+}_{t-1}$	0.1013^{*}
$\triangle ADS^{-}_{t}$	0.1659^{**}	$\triangle VIX^{-}_{t-1}$	-0.1478^{**}
$\triangle ADS^{+}_{t-1}$	0.3315^{***}		
$\triangle ADS^{-}_{t-1}$	-0.3097^{***}		
Long-run parameters			
VIX^{+}_{t-1}	-3.2945^{***}	VIX^{+}_{t-1}	7.0170^{***}
VIX^{-}_{t-1}	-3.2352^{***}	VIX^{-}_{t-1}	6.7842^{***}
EPU^{+}_{t}	0.0368	EPU^{+}_{t-1}	-0.3478
EPU^{-}_{t}	0.0352	EPU^{-}_{t-1}	-0.3181
ADS^{+}_{t-1}	-0.1291^{*}	ADS^{+}	0.0187
ADS^{-}_{t-1}	-0.2480^{***}	ADS^{-}	0.0369
Long-run coefficient symmetry F-test			
ADS	1.6	ADS	0.9
EPU	1.0	EPU	7.2^{***}
VIX	5.3^{**}	VIX	6.4^{***}
Short-run coefficient symmetry F-test			
ADS	6.1^{***}	ADS	NA
EPU	NA	EPU	NA
VIX	0.0	VIX	9.2^{***}
Diagnostics and stats			
R^2	0.02	R^2	0.04
Log likelihood	5220	Log likelihood	959
F-stat	8.5^{***}	F-stat	10.4^{***}
AIC	-2.1	AIC	-0.5
Bounds F-stat	11.6^{***}	Bounds F-stat	8.2^{***}
Bounds t-stat	-8.3^{***}	Bounds t-stat	-6.6^{***}
Wald test	3.9^{***}	Wald test	4.4^{***}
Serial Correlation Test:	1.2	Serial Correlation Test	0.4
Heteroscedasticity Test	42.1^{***}	Heteroscedasticity Test	28.8^{***}

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table B.4: NARDL regression results – WTI futures Cokurtosis

Pre-GFC		Post-GFC	
Asymmetric conditional error correction			
Const.	-0.0458^{*}	Const.	0.5667^{***}
$WTICokurt_{t-1}$	-0.0247^{***}	$WTICokurt_{t-1}$	-0.0620^{***}
VIX^{+}_{t-1}	-0.2173	VIX^{+}_{t-1}	-3.9974^{***}
VIX^{-}_{t-1}	-0.2191	VIX^{-}_{t-1}	-4.0107^{***}
EPU^{+}_{t-1}	-0.01690	EPU^{+}_{t-1}	0.0264
EPU^{-}_{t-1}	-0.01601	EPU^{-}_{t-1}	0.0280
ADS^{+}_{t-1}	0.0220^{**}	ADS^{+}_{t-1}	-0.0296^{***}
ADS^{-}_{t-1}	-0.0215^{*}	ADS^{-}_{t-1}	-0.0276^{***}
$\triangle VIX^{+}_{t}$	-0.1242	$\triangle WTICokurt_{t-1}$	-0.1676^{***}
$\triangle VIX^{-}_{t}$	0.0218	$\triangle WTICokurt_{t-2}$	-0.0380^{**}
$\triangle VIX^{+}_{t-1}$	-0.2554^{**}	$\triangle WTICokurt_{t-3}$	0.0120
$\triangle VIX^{-}_{t-1}$	0.1453	$\triangle WTICokurt_{t-4}$	-0.0759^{***}
$\triangle EPU^{+}_{t}$	-0.0010	$\triangle VIX^{+}_{t}$	-0.4794
$\triangle EPU^{-}_{t}$	0.0061	$\triangle VIX^{-}_{t}$	2.1691^{***}
$\triangle EPU^{+}_{t-1}$	0.0303^{***}	$\triangle VIX^{+}_{t-1}$	-1.4321^{***}
$\triangle EPU^{-}_{t-1}$	-0.0074	$\triangle VIX^{-}_{t-1}$	2.7892^{***}
$\triangle ADS^{+}_{t}$	-0.6520^{**}	$\triangle EPU^{+}_{t}$	0.0002
$\triangle ADS^{-}_{t}$	0.2172	$\triangle EPU^{-}_{t}$	-0.0174
$\triangle ADS^{+}_{t-1}$	0.5910^{*}	$\triangle EPU^{+}_{t-1}$	0.0438
$\triangle ADS^{-}_{t-1}$	-0.3551	$\triangle EPU^{-}_{t-1}$	-0.0623
$\triangle ADS^{+}_{t-2}$	0.9757^{***}	$\triangle ADS^{+}_{t}$	-0.8990^{***}
$\triangle ADS^{-}_{t-2}$	-0.3152	$\triangle ADS^{-}_{t}$	0.3193
$\triangle ADS^{+}_{t-3}$	-0.7467^{**}	$\triangle ADS^{+}_{t-1}$	1.6365^{***}
$\triangle ADS^{-}_{t-3}$	0.1640	$\triangle ADS^{-}_{t-1}$	-0.7474^{***}
Long-run parameters			
VIX^{+}_{t-1}	-8.7770	VIX^{+}_{t-1}	-64.3965^{***}
VIX^{-}_{t-1}	-8.8490	VIX^{-}_{t-1}	-64.610^{***}
EPU^{+}_{t-1}	-0.6820	EPU^{+}_{t-1}	0.4264
EPU^{-}_{t-1}	-0.6462	EPU^{-}_{t-1}	0.4514
ADS^{+}_{t-1}	0.8908^{***}	ADS^{+}_{t-1}	-0.4769^{***}
ADS^{-}_{t-1}	-0.8720^{*}	ADS^{-}_{t-1}	-0.4457^{***}
Long-run coefficient symmetry F-test			
ADS	14.7^{**}	ADS	0.3
EPU	19.6^{***}	EPU	0.7
VIX	0.3	VIX	0.7
Short-run coefficient symmetry F-test			
ADS	0.6	ADS	11.2^{***}
EPU	4.1^{**}	EPU	1.8
VIX	8.0^{***}	VIX	111.3^{***}
Diagnostics and stats			
R^2	0.02	R^2	0.20
Log likelihood	483	Log likelihood	4332
F-stat	4.6^{***}	F-stat	36.2^{***}
AIC	0.5	AIC	3.1
Bounds F-stat	9.2^{***}	Bounds F-stat	26.8^{***}
Bounds t-stat	-7.2^{***}	Bounds t-stat	-9.5^{***}
Wald test	5.1^{***}	Wald test	11.7^{***}
Serial Correlation Test	0.4	Serial Correlation Test	1.1
Heteroscedasticity Test	7.2^{***}	Heteroscedasticity Test	31.0^{***}

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Bibliography

References

Adams, P. A., Adrian, T., Boyarchenko, N., & Giannone, D. (2021). Forecasting macroeconomic risks. International Journal of Forecasting, 37(3), 1173–1191.

Agarwal, V., Ruenzi, S., & Weigert, F. (2017). Tail risk in hedge funds: A unique view from portfolio holdings. Journal of Financial Economics, 125(3), 610–636.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. The Journal of Economic Asymmetries, 20, e00133.

Ameur, H. B., Jawadi, F., Louhichi, W., & Cheffou, A. I. (2018). Modeling international stock price comovements with high-frequency data. Macroeconomic Dynamics, 22(7), 1875–1903.

Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. Journal of Business & Economic Statistics, 27(4), 417–427.

Baba, Y., Engle, R. F., Kraft, D. F., & Kroner, K. F. (1990). Multivariate simultaneous generalized arch. Manuscript, University of California, San Diego, Department of Economics.

Baillie, R. T., & Bollerslev, T. (2002). The message in daily exchange rates: a conditional-variance tale. Journal of Business & Economic Statistics, 20(1), 60–68.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. The quarterly journal of economics, 131(4), 1593–1636.

Bali, T. G., Cakici, N., Chabi-Yo, F., & Murray, S. (2017). The risk-neutral distribution of option returns. Georgetown McDonough School of Business Research Paper(2902209).

Bauwens, L., & Xu, Y. (2022). Dcc-and deco-heavy: Multivariate garch models based on realized variances and correlations. International Journal of Forecasting.

Bernanke, B. (2016). The relationship between stocks and oil prices. Ben Bernanke's Blog on Brookings posted on February, 19(2016).

Billio, M., Getmansky, M., & Pelizzon, L. (2012). Dynamic risk exposures in hedge funds. Computational Statistics & Data Analysis, 56(11), 3517–3532.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. The review of economics and statistics, 542–547.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. Journal of International Money and Finance, 42, 38–70.

Cai, L., & Liang, B. (2012a). Asset allocation dynamics in the hedge fund industry. Journal of Investment Management, 10(2), 35.

Cai, L., & Liang, B. (2012b). On the dynamics of hedge fund strategies. The Journal of Alternative Investments, 14(4), 51–68.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial econometrics, 4(4), 537–572.

Chan, K., Yang, J., & Zhou, Y. (2018). Conditional co-skewness and safe-haven currencies: A regime switching approach. Journal of Empirical Finance, 48, 58–80.

Chiang, I.-H. E. (2016). Skewness and coskewness in bond returns. Journal of Financial Research, 39(2), 145–178.

Chong, J., & Miffre, J. (2010). Conditional return correlations between commodity futures and traditional assets. Journal of Alternative Investments, 12(3), 61–75.

Christoffersen, P., Lunde, A., & Olesen, K. V. (2019). Factor structure in commodity futures return and volatility. Journal of Financial and Quantitative analysis, 54(3), 1083–1115.

Christoffersen, P., & Pan, X. N. (2018). Oil volatility risk and expected stock returns. Journal of Banking & Finance, 95, 5–26.

Cici, G., & Palacios, L.-F. (2015). On the use of options by mutual funds: Do they know what they are doing? Journal of Banking & Finance, 50, 157–168.

Cochrane, J. H. (2009). Asset pricing: Revised edition. Princeton university press.

Crow, E. L., & Siddiqui, M. (1967). Robust estimation of location. Journal of the American Statistical Association, 62(318), 353–389.

Del Negro, M., & Primiceri, G. E. (2015). Time varying structural vector autoregressions and monetary policy: a corrigendum. The review of economic studies, 82(4), 1342–1345.

Dittmar, R. F. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. The Journal of Finance, 57(1), 369–403.

Elyasiani, E., & Mansur, I. (2017). Hedge fund return, volatility asymmetry, and systemic effects: A higher-moment factor-egarch model. Journal of financial Stability, 28, 49–65.

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. Econometrica: Journal of the econometric society, 987–1007.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339–350.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. The journal of finance, 48(5), 1749–1778.

Fama, E. F., & French, K. R. (2016). Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. In The world scientific handbook of futures markets (pp. 79–102). World Scientific.

Fang, H., & Lai, T.-Y. (1997). Co-kurtosis and capital asset pricing. Financial Review, 32(2), 293–307.

Fattouh, B., Kilian, L., & Mahadeva, L. (2013). The role of speculation in oil markets: What have we learned so far? The Energy Journal, 34(3).

Francq, C., & Zakoian, J.-M. (2019). Garch models: structure, statistical inference and financial applications. John Wiley & Sons.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. The review of financial studies, 14(2), 313–341.

Gjika, D., & Horvath, R. (2013). Stock market comovements in central europe: Evidence from the asymmetric dcc model. Economic Modelling, 33, 55–64.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The journal of finance, 48(5), 1779–1801.

Gorton, G. B., Hayashi, F., & Rouwenhorst, K. G. (2013). The fundamentals of commodity futures returns. Review of Finance, 17(1), 35–105.

Gregoriou, G. N., Racicot, F.-É., & Théoret, R. (2021). The response of hedge fund tail risk to macroeconomic shocks: A nonlinear var approach. Economic Modelling, 94, 843–872.

Groeneveld, R. A., & Meeden, G. (1984). Measuring skewness and kurtosis. Journal of the Royal Statistical Society: Series D (The Statistician), 33(4), 391–399.

Guidolin, M., & Timmermann, A. (2008). International asset allocation under regime switching, skew, and kurtosis preferences. The Review of Financial Studies, 21(2), 889–935.

Hachicha, N., Amar, A. B., Slimane, I. B., Bellalah, M., & Prigent, J.-L. (2022). Dynamic connectedness and optimal hedging strategy among commodities and financial indices. International Review of Financial Analysis, 83, 102290.

Hamilton, J. D., & Wu, J. C. (2014). Risk premia in crude oil futures prices. Journal of International Money and Finance, 42, 9–37.

Harris, R., & Sollis, R. (2003). Applied time series modelling and forecasting. Wiley.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. The Journal of finance, 55(3), 1263–1295.

Heath, D. (2019). Macroeconomic factors in oil futures markets. Management Science, 65(9), 4407–4421.

Hitzemann, S. (2016). Macroeconomic fluctuations, oil supply shocks, and equilibrium oil futures prices. Oil Supply Shocks, and Equilibrium Oil Futures Prices (September 1, 2016).

Hoepner, A. G., McMillan, D., Vivian, A., & Wese Simen, C. (2021). Significance, relevance and explainability in the machine learning age: an econometrics and financial data science perspective. The European Journal of Finance, 27(1-2), 1–7.

Hou, Y., & Li, S. (2016). Information transmission between us and china index futures markets: An asymmetric dcc garch approach. Economic Modelling, 52, 884–897.

Hu, M., Zhang, D., Ji, Q., & Wei, L. (2020). Macro factors and the realized volatility of commodities: a dynamic network analysis. Resources Policy, 68, 101813.

Jawadi, F., & Khanniche, S. (2012). Modeling hedge fund exposure to risk factors. Economic Modelling, 29(4), 1003–1018.

Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. Journal of International Financial Markets, Institutions and Money, 56, 255–280.

Karkowska, R., & Urjasz, S. (2021). Connectedness structures of sovereign bond markets in central and eastern europe. International Review of Financial Analysis, 74, 101644.

Kilian, L. (2014). Oil price shocks: Causes and consequences. Annual Review of Resource Economics, 6(1), 133–154.

Kilian, L., & Lütkepohl, H. (2017). Structural vector autoregressive analysis. Cambridge University Press.

Kim, T.-H., & White, H. (2004). On more robust estimation of skewness and kurtosis. Finance Research Letters, 1(1), 56–73.

Knittel, C. R., & Pindyck, R. S. (2016). The simple economics of commodity price speculation. American Economic Journal: Macroeconomics, 8(2), 85–110.

Kozlowski, J., Veldkamp, L., Venkateswaran, V., et al. (2015). The tail that wags the economy: Belief-driven business cycles and persistent stagnation.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. The Journal of finance, 31(4), 1085–1100.

Lagunoff, R., & Schreft, S. L. (2001). A model of financial fragility. Journal of Economic Theory, 99(1-2), 220–264.

Laurent, S., Rombouts, J. V., & Violante, F. (2012). On the forecasting accuracy of multivariate garch models. Journal of Applied Econometrics, 27(6), 934–955.

Li, Y., & Kazemi, H. (2007). Conditional properties of hedge funds: Evidence from daily returns. European Financial Management, 13(2), 211–238.

Mitchell, M., & Pulvino, T. (2001). Characteristics of risk and return in risk arbitrage. the Journal of Finance, 56(6), 2135–2175.

Mohaddes, K., & Pesaran, M. H. (2017). Oil prices and the global economy: Is it different this time around? Energy Economics, 65, 315–325.

Nakajima, J., et al. (2011). Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications.

Noguera-Santaella, J. (2016). Geopolitics and the oil price. Economic Modelling, 52, 301–309.

Nowzohour, L., & Stracca, L. (2020). More than a feeling: Confidence, uncertainty, and macroeconomic fluctuations. Journal of Economic Surveys, 34(4), 691–726.

Patton, A. J., & Ramadorai, T. (2013). On the high-frequency dynamics of hedge fund risk exposures. The Journal of Finance, 68(2), 597–635.

Pesaran, M. H., Shin, Y., et al. (1995). An autoregressive distributed lag modelling approach to cointegration analysis.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289–326.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. The Review of Economic Studies, 72(3), 821–852.

Racicot, F.-É., & Théoret, R. (2019). Hedge fund return higher moments over the business cycle. Economic Modelling, 78, 73–97.

Ready, R. C. (2018). Oil prices and the stock market. Review of Finance, 22(1), 155–176.

Roncalli, T., & Weisang, G. (2009). Tracking problems, hedge fund replication and alternative beta. Hedge Fund Replication and Alternative Beta (January 9, 2009).

Rossi, B., Sekhposyan, T., & Soupre, M. (2016). Understanding the sources of macroeconomic uncertainty. Available at SSRN 2816841.

Rubinstein, M. E. (1973). The fundamental theorem of parameter-preference security valuation. Journal of Financial and Quantitative Analysis, 8(1), 61–69.

Samitas, A., Kampouris, E., & Kenourgios, D. (2020). Machine learning as an early warning system to predict financial crisis. International Review of Financial Analysis, 71, 101507.

Samuelson, P. A. (1975). The fundamental approximation theorem of portfolio analysis in terms of means, variances and higher moments. In Stochastic optimization models in finance (pp. 215–220). Elsevier.

Santos, A. A., Nogales, F. J., & Ruiz, E. (2013). Comparing univariate and multivariate models to forecast portfolio value-at-risk. Journal of financial econometrics, 11(2), 400–441.

Schwartz, E. S. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. The Journal of finance, 52(3), 923–973.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of finance, 40(3), 777–790.

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ardl framework. In Festschrift in honor of peter schmidt (pp. 281–314). Springer.

Singleton, K. J. (2014). Investor flows and the 2008 boom/bust in oil prices. Management Science, 60(2), 300–318.

Stafylas, D., Anderson, K., & Uddin, M. (2018). Hedge fund index-engineering methodologies: a comparison and demonstration. Applied Economics, 50(6), 596–612.

Susmel, R., & Engle, R. F. (1994). Hourly volatility spillovers between international equity markets. Journal of international Money and Finance, 13(1), 3–25.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68(6), 54–74.

Tsay, R. S. (2013). Multivariate time series analysis: with r and financial applications. John Wiley & Sons.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: journal of the Econometric Society, 817–838.

Working, H. (1949). The theory of price of storage. The American Economic Review, 39(6), 1254–1262.

Yang, J., Zhou, Y., & Wang, Z. (2010). Conditional coskewness in stock and bond markets: time-series evidence. Management Science, 56(11), 2031–2049.