Essays in Energy Finance

by

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Declaration

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Dedication

To whom it may concern.

Abstract

This dissertation is composed of three main chapters related to energy finance, where the first two chapters each contain one essay and the third chapter contains two essays.

In the first chapter (published in the *Economic Modelling*, co-authored with Dr. Brian Lucey), study the relationship between the news tone, extracted using dictionary-based textual analysis, and the monthly oil prices. We directly measure the sentiment of Financial Times oil news articles from 1 June 2008 to 30 September 2020 using a oil-specific dictionary and the approach à la Loughran et al. (2019) as well as a commonly employed Henry's general financial dictionary. We find non-linear (linear) Granger-causality between news tone computed using the oil-specific (Henry's financial) dictionary and the oil prices. Since the preliminary results show predictive power of the news tone on oil prices, we perform out-of-samples forecasts over short (1-), medium (2-), long (3-month) horizons, controlled by other popular macroeconomic and sentiment variables. Unlike previous studies show that the $News\ Tone_{Henry}$ is useful in oil price trend forecasting, our results indicate that it has no ability to forecast the actual oil prices across all horizons. Instead, we find that the $News\ Tone_{Oil}$ exhibits strong (weak) forecasting power over short (medium) terms, checked by robustness tests which further consider the Global Real Economic Activity, oil production and supply. We further verify the economic significance of the forecasting models by comparing the performance with those of a naive buy & hold strategy. Our study documents the use of domain-specific dictionary in relevant financial analysis.

In the second chapter (published in the *Energy Economics*, co-authored with Dr. Brian Lucey), we examine the role of renewable energy stocks could play during cryptocurrency market turmoils from 1 January 2018 to 17 September 2021. Cryptocurrencies could be roughly classified as "dirty" and "clean" types based on the estimated energy consumption, depending on what underlying algorithm (e.g., Proof-of-Work (PoW), and non-PoW) is used. We first analyse the dynamic

spillover patters among the renewable energy stocks, cryptocurrencies, S&P 500 (as a proxy for general stock market), and gold. We show that there is only weak connectedness between the renewable energy and cryptocurrency markets, which implies the possibility of renewable energy stocks to provide hedge and diversification benefits in the future. We further perform statistical analysis to examine the hedge and safe haven property of renewable energy stocks for cryptocurrencies' extreme negative movements and uncertainties, and vice versa. We confirm that renewable energy stocks have not yet become direct long-term hedge for either type of cryptocurrencies. However, it could at least serve as a weak safe haven for both types in extreme bearish markets. Moreover, renewable energy stocks are more likely to be a safe haven for "dirty" than "clean" cryptocurrencies during heightened market uncertainty. By contrast. cryptocurrencies are not general safe havens for renewable energy stocks. This study provides significant implications for investors, policy-makers, and founders of cryptocurrencies.

In the third chapter (co-authored with Dr. Brian Lucey), we research the herd behaviour in emerging assets such as cryptocurrencies and renewable energy stocks. In this chapter's first essay (published in the *Finance Research Letters*), similar to what we do in the previous chapter, we classify the cryptocurrencies into "dirty" and "clean" types, where we find empirical evidence that herding generally exists only in the dirty cryptocurrency market and is more significant in down than up markets. Moreover, we find that clean cryptocurrencies do herd, but with dirty cryptocurrencies, when the two markets are both in positive condition. The results are robust across value- and equal-weighted portfolios and provide valuable insights to cryptocurrency investors and policy makers. In the second essay which focuses on the renewable energy market in China (published in the *Energy Economics*), we find that the herds of renewable energy stocks significantly show up in the Chinese exchanges, which on the one hand, contradicts previous literature that declares that such market do not herd. On the other hand, our findings support literature that Chinese stock market is significantly inefficient and immature. We further investigate the asymmetric and time-varying characteristics of such behaviour in the Chinese market. We find that herding asymmetry is more pronounced during bullish markets and among smaller firms. When within-industry herding weakens, large price movements in the overall stock market provide additional trading signals for herding formation in this sector.

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CHAPTER 1

DOES NEWS TONE HELP FORECAST OIL PRICES?

1.1 Introduction

Crude oil is regarded as one of the most important energy commodities, or even the single most important energy commodity in finance, mainly because it is non-renewable and is the primary source of energy production. Therefore, forecasting oil prices has long been a challenge as well as a promising task in academia and industry due to the heavy impact of oil price fluctuations on global economic activities. However, the high sensitivity to global factors has made the oil price forecasts difficult to be accurate [Adrangi et al. (2001), Moshiri and Foroutan (2006), Hamilton (2009)].

A strand of the literature follows the earliest attempts whose forecasts solely depend on the historical values. They seek to improve the forecasting results by introducing more advanced models and better combination and treatment of the past values [Moshiri and Foroutan (2006), Zhang et al. (2015), Guo (2019)]. Other strands believe that oil prices could be affected by many other macroeconomic factors. They have been managing to lower the forecasting errors using not only the fundamental factors such as economic growth [Kilian and Hicks (2013), Ready (2018)], supply and demand [Lippi and Nobili (2012), Kilian (2009)], exchange rates [Basher et al. (2012), Sadorsky (2000)], interest rates [Frankel (2008), Akram (2009)], precious metal prices [Narayan et al. (2010), Zhang and Wei (2010)] among others, but also non-fundamental factors such as economic policy uncertainty (EPU)

[Balcilar et al. (2017)], geopolitics [Phan et al. (2021)], and so on. More recently, market sentiment, more specifically the investor sentiment, stemmed from the theory of behavioural finance or broadly behavioural economics, has also found to be useful in anticipating financial markets' moves.

As defined in behavioural finance, financial participants, especially investors, are not completely rational. Different levels of individual's risk tolerance can significantly influence one's sensitivity to volatility or risks, which in turn governs and triggers their trading decisions, thereby the market tendency. There are a fruitful list of measures that are used as proxies for investor sentiment or attention, such as the Implied Volatility Index (VIX), the Crude Oil Volatility Index (OVX), EPU Index, the American Association of Individual Investors' Sentiment Survey (AAII), and the Google Search Volume Index (GSV) based on Google Trends, etc [Reboredo and Uddin (2016), He et al. (2019), Yin and Feng (2019), Qadan and Nama (2018), Balcilar et al. (2017)]. Apart from these, a newly developed concept, news sentiment, has drawn considerable attention from researchers.

Newspapers are known widespread sources that provide both informative news and relevant comments/analysis. As for oil market, business or financial newspapers are the primary platforms that inform the public about supply and demand states and shocks. While investors are sophisticated, most are sensitive and speculative and may act on the signals conveyed by such news. Thus, it would be interesting and useful if we could find the connection between the sentiment aroused from news and the oil price changes.

Discovering the linkage between the changes in the *tone* of news and the oil price is one of the purposes but not the primary purpose of our study. It serves as a preliminary indicator for our further process. In fact, a few of studies have attempted to extract the news sentiment regarding the oil market. Our study follows one strand of the literature that uses dictionary-based approach to calculate the tone of news articles, which is more straightforward than machine learning approach as it does not involve human manipulations. However, our study differs to most previous studies that we adopt a new oil-specific dictionary and the subsequent approach presented by Loughran et al. (2019). We use *Financial Times* as our news source which is not commonly considered, despite being a world-leading news provider and mostly operates for business and financial sector. Moreover, unlike many studies which only focus on the headlines, we use the full texts as we believe that only full texts would tell a complete story of an event. For comparison, we consider the commonly used Henry's general financial dictionary [Henry (2008)].

After we compute the monthly aggregate *News Tone* indices, we then perform Granger-causality tests to investigate the interactions between the news tone indices and the oil prices, where we adds to the closest literature by using a nonlinear Granger-causality measure following the standard linear Granger (1969) test. Our first results show that the news tone indices constructed using different dictionaries interact with oil price changes differently. Specifically, we find that the change in news tone constructed using the Henry's dictionary (hereafter: $News\ Tone_{Henry}$) linearly Granger-causes the change in oil price, while the change in the news tone constructed using the oil-specific dictionary (hereafter: $News\ Tone_{Oil}$) nonlinearly Granger-causes the oil price. These suggest that both news tone indices are possible predictive variables of the oil price.

Next, we are confident to perform the oil price forecasting incorporating the *News Tone* indices. We test it over 1-, 2-, and 3-month horizons (corresponding to short-, medium-, and long-term investing). Our empirical results show $News\ Tone_{Oil}$ helps in the out-of-sample oil price forecasting over a short horizon, while the $News\ Tone_{Henry}$ does not help at all time horizons. These underscore the importance of using domain-specific dictionary in financial analysis. We proceed to analyse the economic significance of our forecasts by comparing the profits and Sharpe ratios obtained by using long-short trading strategies based on the forecasting models with that by a naive buy & hold strategy. We show that the strategy based on the model incorporating the $News\ Tone_{Oil}$ significantly outperforms all other strategies (models).

The rest of this chapter is structured as follows. In Section 1.2, we review some previous literature. In Section 1.3, we present the methodology, whereas in Section 1.4 we describe the data. In Section 1.5, we discuss the main empirical findings and robustness checks. Finally, We conclude this chapter with Section 1.6.

1.2 Literature Review

Crude oil prices are hardly stable. A substantive part of the energy commodity literature has therefore investigated what economic changes can explain or contribute to the behaviour of crude oil prices. While Hamilton (1983, 1996, 2003) among others pointed out that oil price changes significantly affect the macroeconomy (e.g., the economic growth and recession) using the U.S. data, studies on the reverse such as Al-Yousef (2018) showed that global economic growth also causes change of the crude oil prices. Their recent evidence has showed that the rise in the global GDP growth stimulated the oil prices from 2003 to 2008 and the drop of the economic growth contributed to the oil price decrease in 2014-2015, which is in line with the arguments of Kilian and Hicks (2013). Just as other commodities, the variations of crude oil price suffered from the demand and supply shocks. Kilian (2009) found that the price of oil responds differently and with delays to the heterogeneous and asymmetric supply and demand shocks, while Lippi and Nobili (2012) suggested that the such price adjustments could be simultaneously. The turmoils in especially in the oil producing countries, such as worker strikes, wars, terrorist attacks, etc, may induce the supply risk and further affect the oil price [e.g., Hamilton (1985, 2003), Song et al. (2022)]. Phan et al. (2021) used measures of terrorism as indicators in oil price return forecasting. Their findings suggest that the terrorist attacks indirectly causes the turbulence in oil prices from both oil production and investing aspects. There are also factors affecting the demand side such as the inflation, currency exchange, etc, which may further influence the oil prices. For example, Sadorsky (2000) showed that the the price of crude oil futures react to the variations in exchange rates. Akram (2009) analysed the relationship between U.S. real interest rate, exchange rate, and prices of several commodities. They found that the interest rate can be viewed as a potential price indicator for commodities. Moreover, Narayan et al. (2010) showed that the crude oil and the gold markets are actually cointegrated, which implies that the the price of gold can be used as a predictor of crude oil prices.

The futures products of oil have been exceptionally popular and liquid hedging tools for the spot markets among investors. Investors' trading logic and decisions, which heavily depend on their emotions and the attitudes towards risks (e.g., volatilties and extreme movements, etc), undoubtedly have a huge impact on current and expected prices of the oil products. Hence, the change in the oil price cannot be solely explained by the fundamentals. Extensive studies have examined the relationship between the investor/market sentiment and the oil markets. For example, Sari et al. (2011) studied the long-term nexus among the price of previous metals, the exchange rate, the VIX as a proxy for investors' risk perception, and the price of oil. They found significant influences from risk expectations to the oil prices. Findings of Shaikh (2019) reveal a strong and asymmetric relationship between oil prices and the OVX as a proxy for investors' fear. Similarly, Li et al.

(2022) discovered a nonlinear association between crude oil prices and OVX. They also find that the multifractal strength between the oil prices and OVX is more significant than that between the prices and the VIX. They believe that investors can use the OVX as price indicators in forecasting. He et al. (2019) discovered a nonlinear Granger-causality between the AAII sentiment survey index, a proxy for the aggregate sentiment of the members from the American Association of Individual Investors, and the oil returns. The time-varying association between them implies that investor sentiment has an impact on the variations of the oil price. Bekiros et al. (2015) used various VAR models and document the forecastability of a news-based (by counting the number of newspapers addressing specific keywords) EPU [Baker et al. (2016)]in oil returns. Balcilar et al. (2017) analysed the quantile casuality running from the EPU and the Equity Market-related Economic Uncertainty (EMEU) [Baker et al. (2016)] to the crude oil market. Evidence presents the ability of the two news-based uncertainty measures to predict the oil returns. Bonaparte (2019) created a textual Geopolitical Oil Price Risk Index (GOPRX) based on Google Trends/GSV and factor analysis. The price of oil is found significantly correlated with the GOPRX. Qadan and Nama (2018) compared nine types of sentiment variables, including VIX, OVX, EPU, GSV, etc, to show that investor sentiment drives the oil price changes.

In the meantime, as we introduced earlier, a newly developed behavioural factor, textual sentiment, similar to other sentiment-type proxies such as uncertainties, becomes increasing popular as a new explanatory variable in forecasting the oil markets. Both machine learning (ML) and the state-of-art Dictionary-based approaches have been widely adopted in the process of content analysis.

Here we introduce some machine learning applications first as we in this study use the another. For instance, Li et al. (2019) employed a deep learning technique—a convolutional neural network (CNN) algorithm—to extract the hidden information in *Investing.com* news. They further normalised and smoothed the short-lived variations by a Hodrick-Prescott (HP) filter (Hodrick and Prescott (1997)) and proceeded with a linear Granger-causality test to examine the predictive power of text features, particularly, the subjectivity and emotions in oil prices. Empirical results indicate that most of the text features significantly Granger-cause the oil prices and combining the text features with traditional financial data reduces the forecasting errors. Wu et al. (2021) also used a CNN model to measure the sentiment of news headlines. They showed that the quantified textual news information along with GSV data improves accuracy of oil price forecasts.

With respect to the dictionary-based approach, Henry's financial dictionary [Henry (2008)] is perhaps the first widely used dictionary in financial analysis, which was invented by analysing the earnings press releases from firms in telecommunications and computer services industries and related equipment manufacturers. Henry (2008) used it in the first instance to investigate the correlation between the tone of these firms' earning press releases and the corresponding returns of their stocks. Subsequently, scholars in other fields of finance started adopting this and other competing dictionaries in their studies. Regarding oil market-related research, for example, Li et al. (2017) used the Henry's dictionary [Henry (2008)] to construct a tone series based on the Thomson Reuters's oil market news and then applied a normalisation and HP smoothing process on both the tone and price series. They found that the news tone can Granger-cause the oil price change and can help predict the oil price up-down movements. Zhao et al. (2019) considered a rule-based lexicon/dictionary—the VADER (**V**alence **A**ware **D**ictionary and s**E**ntiment **R**easoner)—to quantify the sentiment of news from *Reuters* and *United Press International*. After normalisating and performing forecasts, they found that text sentiment helps forecast oil prices when the magnitude of the tone is strong enough. The most recent field-specific invention is by Loughran et al. (2019) who created a special dictionary of 130 keywords and 827 modifiers correlated to the oil market to gauge the polarity of oil market-related news from Dow Jones company. They discovered that more signals suggesting a oil price decrease, the higher the exact oil price, after controlling the effect from the interest rate, U.S. dollar, gold price, VIX, etc. The more signals suggesting a oil price increase, the lower the actual oil price.

Compared to traditional lexicon/dictionary-based approach, machine learning techniques seem to be more advanced and complex. However, machine learning techniques "may not necessarily outperform" the state-of-art dictionary-based approach in real world practice, argued by Loughran and McDonald (2016) and Loughran et al. (2019) and partially evidenced by Guo et al. (2016) among others.

The success of using machine learning techniques heavily relies on a thorough "training" process [Guo et al. (2016); Li (2020)]. Researchers must select their parameters of a machine learning model and adjust them to improve the in-sample results in the training process, from probably hundreds or even thousands of combinations [Loughran and McDonald (2016); Loughran et al. (2019)]. Without being pre-trained on selected documents, models cannot be used for a general or random news item. Moreover, results from analysis of target files may (significantly) vary if the feed files are selected (completely) differently during model training. If either of their choice of tuning such as parameters or the corpus used for model training is not provided, researchers will find it hard or impossible to replicate previous scholars' results [Loughran and McDonald (2016); Loughran et al. (2019)]. Although leading financial news/data providers such as *Thomson Reuters* or *Bloomberg* provide reliable scoring or ratings through their comprehensive and sophisticated algorithms, their data is behind paywalls, and their implementations are confidential as intellectual property and commercial competitiveness. Using dictionaries that are open to public is therefore considered more "transparent" and "straightforward" in the calculation process than using machine learning for financial textual analysis [Loughran and McDonald (2016); Loughran et al. (2019); Guo et al. (2016)].

1.3 Methodology

1.3.1 Sentiment Analysis

We followed a common approach to calculate the tone of an article [Loughran et al. (2019)], which is formulated as Eq. 1.1. We then created the monthly oil news tone indices by aggregating the tone scores of all days in a month.

$$News\ Tone_i\ per\ article = \frac{(Pos. - Neg.)}{(Tot.)} \tag{1.1}$$

where the $Pos.$, $Neg.$, and $Tot.$ refer to the number of positive, negative, total words in an article, respectively. The i refers to the particular dictionary we used.

With respect to components in Eq. 1.1, we used a dictionary-based approach following Loughran et al. (2019). We first updated the original Loughran-McDonald (LM) Stopwords list[1] that we deleted the word *"up"* as *"up"* is considered as a modifier in the Loughran et al. (2019) approach. Moreover, we added 14 acronyms specified in Loughran et al. (2019) to the 2018-version LM Master Dictionary[2] Then, we excluded all meaningless words that are neither in the Stopwords list and

[1] Available at `https://sraf.nd.edu/textual-analysis/resources/#StopWords`.

[2] This is the most recent Master Dictionary when we conducted this analysis. It is available at `https://sraf.nd.edu/textual-analysis/resources/#Master%20Dictionary`.

the Master Dictionary. The total word count is equal to the number of words left. To calculate the polarity of the article, we considered two comparable dictionaries, a Oil-specific Dictionary [Loughran et al. (2019)] and the Henry's Financial Dictionary [Henry (2008)]. The Loughran et al. (2019) oil-specific dictionary identifies 59 positive, 19 negative, and 52 inconclusive words. The positive (negative) keywords indicates an increase (decrease) in the expected oil price, while the inconclusive keywords are not sign-defined before being assigned a modifiers which are also provided as complements by Loughran et al. (2019). There are in total of 291 positive and 536 negative modifiers. We screened any modifiers around an inconclusive keyword with a range of four. If we did not find a modifier, we ignored such keyword. If we did find a modifier, such as a negative modifier *"fall"* appearing right before an inconclusive keyword *"production"*, we treated them as a positive phrase, *"production fall"*, which indicates a expected increase in the price. We only counted the keywords once in the screening process. As a competitor, the Henry's dictionary only comprises of 105 positive and 85 negative keywords. A calculation example of a sample news article which illustrates the difference of the two dictionaries is in the Appendix A.

1.3.2 Linear Granger-Causality Test

We first used a linear Granger-causality test [Granger (1969)] to investigate the linear causal relationship between the news tone indices and the oil price series via a Vector Autoregressive (VAR) model:

$$\begin{aligned} Y_t &= c_1 + \sum_{i=1}^{m} \alpha_{11i} Y_{t-i} + \sum_{j=1}^{n} \alpha_{12j} X_{t-j} + \epsilon_{1t}, \\ X_t &= c_2 + \sum_{i=1}^{m} \alpha_{21i} X_{t-i} + \sum_{j=1}^{n} \alpha_{22j} Y_{t-j} + \epsilon_{2t}, \end{aligned} \tag{1.2}$$

where Y_t and X_t for t = 1, ..., T are the two time series being tested, ϵ_t is the error term assumed to be mutually independent and identically distributed with a zero mean and constant variance, and m and n are the maximum lag lengths.

Examining the null hypothesis H_0 of the linear Granger-causality, for example, that X_t does not Granger-cause Y_t, is equivalent to examining whether $\alpha_{12j} = 0$ when $j = 1, 2, \ldots, n$. The H_0 that Y_t does not Granger-cause X_t is equivalent to evaluating whether $\alpha_{2j} = 0$ when $j = 1, 2, \ldots, m$. $F-$test is used in this process.

1.3.3 Nonlinear Granger-Causality Test

We further used a nonlinear Granger-causality test introduced by Diks and Panchenko (2006) to explore the possibly nonlinear causal relationship between the news tone indices and the oil price series.

The null hypothesis H_0 that X_t does not Granger-cause Y_t is written as:

$$Y_{t+1}|(X_t^{l_X};Y_t^{l_Y}) \sim Y_{t+1}|Y_t^{l_Y}, \tag{1.3}$$

where $X_t^{l_X}$ and $Y_t^{l_Y}$ are the lagged values of X_t and Y_t. Assuming that the bivariate time series $\{(X_t, Y_t)\}$ are strictly stationary, Equation (1.3) then represents the invariant distribution of the $(1+l_X+l_Y)$-dimensional vector $W_t = (X_t, Y_t, Z_t)$, where $Z_t = Y_{t+1}$. Under the H_0, the conditional distribution of Z given $(X,Y) = (x,y)$ is identical to that of Z given $Y = y$ only; thus joint probability density function $f_{X,Y,Z}(x,y,z)$ and its marginals should meet the criteria:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)}\frac{f_{Y,Z}(y,z)}{f_Y(y)}, \tag{1.4}$$

where X and Z are conditionally independent of $Y = y$. Hence, we treat the H_0 as:

$$q = E[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)] = 0 \tag{1.5}$$

If we define the local density estimators of a d_W-variate random vector W as $\hat{f}_W(W_i) = \frac{(2\epsilon_n)^{-d_W}}{n-1}\sum_{j,j\neq i} I_{ij}^W$, where $I_{ij}^W = I\ (\parallel W_i - W_j \parallel < \epsilon)$. The estimation of the test statistic T_n then can be calculated as:

$$T_n(\epsilon) = \frac{(n-1)}{n(n-2)}\sum_i(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)) \tag{1.6}$$

For a bandwidth $\epsilon_n = Cn^{-\beta}$, where C is positive and β is ranged from $\frac{1}{4}$ to $\frac{1}{3}$, $T_n(\epsilon)$ satisfies:

$$\sqrt{n}\frac{T_n(\epsilon_n) - q}{S_n} \xrightarrow{d} N(0,1), \tag{1.7}$$

where S_n is the robust estimation of the asymptotic variance of the test statistic and $\xrightarrow{d}$ stands for distribution convergence. Empirical studies generally truncate the bandwidth within the range of [0.5, 1.5], following Diks and Panchenko (2006).

1.3.4 Oil Price Forecasting

1.3.4.1 Forecasting Models

The h-step ahead forecasts of oil price were simulated via a multivariate VAR model:

(1.8)

$$P^{oil}_{t+h} = c_1 + \sum_{i=1}^{n} \alpha_{1i} P^{oil}_{t-i+1} + \sum_{i=1}^{n} \alpha_{2i} NewsTone_{t-i+1} + \sum_{i=1}^{n} \alpha_{3i} Econ_{t-i+1} \sum_{i=i}^{n} \alpha_{4i} Control_{t-i+1} + \epsilon_t$$

where n is the number of lags used, P^{oil}_t is the futures price of oil, $NewsTone_t$ is one of the news tone index series, $Econ_t$ are economic variables, and $Control_t$ stands for control variables. Details of data is described in the section 1.4.

1.3.4.2 Performance Evaluation

The expanding window procedure was used in our forecasting to ensure robustness. We used the first 70% of observations in initial model estimation and increment the estimation sample by one month. The performance of the out-of-sample forecasts was measured by root mean square error (RMSE) and mean absolute percentage error (MAPE) which are defined as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{1.9}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} * 100 \tag{1.10}$$

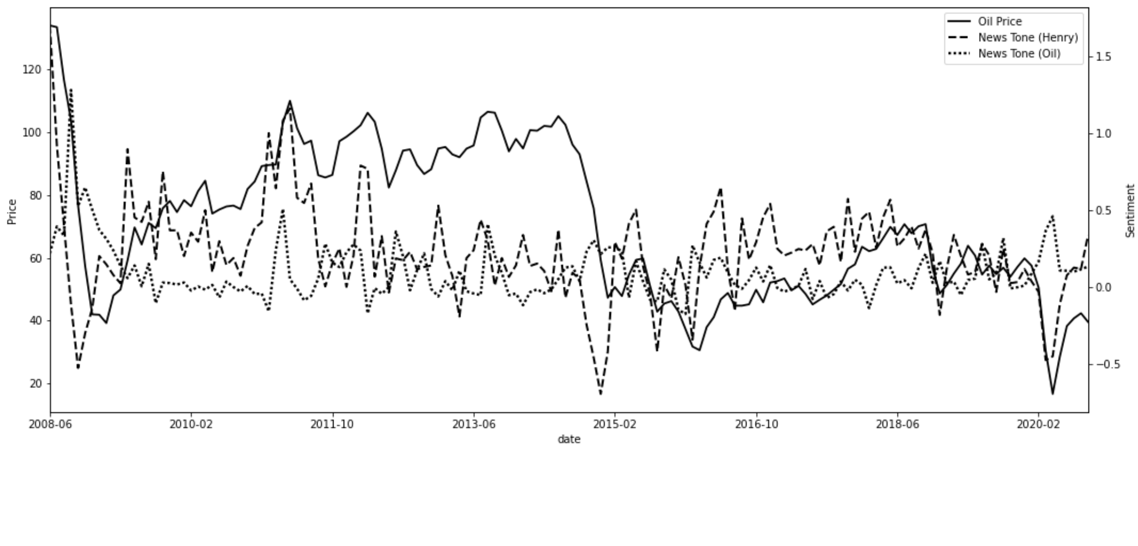
where y_i is the actual oil price, $\hat{y}_i$ is the predicted price and N is the number of forecasting observations.

1.4 Data

We considered *LexisNexis* electronic database as our source of business news articles. We searched for articles published by the *Financial Times* that contain one of following specific oil market-related keywords, including *crude*, *brent*, *oil*, *OPEC*, *WTI (West Texas Intermediate)*, appearing in both the headlines and body texts at the same time. We ignored the case sensitivity. We also excluded firm-specific articles as we focus on the market-level sentiment. We then narrowed our results by only selecting articles whose major terms fall within the *"Crude Oil Market"* section of the publisher to avoid mismatch, and we only retained informative articles that are defined as having more than 180 words. Moving forward, we excluded high-similarity duplicates using the built-in function of *LexisNexis*. We needed to be careful in this step as the similarity detection function only works for the first 200 documents in a row. Hence, we had to restrict the number of the results each time. At last, we had 3579 pieces of news articles available from 1 June 2008 to 30 September 2020 for our analysis. We then proceeded to apply the sentiment analysis specified in Section 1.3.1 on these news documents to produce our independent variables in the forecasting, the $News\ Tone_i$. Specifically, *News Tone*$_{Henry}$ was constructed using Henry's Financial Dictionary [Henry (2008)], while *News Tone*$_{Oil}$ was constructed using the Oil-specific Dictionary by Loughran et al. (2019).

Our dependent variables, the monthly prices of the WTI crude oil futures, denominated in USD/Barrel, were sourced from the *Energy Information Administration* (EIA) website[3] for the same period. We plot the movements of the monthly *News Tone* indices and the oil prices in Figure 1.1, where both exhibit significant variations over the whole period.

Figure 1.1: Movements of Monthly Oil Price and News Tone Indices

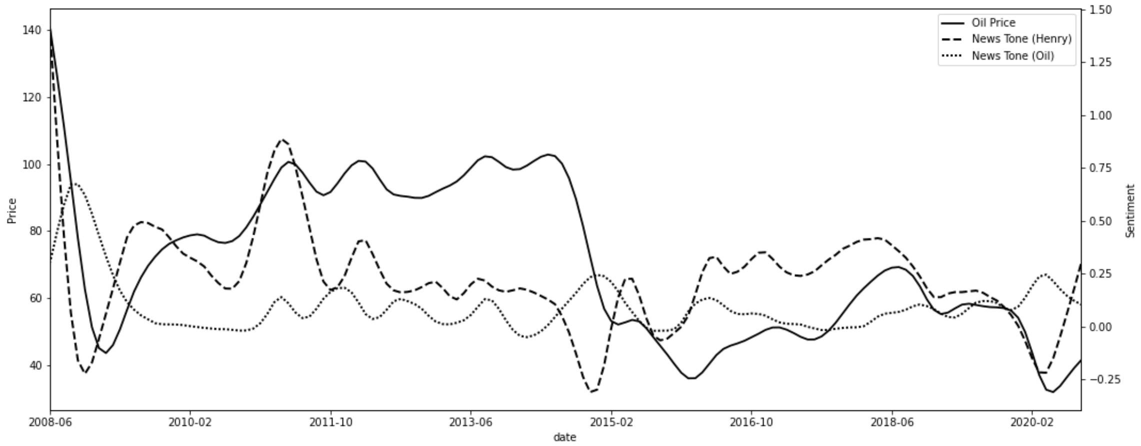


To obtain a better picture of the potential co-movements, we smoothed the index series using the Hodrick-Prescott filter. The outcomes are depicted in the Figure 1.2. In this time, from the plot we see that *News Tone* indices co-move with the oil price.

[3] `https://www.eia.gov/`.

One would say that co-movement between *News Tone*$_{Henry}$ and oil prices is more obvious than that between the *News Tone*$_{Oil}$ and oil price. *News Tone*$_{Henry}$ reaches the peaks and troughs before the price series does so most of the time, while *News Tone*$_{Oil}$ depicts the same trend as oil price during the period from 2010 to 2015, and generally reacts to the opposite at other time. Thus, it's worth investigating whether there are statistical causal relationships between the *News Tone* indices and the oil price.

Figure 1.2: Movements of Smoothed Monthly Oil Price and News Tone indices



Finally, we retrieved the data of several oil price predictors. According to the findings of Sadorsky (2000), Akram (2009), Qadan and Nama (2018) Narayan et al. (2010) among others, we considered three economic variables as our basic predictors: the spot gold price, a proxied USD exchange rate by the Trade-weighted USD Index, and a proxied US interest rate by the 10 years Treasury constant maturity rate. Following Loughran et al. (2019), Bonaparte (2019), Qadan and Nama (2018), Balcilar et al. (2017), Narayan et al. (2010), Dutta (2017), we used several sentiment-type measures as our control variables: the VIX, the OVX, the EPU, the EMEU, and the GOPRX. The source of the control variables is the *Federal Reserve Economic Database* (FRED)[4] except the GOPRX which was downloaded from the *J.P. Morgan Center for Commodities*[5].

[4]`https://fred.stlouisfed.org`.

[5]Publicly available at `https://business.ucdenver.edu/commodities/applied-research/geopolitical-oil-price-risk-index-goprx`.

1.5 Results

1.5.1 Unit Root Tests

The stationarity of *News Tone* indices and WTI crude oil futures prices is examined by Augmented Dicky-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, shown in Table 1.1. The results of the ADF tests indicate that *News Tone* indices are both stationary at the significance level of 1%, while the the price of the WTI oil futures is only stationary at the significance level of 5%. The KPSS tests reject the null of stationarity of oil price and $News\ Tone_{Henry}$ at the significance level of 1% and 10%, respectively, while $News\ Tone_{Oil}$ is stationary. After first-order differencing, the oil prices and *News Tone* indices are all stationary at the same significance level of 1%, so that they could be proceeded to identify a possible causal relationship in the following step.

Table 1.1: Results of Unit Root Tests on Monthly News Tone Indices and Oil Futures Prices

	ADF	KPSS
News $\text{Tone}_{\text{Henry}}$	-7.3298***	0.3934*
News Tone_{Oil}	-6.7855***	0.2485
Oil Price	-3.2519**	0.8660***
ΔNews $\text{Tone}_{\text{Henry}}$	-6.6265***	0.1007
ΔNews Tone_{Oil}	-6.1484***	0.1240
ΔOil Price	-6.6262***	0.0754

Note: ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

1.5.2 Linear and Nonlinear Granger-Causality Tests

The results of linear Granger causality tests between the oil price and the $News\ Tone_{Henry}$ is showin in Table 1.2, where we find that changes in $News\ Tone_{Henry}$ only weakly linearly Granger-cause the changes in oil prices within the first two lags at the 10% level, while the linear causality from oil price to $News\ Tone_{Henry}$ is only found at the third lag at 5%. On the contrary, there is no linear Granger causality found from $News\ Tone_{Oil}$ to oil prices. Instead, such causality can be found from the prices to news tone at all lags (Table 1.3).

Table 1.2: Linear Granger Causality between Monthly News Tone$_{\text{Henry}}$ & Oil Futures Prices

Lags	ΔNews Tone$_{\text{Henry}}$ does not cause ΔOil Price		ΔOil Price does not cause ΔNews Tone$_{\text{Henry}}$	
	F-Stats	P-Value	F-Stats	P-Value
1	3.8154*	0.0527	0.3800	0.5386
2	2.9284*	0.0568	2.1560	0.1196
3	2.0672	0.1074	3.7601**	0.0124

Note: ** and * denote the rejections of the null hypothesis at the 5% and 10% significance levels, respectively.

Table 1.3: Linear Granger Causality between Monthly News Tone$_{\text{Oil}}$ & Oil Futures Prices

Lags	ΔNews Tone$_{\text{Oil}}$ does not cause ΔOil Price		ΔOil Price does not cause ΔNews Tone$_{\text{Oil}}$	
	F-Stats	P-Value	F-Stats	P-Value
1	1.8625	0.1745	3.1685*	0.0772
2	1.0107	0.3666	4.833**	0.0093
3	1.5327	0.2088	2.2866*	0.0815

Note: ** and * denote the rejections of the null hypothesis at the 5% and 10% significance levels, respectively.

The results of nonlinear Granger causality tests between the oil price and the $News\ Tone_{Henry}$ and between the oil price and $News\ Tone_{Oil}$ are shown in Table 1.4 and Table 1.5, respectively. The bandwidths used in estimating DP test statistics are set to 1, which is within the commonly used range of [0.5, 1.5]. We can conclude from Table 1.4 that changes in $News\ Tone_{Henry}$ do not nonlinearly Granger-cause oil price change, and oil prices only nonlinearly Granger-cause $News\ Tone_{Henry}$ at the first lag at the level of 10%. However, $News\ Tone_{Oil}$ tend to nonlinearly Granger-cause the oil price at the first lag at 5%, and oil price also nonlinearly Granger-causes the $News\ Tone_{Oil}$ at the first 2 lags at 10%.

Overall, both news tone indices show predictive power of oil price over short horizons. Specifically, the causality running from $News\ Tone_{Henry}$ to oil price is found linear, while the causality from $News\ Tone_{Oil}$ to oil price is likely to be nonlinear.

Table 1.4: Nonlinear Granger Causality between Monthly News $\text{Tone}_{\text{Henry}}$ & Oil Futures Prices

Lags	ΔNews $\text{Tone}_{\text{Henry}}$ does not cause ΔOil Price		ΔOil Price does not cause ΔNews $\text{Tone}_{\text{Henry}}$	
	F-Stats	P-Value	F-Stats	P-Value
1	0.250	0.401	1.552*	0.060
2	0.878	0.190	0.951	0.171
3	0.197	0.578	0.945	0.828

Note: * denotes the rejections of the null hypothesis at the 10% significance level.

Table 1.5: Nonlinear Granger Causality between Monthly News Tone_{Oil} & Oil Futures Prices

Lags	ΔNews Tone_{Oil} does not cause ΔOil Price		ΔOil Price does not cause ΔNews Tone_{Oil}	
	F-Stats	P-Value	F-Stats	P-Value
1	1.961**	0.025	1.507*	0.066
2	0.797	0.213	1.44*	0.075
3	0.842	0.200	1.145	0.126

Note: ** and * denote the rejections of the null hypothesis at the 5% and 10% significance levels, respectively.

1.5.3 Performance of Out-of-Sample Forecasts

To examine the forecasting power of additional predictive variables $\textit{News Tone}_{\textit{Henry}}$ and $\textit{News Tone}_{\textit{Oil}}$, three groups of models are formulated for comparison, i.e., four Benchmark models (labelled as 1, 2, 3 and 4), four models with $\textit{News Tone}_{\textit{Henry}}$ added to the benchmarks (labelled as 1a, 2a, 3a and 4a), and another four with $\textit{News Tone}_{\textit{Oil}}$ added (labelled as 1b, 2b, 3b and 4b). Benchmark model 1 uses the basic economic variables only as the control variables, including $\text{Price}_{\text{gold}}$, IR, and EX. Benchmark model 2 adds the volatility sentiment measures VIX and OVX as additional control variables. Benchmark model 3 further considers the economic uncertainty measures, i.e., EPU and EMEU. Benchmark model 4 takes all above control variables into account and additionally considers the geopolitical sentiment measure GOPRX. All variables used for forecasts are of the same integration order of 1 to account for unit root. Lag orders used in all the model estimations are based on the Akaike Information Criteria (AIC).

Results of the forecasting performance for each model over short to long horizons

Table 1.6: Forecasting performance

Models (labels)	h = 1		h = 2		h = 3	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Benchmark 1 (1)	5.539	11.247	5.619	10.531	5.740	10.355
Benchmark 1 + News Tone$_{\text{Henry}}$ (1a)	5.633	11.001	5.687	10.424	5.786	10.310
Benchmark 1 + News Tone$_{\text{Oil}}$ (1b)	5.501	11.386	5.603	10.542	5.710	10.308
Benchmark 2 (2)	5.213	8.861	5.723	10.702	5.702	9.915
Benchmark 2 + News Tone$_{\text{Henry}}$ (2a)	5.356	9.181	5.784	10.264	5.774	9.958
Benchmark 2 + News Tone$_{\text{Oil}}$ (2b)	5.154	8.691	5.750	10.331	5.705	9.909
Benchmark 3 (3)	5.612	11.077	5.834	10.579	5.709	10.055
Benchmark 3 + News Tone$_{\text{Henry}}$ (3a)	5.766	11.577	5.865	10.521	5.788	10.125
Benchmark 3 + News Tone$_{\text{Oil}}$ (3b)	5.485	10.291	5.828	10.562	5.735	10.128
Benchmark 4 (4)	5.635	10.859	5.828	10.610	5.684	10.015
Benchmark 4 + News Tone$_{\text{Henry}}$ (4a)	5.774	11.315	5.861	10.572	5.753	10.081
Benchmark 4 + News Tone$_{\text{Oil}}$ (4b)	5.492	10.036	5.808	10.582	5.716	10.089

Notes: Benchmark model 1 only uses economic variables which are the gold spot price, the USD exchange rate, and the US interest rate. Benchmark model 2 adds VIX and OVX into Benchmark model 1. Benchmark model 3 further adds EPU and EMEU. Benchmark model 4 uses all above and additionally GOPRX.

(1 to 3 months) are presented in Table 1.6. For easier inspection, we also visualise the results of forecast errors generated by different models over 1-, 2-, 3-month horizons as Figure B.1 and B.2 (see B).

For 1-month ahead (h = 1) forecasts, we found that Model 2b generated the lowest RMSE and MAPE, which suggests that *News Tone$_{Oil}$*, with economic and volatility measures complemented together, has the strongest forecasting power. Moreover, *News Tone$_{Oil}$* helped to steadily reduce the forecasting errors in all other its combinations stably, with only one exception being that Model 1b did not lower the MAPE. On the contrary, *News Tone$_{Henry}$* nearly showed no forecasting ability as none of the model outperformed the benchmarks, excepting for Model 1a which slightly lowered the MAPE but not the RMSE.

For 2-month ahead (h = 2) forecasts, results show that Model 1b generated the lowest RMSE, but it did not reduce the MAPE. Model 3b and 4b slightly outperformed the benchmarks with lower RMSE and MAPE. These indicate that *News Tone$_{Oil}$* exhibits quite weak forecast-ability over the medium horizon. *News*

$Tone_{Henry}$, on the other hand, has nearly no forecasting power over medium horizon since Model 1a, 2a, 3a, and 4a only reduce the MAPE but not the RMSE. Although Model 2a has the lowest MAPE, but its RMSE is the highest among group 2.

For 3-month ahead (h = 2) forecasts, Benchmark model 2 performs the best. Neither of the news tone indices has satisfying forecasting power as the forecast errors were not reduced in all combinations, except Model 1b which slightly reduced the MAPE and RMSE and Model 1a which slightly lowered the MAPE but not the RMSE.

The focal point of this study is to verify whether news tones constructed by the use of two competing state-of-art and user-friendly dictionaries help in forecasting the oil prices. Our results show that the news tone captured using the Loughran et al. (2019)'s oil dictionary ($News\ Tone_{Oil}$) does help forecast the oil prices out-of-sample over short horizon. It shows much weaker forecasting power over medium horizon and no forecasting power over long horizon. By contrast, $News\ Tone_{Henry}$ constructed using the financial dictionary (Henry (2008)) does not help forecast the oil prices out-of-sample at all. Till this point, we argue that the forecasting power of news tone is data and method dependent as the different results of using $News\ Tone_{Oil}$ and $News\ Tone_{Henry}$ emphasise the use of domain-specific dictionary in relevant financial analysis.

Lower statistical forecast errors do not necessarily guarantee higher economic profits. Hence, we further evaluated the trading performance of the best performing model (Model 2b) in the last section against the others in the same group. We allowed the use of shorts and we neglected other trading constraints such as the transaction costs, given that oil futures contracts are highly liquid and we only trade once a month. Similar to He et al. (2021), our trading logic is simple: if we predict the oil price in the next month is higher than the current price, we will long the oil futures now and close out the position in the next month; If the predicted price is lower than the current price, we will short the futures now and buy back in next month. We simulated trades based on forecasts in the same testing period from January 2017 to September 2020 and calculated the cumulative returns continuously till the end. Additionally, we used a naïve Buy-Hold strategy as our benchmark, in which we long the oil futures at the beginning of each sample period, and hold the position until the period ends. This allows us to compare whether the proposed strategies are economically viable in more recent periods. As shown in Table 1.7, all of the long-short strategies based on previous forecasting models in Group 2 were able to outperform the naïve buy & hold strategy at the end. Among all, the strategy based on Model 2b, again, was best performing, generating the highest geometric return, cumulative return, and annualised Sharpe ratio. It generated a geometric return of 3.95% which is 1.81% higher than that of Benchmark model 2 and a cumulative return of 472.13% which is more than doubling that of Benchmark model 2. Moreover, it generated a annualised Sharpe ratio of 1.090 which is much higher than the other three. By contrast, neither the naïve buy & hold strategy nor the strategy based on Model 2a generated a positive geometric or cumulative return, or a satisfying Sharpe ratio. Overall, the superior ability of the *News Tone*$_{Oil}$-incorporated model (Model 2b) in oil price forecasting translated into higher profitability in the context of a long-short trading strategy.

Table 1.7: Economic Significance

	Geo Ret	Cum Ret	Sharpe ratio
Buy & Hold	-0.0063	-0.248	0.137
Benchmark 2	0.0214	1.596	0.692
Model 2a	-0.0032	-0.135	0.312
Model 2b	**0.0395**	**4.721**	**1.090**

Notes: The Sharpe ratio is annualized.

1.5.4 Robustness Check

In main section, we only used the spot gold price, a proxied USD exchange rate, and a proxied interest rate to represent economic variables. We further considered the Kilian (2009) Index of Global Real Economic Activity (IGREA) as an additional economic variable to test the robustness of previous results[6].

The conditions of global supply and demand are likely to affect oil prices (Kilian (2009)), while the IGREA composed by Kilian (2009) from global dry bulk shipping freight rates is a good indicator of global supply and demand conditions, being a proxy for the shipping volume of industrial commodities. We chose the corrected version of this index with details clarified in Kilian (2019) from the FRED. The forecasting results in Table 1.8 in this section are similar to those obtained in Table 1.6 in Section 1.5.3, with majority of the forecast errors being reduced. However, the improvements with the help of *News Tone*$_{Oil}$ over short to medium horizons have

[6] We also considered monthly oil inventory and oil production as additional economic variables which were downloaded from the Energy Information Administration Website. We put the relevant results in Appendix as they are not robust.

been less significant. For instance, Model 2b no longer provided lower RMSE at h=2 and lower MAPE at h = 1 than Benchmark 2. Moreover, as Model 2b still provided the lowest RMSE over h = 1, we tested it in regard to the economic significance. Table 1.9 shows that model 2b could still generate the highest geometric returns, cumulative returns, and annualised Sharpe ratio. However, these values are lower than those in Section 1.5.3. IGREA seems to be a stronger predictor than sentiment-type variables in oil price forecasting.

Overall, although the ability of *News Tone*$_{Oil}$ in forecasting oil prices were somewhat weakened after IGREA was fed in, our results remained robust and similar conclusions could be drawn.

Table 1.8: Performance of Monthly Forecasts

Models (labels)	h = 1		h = 2		h = 3	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Benchmark 1 (1)	5.517	11.108	5.607	10.386	5.712	10.239
Benchmark 1 + News Tone$_{\text{Henry}}$ (1a)	5.627	10.940	5.694	10.215	5.761	10.190
Benchmark 1 + News Tone$_{\text{Oil}}$ (1b)	5.463	11.194	5.580	10.385	5.675	10.174
Benchmark 2 (2)	5.176	9.036	5.673	9.927	5.627	9.650
Benchmark 2 + News Tone$_{\text{Henry}}$ (2a)	5.344	9.374	5.731	9.869	5.704	9.710
Benchmark 2 + News Tone$_{\text{Oil}}$ (2b)	5.126	9.051	5.693	9.955	5.630	9.646
Benchmark 3 (3)	5.583	10.565	5.826	10.328	5.636	9.811
Benchmark 3 + News Tone$_{\text{Henry}}$ (3a)	5.785	11.294	5.854	10.214	5.721	9.898
Benchmark 3 + News Tone$_{\text{Oil}}$ (3b)	5.461	10.291	5.828	10.562	5.735	10.128
Benchmark 4 (4)	5.615	10.394	5.829	10.370	5.625	9.785
Benchmark 4 + News Tone$_{\text{Henry}}$ (4a)	5.800	11.067	5.858	10.283	5.699	9.862
Benchmark 4 + News Tone$_{\text{Oil}}$ (4b)	5.480	9.739	5.794	10.288	5.659	9.859

Table 1.9: Economic Significance

	Geo Ret	Cum Ret	Sharpe ratio
Buy & Hold	-0.0063	-0.248	0.137
Benchmark 2	0.0216	1.619	0.696
Model 2a	0.0193	1.362	0.645
Model 2b	**0.0228**	**1.756**	**0.722**

Notes: The Sharpe ratio is annualised.

1.6 Conclusion

It is universally argued that the oil price fluctuations have a huge impact on world economic activities. Yet researchers appear to be somewhat hamstrung to accurately predict the oil prices. Newspapers as major information providers carry important information, comments and tone which can influence or drive investors' behaviour. Can news tone help forecast the oil price? We performed sentiment analysis on 3579 full texts of crude oil market news collected from the world leading business news publisher *Financial Times* from 1 June 2008 to 30 September 2020. In this process, the tone/sentiment of each document was measured using two dictionaries, a widely used financial dictionary from Henry (2008) and a newly developed oil dictionary from Loughran et al. (2019). We then aggregated the sentiment scores to tabulate monthly $News\ Tone_{Henry}$ and $News\ Tone_{Oil}$ indexes.

Subsequently, we adopted both linear and nonlinear Granger causality tests to study the interactions between the news tone indices and the oil prices, where we found that the causality running from $News\ Tone_{Henry}$ to oil prices is linear, while the causality from $News\ Tone_{Oil}$ to oil prices is nonlinear. Both news tone indices exhibited predictive power over short horizon in preliminary causality tests. We then performed 1-, 2-, 3-month ahead price forecasts with the two news tone indices using VAR models, controlling for macroeconomic and other sentiment measure variables. We found that $News\ Tone_{Oil}$ does help forecast the 1-month ahead oil prices. It shows weak forecasting power over medium horizon and no forecasting power over long horizon. At the same time, although $News\ Tone_{Henry}$ was found useful in forecasting oil price trends in other studies (i.e., Li et al. (2017)), it shows nearly no ability to forecast the actual oil prices across all time horizons in our case[7].

We further examined the economic significance of best performing models in previous statistical analysis under a long-short trading strategy. Our result is consistent with previous analysis that the best performing $News\ Tone_{Oil}$-incorporated model in previous statistical forecasting outperforms the others in the same group and a naive buy-hold strategy.

Lastly, we included an extra economic variable IGREA in the forecasting models to check the robustness of our previous analysis.

Overall, in line with the prior studies, we found that news tone is helpful in

[7]Note that we used different news source and frequency.

forecasting oil price, which is beneficial for regulators and investors, especially for traders who care about actual prices. However, we suggest that the forecasting power of news tone is data and method dependent. $\textit{News Tone}_{Oil}$ constructed by oil dictionary Loughran et al. (2019) seems to outperform $\textit{News Tone}_{Henry}$ constructed by the financial dictionary (Henry (2008)) in our forecasts, which highlights the importance of using domain-specific dictionary in relevant financial analysis. The findings also add to extending the methodological framework of sentiment construction in the context of oil price forecasting.

APPENDIX A

AN EXAMPLE OF SENTIMENT CALCULATION

For parsed news stories used in this study, only keywords included in the revised 2018 LM Master Dictionary and not included in the LM revised Stopwords list were considered in sentiment calculation. Below is a sample *Financial Times* oil news on 13 September 2018 used in our study. The total word count of this article is 247. Words in bold were detected by the oil dictionary (Loughran et al. (2019)) while underlined words were detected by the Henry (2008)'s dictionary.

Title - Oil heads towards 4-year high as hurricane heightens supply fears; Storm to hit US east coast ; Crude price tops $80 ; Jitters rise as Iran sanctions loom

Body - Oil prices rose to more than $80 a barrel yesterday, nearing a four-year high as traders braced themselves for a series of tropical **storms** barrelling towards the US, which are coinciding with mounting concerns about a global **supply shortfall**. **Hurricane** Florence spiralled towards the US eastern seaboard maintaining category four winds at 130mph (210kph); its course shifted slightly to the south but remained headed towards North and South Carolina. Fuel supplies were in focus as motorists fill their tanks in anticipation of the eye of the **storm** making landfall in the Carolinas tomorrow. Oil market watchers were also monitoring any impact on supplies from the Colonial Pipeline, which runs through both states and sends crude products to the north-east, as flooding or power **outages** could hit pumping stations. President Donald Trump warned residents of the Carolinas and Virginia to move away from the **hurricane**'s path; some were already heading inland, as authorities warned that the powerful **storm** would be life-threatening. "They say it's about as big as they've seen coming to this country," Mr Trump said in a video. "Get out of its way. Don't play games with it." A second tropical **storm**, Isaac, is also being watched as it may have a bigger impact on the oil sector if it heads towards the Gulf of Mexico - a hub for production and refining operations. "The **hurricane** story is transitory but the oil market is particularly sensitive to such events as we have a pretty **tight supply** situation looming," said Helima Croft, RBC Capital Markets' global head of commodity strategy. The start of the US **storm** season has coincided with other jolts to the oil market, including an expected hit on exports from Iran as US sanctions come into effect in November, which is likely to create a squeeze despite Mr Trump's calling on other producers to **lift output**. "The Iran story is the dominant factor for prices," said Ms Croft. Big Asian consumers, such as India and China, have begun to reduce their purchases of Iranian oil while South Korea has already **dropped imports** to zero on the orders of the White House. Saudi Arabia and allies inside and outside Opec, such as Russia, have pledged to **raise output** but the increase has been **slower** than expected, helping propel prices. Though the **storm**'s hit to the energy sector is likely to be modest, Jeff Byard of the Federal Emergency Management Agency said it would be "a Mike Tyson punch to the Carolina coast". Insurance companies were preparing for it to be the most expensive natural catastrophe so far this year. According to RMS, a modelling company, nine big hurricanes have made landfall in the Carolinas in the past 167 years, with the last being Hugo in 1989. However, it has been a very damp year with already wet soil raising the flood risk.

1. Using Loughran et al. (2019)'s oil dictionary:

The list of 15 positive words found in the order of appearance: ['storms', 'supply shortfall', 'Hurricane', 'storm', 'outages', 'hurricane', 'storm', 'storm', 'hurricane', 'tight supply', 'storm', 'dropped imports', 'output slower', 'storm', 'hurricanes'].

The list of 2 negative words found in the order of appearance: ['lift output', 'raise output'].

The news tone = (15-2)/287 = 0.0453

2. Using Henry (2008)'s financial dictionary:

The list of found positive words in the order of appearance: ['rose', 'high', 'increase’].

The list of found negative words in the order of appearance: [’dropped’, ’risk’].

The news tone = (3-2)/287 = 0.00348

APPENDIX B

Forecasting Performance over 1-, 2-, and 3-Month Horizons

Figure B.1: RMSE over short to long horizons

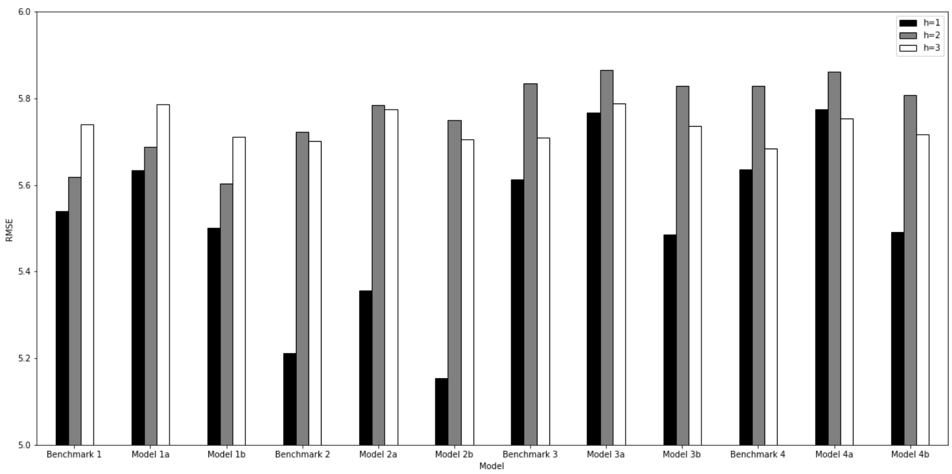
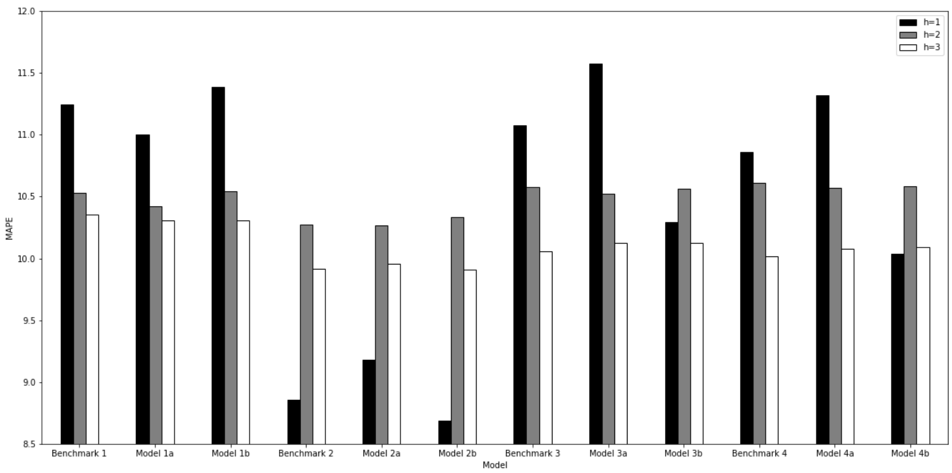


Figure B.2: MAPE over short to long horizons



APPENDIX C

Out-of-Sample Analysis with IGREA, Oil Inventory and Oil Production

Table C.1: Performance of Monthly Forecasts

Models (labels)	h = 1		h = 2		h = 3	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Benchmark 1 (1)	5.689	13.148	5.664	11.147	5.774	10.861
Benchmark 1 + News Tone$_{\text{Henry}}$ (1a)	5.769	12.777	5.753	10.967	5.810	10.771
Benchmark 1 + News Tone$_{\text{Oil}}$ (1b)	5.615	13.196	5.637	11.198	5.734	10.804
Benchmark 2 (2)	5.327	9.511	5.751	10.410	5.621	9.928
Benchmark 2 + News Tone$_{\text{Henry}}$ (2a)	5.464	9.940	5.803	10.385	5.696	10.003
Benchmark 2 + News Tone$_{\text{Oil}}$ (2b)	5.235	9.333	5.743	10.404	5.622	9.938
Benchmark 3 (3)	5.763	12.384	5.892	10.909	5.679	10.516
Benchmark 3 + News Tone$_{\text{Henry}}$ (3a)	5.972	13.545	5.905	10.766	5.769	10.660
Benchmark 3 + News Tone$_{\text{Oil}}$ (3b)	5.636	11.575	5.865	10.877	5.695	10.536
Benchmark 4 (4)	5.804	12.320	5.899	11.098	5.662	10.531
Benchmark 4 + News Tone$_{\text{Henry}}$ (4a)	5.999	13.433	5.905	10.933	5.742	10.659
Benchmark 4 + News Tone$_{\text{Oil}}$ (4b)	5.651	11.431	5.858	11.046	5.681	10.542

Notes: We use the natural logarithm of oil inventory and production data to avoid the scale effect.

Table C.2: Economic Significance

	Geo Ret	Cum Ret	Sharpe ratio
Buy & Hold	-0.0063	-0.248	0.137
Benchmark 2	**-0.0058**	**-0.232**	**0.269**
Model 2a	-0.0155	-0.505	0.061
Model 2b	-0.0170	-0.538	-0.028

Notes: The Sharpe ratio is annualized.

CHAPTER 2

An Examination of the Relationship between Renewable Energy Stocks and Cryptocurrencies

2.1 Introduction

The cryptocurrency market is rapidly growing in size and is becoming more and more sought-after by investors. Despite the high volatility, the high rate of returns attracts an increasing number of institutional investors to pour their money into this hype market, considering cryptos a valuable portfolio diversification asset [1,2]. The value of one Bitcoin, the most recognizable and representative cryptocurrency coin, peaked exceptionally high—around 67,000 U.S. dollar—in November 2021 and has still been the most valuable coin among the whole market [3]. However, the algorithm behind the Bitcoin and many other conventional coins, generally called the 'Proof-of-Work' (PoW) consensus, is computationally complex and expensive, which requires massive electricity power to support the operations and leads to substantial carbon footprints. Surprisingly, a single transaction of Bitcoin is estimated to consume approximately 1834.02 kWh electricity, which is equivalent

[1] https://www.prnewswire.com/news-releases/institutional-investors-continue-warming-up-to-cryptocurrencies-301666266.html

[2] https://www.forbes.com/sites/lawrencewintermeyer/2021/08/12/institutional-money-is-pouring-into-the-crypto-market-and-its-only-going-to-grow/

[3] https://coinmarketcap.com

to the amount of power used by an American family for more than 62 days. The estimated yearly energy usage of Bitcoin now has increased to 169.98 TWh, not just comparable but even higher than the gross power consumption of Poland [4]. Moreover, according to a recent research of Mora et al. (2018), the authors projected that the carbon emissions from the continuous adoption of Bitcoin might itself lift global warming beyond two degrees Celsius within next thirty years, which is because the power supporting the mining and validation of PoW cryptocurrencies usually sources from fossil energy. Hence, the adoption of Bitcoin and the other energy-intensive cryptos that use the same PoW mechanism (hereinafter referred to as "dirty" cryptocurrencies) has been criticised for causing and accelerating pollution and damage to the environment and has drawn significant public attention and heightened concerns [Corbet and Yarovaya (2020)].

Academia and environmental groups have been calling for a reduction in cryptocurrency mining activities and a switch to non PoW cryptocurrencies [Schinckus (2021)]. Cryptocurrencies that use alternative protocols such as "Proof-of-Stake" (PoS) and "Proof-of-Authority" (PoA) consensus, among others, require significantly lower computing energy and hence are considered more sustainable [Platt et al. (2021)]. For example, according to the report by TRG Houston Data Centre [5], IOTA, a cryptocurrency that uses a "Fast Probabilistic" consensus, consumes 0.00011 KWh per transaction, compared to Bitcoin's 707 KWh. In fact, in recent years, an increasing number of eco-friendly cryptocurrencies (hereinafter, "clean" cryptocurrencies) have been launched to compete in the market. Some of the new players have already become leading cryptocurrencies by market capitalisation such as Cardano, Solana, etc, and some long-existing clean players such as XRP and XLM, among others, remain top in the market. The development and adoption of such cleaner altcoins seem to be more valued and appreciated in present context of pursuing green economy.

The extant literature on the relationship between cryptocurrencies and other assets has often considered traditional energy assets due to the tremendous energy use involved in most cryptocurrency mining and transactions [see, as examples, studies of Jiang et al. (2022), Rehman and Kang (2021), Corbet et al. (2021), Okorie and Lin (2020), among others]. Relatively little literature has focused attention on the linkage between cryptocurrency and green markets, even after the latter

[4] Retrieved from `https://digiconomist.net/bitcoin-energy-consumption` on Oct 5, 2021

[5] https://www.trgdatacenters.com/most-environment-friendly-cryptocurrencies/

market has witnessed a major rise in recent years, especially for clean energy actions which are sustainable alternatives to traditional carbon-intensive energy such as electricity, oil, and coal. We have seen a strong growth track in clean energy sectors. Revenue of clear energy companies is just under $700b, with an annual growth rate of 6.8%[6]. There have been created a wide range of clean energy industry stock indices to represent the performance of publicly listed clean energy related companies, and much research has emerged showing their usefulness from investment perspective such as assessing the benefits of clean energy stocks as portfolio constituents against conventional stocks and treasury products [e.g., Rezec and Scholtens (2017), Ahmad and Rais (2018), Kuang (2021)]

There are few studies which can be regarded as closely related to our research. For instance, Naeem and Karim (2021) examined the tail dependence between Bitcoin and green investments. They suggested that clean energy is a potential diversification tool for Bitcoin as the hedge ratio and hedge effectiveness are better-off with clean energy stocks. Pham et al. (2021) gave similar comment that green investments offer diversification benefits to cryptocurrencies since connectedness between Bitcoin & Ethereum and green assets is weak during non-crisis periods. However, these papers actually opened up a question - is clean energy a direct hedge or even a safe haven for Bitcoin or Ethereum, or more broadly, for cryptocurrencies? If we find that particular types of clean energy stocks can act as safe havens or hedges against particular types of cryptocurrency, or vice versa, it has implications for investors. For example, it may be practical to protect against extreme downturns in cryptocurrencies using clean energy stocks or vice versa. But the form of currency matters. If we find that only dirty cryptocurrencies are a useful hedge or safe haven against clean energy, that suggests that the economic incentive to invest in clean energy will be counter to the ecological argument. Moreover, although there has been quite a lot of work done on the interconnection of cryptocurrency with other financial assets, the debate on whether Bitcoin or cryptocurrency market is isolated from other assets (markets) has not come to an end [7].

To answer the above questions we first measured the spillovers across two distinct types of cryptocurrencies, based on their characteristics of eco-efficiency, clean

[6] https://www.businesswire.com/news/home/20210902005385/en/Global-Renewable-Energy-Industry-Guide-2021-Value-and-Volume-2016-2020-and-Forecast-to-2025---ResearchAndMarkets.com

[7] See Ji et al. (2018) and Corbet et al. (2020) as examples.

energy stocks, S&P500 and gold markets [8] and vice versa, and then we tested the potential role for clean energy as a hedge or safe have for different cryptocurrencies, and vice versa. The spillover effects were measured using the Diebold and Yılmaz (2012, 2014) (DY) connectedness approach, following previous studies in the area of connectedness analysis. For instance, Ji et al. (2019a) employed this framework to analyse the connectedness and inter-dependency among six large cryptocurrencies. Similarly, Umar et al. (2021) studied the connectedness between cryptocurrency and international technology companies. The hedge and safe haven properties were examined using a dynamic conditional correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. The DCC-GARCH type models have been extensively employed in safe haven analysis [Ratner and Chiu (2013), Akhtaruzzaman et al. (2021), Urquhart and Zhang (2019), among others].

Our study contributes to the literature from at least four aspects. First, we provide statistical evidence that clean energy is not a direct hedge for either dirty or clean cryptocurrencies currently.

Second, our study is among the first to empirically examine the safe haven property of a wide range of clean energy indices during dirty and clean cryptocurrency market turmoils and its reverse. We find that, in general, clean energy stocks serve as at least weak safe havens in times of extreme falling cryptocurrency markets. In times of increased volatility, clean energy is more likely to serve as a safe haven for dirty cryptocurrencies than for clean cryptocurrencies.

Third, we measured the dynamic connectedness between different clean energy subsectors and cryptocurrencies, which has not been done in previous literature. Findings reveal that none of the clean energy subsectors, nor general stock, or the gold market is strongly associated with cryptocurrency markets, which extends the understanding of the research on the interconnection of cryptocurrencies with other markets.

Fourth, our findings also provide references and implications for regulators and policy makers as well as cryptocurrency founders in designing the framework of further financial integration and promoting greener industry, and ultimately the society.

The remainder of this paper is organised as follows. Section 2.2 reviews some past research. Section 2.4 describes the data, followed by Section 2.3 which details

[8] Corbet et al. (2021) suggested that cryptocurrencies have varying carbon footprints and power usage levels, possibly affecting how they interact with energy and utility businesses.

the methodology used in the analysis. Section 2.5 presents the empirical findings and Section 2.6 checks the robustness of previous results. Lastly, Section 2.7 concludes and addresses the implications of this study.

2.2 Literature Review

The relationship between cryptocurrency and various financial markets has been extensively studied in literature. This section classifies past studies on this relationship into two categories.

The first category consists of studies that focus on the link between the cryptocurrency market and conventional stock and fossil energy markets. For example, Jiang et al. (2022) analysed the role of Bitcoin, gold, equity, foreign exchange and energy (crude oil / natural gas) have played in the global volatility connectedness network. They found that external investor attention between different markets possibly drives overall volatility transmission in the financial system. Moreover, they found that Bitcoin, gold, foreign exchange, and natural gas are volatility transmitters, while crude oil and the stock market are receivers. Ji et al. (2019b) tested the information interdependence between leading cryptocurrencies and several commodities and discover that cryptocurrencies are unexpectedly weakly connected but still integrated with energy markets such as natural gas, unleaded gas, heating oil, and crude oil. Zeng et al. (2020) showed that the financial linkage between Bitcoin and traditional assets such as stock, oil, and gold is weak, but has been increasing. Rehman and Kang (2021) documented the existence of lead-lag relationships between Bitcoin and crude oil and natural gas, while it is not the case for coal, which is quite interesting as we know that China is the largest Bitcoin miner where power generation relies extensively on coal. Akyildirim et al. (2021) further investigated the dynamic correlation and extreme dependence between Bitcoin and Chinese coal markets. They showed that dynamic correlations between Bitcoin and coal indices increases when extreme mining events occur in China and such incidents are likely to induce Bitcoin volatilities. Okorie (2021) and Corbet et al. (2021) discovered significant correlation and volatility spillovers between leading cryptocurrencies and electricity markets. Okorie and Lin (2020) found both bi-directional and uni-directional volatility spillovers between the crude oil market and cryptocurrencies. They further claimed that crude oil is a good hedge tool for risks of holding various cryptocurrencies. While Umar et al. (2021) showed that cryptocurrency market is less connected with global technology sectors. Le et al. (2021a) investigated whether the spillover patterns between financial technology stocks and Bitcoin, gold, global stock, crude oil, and foreign exchange have changed due to the Covid-19 outbreak. The results suggest that the pandemic has shaped and strengthened the volatility spillovers across markets and only gold and the US dollar remain as safe havens, while other assets such as Bitcoin, oil, and financial technology stocks being large volatility spillover receivers are not. Maghyereh and Abdoh (2020), Bouri et al. (2018), and Uzonwanne (2021) examined the direction of spillovers between Bitcoin and other markets. Wang et al. (2021) measured the time and frequency connectedness among Bitcoin and other assets including stock, gold oil, etc, but from a hedge perspective.

The second category of studies looks at the relationship between cryptocurrency and green markets, including green bonds and green equities. A better understanding of such relationships could in turn promote the investment and development of more sustainable financial instruments. For instance, Le et al. (2021b) considered the time and frequency domain connectedness between cryptocurrencies, green bond, and a variety of other assets such as USD, FinTech stocks, etc. Yousaf et al. (2022) examined the safe haven property of several assets for stock market including various green investments such as green bond, clean energy, etc. Symitsi and Chalvatzis (2018) examined the spillovers among Bitcoin, fossil and clean energy, and technology stock indices. They found significant return spillovers from energy and technology markets to Bitcoin, while volatility spillovers are found from Bitcoin to energy markets in the long run and from technology markets to Bitcoin in the short run. Additionally, Corbet et al. (2021) studied the dynamic relationships between volatilities of Bitcoin price along with its underlying characteristics and those of utilities stocks and ETFs, clean energy ETFs, and carbon markets. Their empirical results show that there was no significant linkage between the volatility of Bitcoin price and largest green ETFs markets and carbon credits, suggesting that the market movements of Bitcoin did not have sound impact on the green equities, especially clean energy markets. From a different aspect, Naeem and Karim (2021) used a time-varying optimal copula approach to investigate the tail dependence between Bitcoin and green investments. They found similar evidence that there was no tail dependence between clean energy stocks index and Bitcoin. They further suggested that clean energy is a potential diversification tool for Bitcoin as the hedge ratio and hedge effectiveness are with clean energy in the portfolio. Furthermore, Pham et al. (2021) also pointed out that green investments could offer diversification benefits to cryptocurrency with the evidence of only weak connectedness between cryptocurrencies such as Bitcoin and Ethereum and green assets during non-crisis periods.

Methodologically, our study is related to the application of the safe haven concept [Baur and Lucey (2010) and Baur and McDermott (2010)] and the DY connectedness framework [Diebold and Yılmaz (2012), Diebold and Yılmaz (2014)] which we will explain in detail later in Section 2.3.

The DCC-GARCH model has been widely used in the literature to analyse safe havens. For instance, Ratner and Chiu (2013) followed the definition and applied the standard DCC-GARCH model to examine the hedge and safe haven benefits of credit default swaps for U.S. stock market sectors. Wang et al. (2020) utilised the model to investigate the potential of gold-backed and USD-backed stablecoins as hedge and safe haven tools for prominent cryptocurrencies. Peng (2020) explored the safe haven ability of precious metals for various Chinese financial products. Akhtaruzzaman et al. (2021) analysed the role of gold as a safe haven asset during the first two waves of the COVID-19 crisis using the DCC-GARCH model. Urquhart and Zhang (2019) studied the intra-day hedge and safe haven properties of Bitcoin for major currencies using several asymmetric DCC-GARCH models. Additionally, the application of the DCC-GARCH model in safe haven analysis can be found in other studies, such as Bouri et al. (2017b), Bouri et al. (2017a), Wang et al. (2019), Yousaf et al. (2022), etc.

The DY approach proposed by Diebold and Yılmaz (2012, 2014) is one of the significant methods of measuring the spillover effects between multiple markets. We used the same framework in line with some previously mentioned [e.g., Umar et al. (2021), Zeng et al. (2020), etc], and many other papers in the area of connectedness/spillovers analysis. For instance, Yi et al. (2018) employed the DY approach to investigate the volatility spillovers among three tiers of eight cryptocurrencies and found that Bitcoin did not dominate as expected. Ji et al. (2019a) employed the same framework to analyse the inter-connectedness and dependency among six large cryptocurrencies. Aharon et al. (2021) used the DY method to measure the spillover effects between Bitcoin, five major currencies, and the US yield curve elements. Jalan et al. (2021) applied the DY in investigating the spillovers between Bitcoin, gold, and gold-pegged stablecoins and demonstrated that the gold market had a more pronounced impact on the volatility of these stablecoins than Bitcoin during the studied period.

2.3 Methodology

2.3.1 Spillover measures

We used the DY connectedness framework [Diebold and Yılmaz (2012), Diebold and Yılmaz (2014)] to estimate the spillover effects between clean energy indices and cryptocurrency indices. The DY model is basically a generalised vector autoregressive (VAR) model which can be used to trace the dynamic spillover relationship between two time series in a rolling window basis.

We begin with a VAR model with an infinite order of P:

$$y_t = \sum_{i=1}^{P} \varphi_i y_{t-i} + \varepsilon_t, \tag{2.1}$$

where y_t is the vector of endogenous variables, φ_i is the matrix of parameters, and ε_t represents the vector of $i.i.d.$ residuals.

In addition, we write the moving average representation of the model defined in Equation 2.1 as:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2.2}$$

where the coefficient of the $N \times N$ matrix A_i is recursively determined as $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \ldots + \varphi_{k-1} A_{i-k+1} + \varphi_k A_{i-k}$, but noted that A_i equals to zero if i is a negative number. A_0 is an identity matrix.

Under the framework of generalised VAR model, $\phi_{ij}(H)$, the H-step ahead generalized forecast error variance will be first decomposed and then normalised by its row sum as the following:

$$\begin{gathered}\phi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \\ \tilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)}\end{gathered} \tag{2.3}$$

where the σ_{jj} denotes the estimated SD of the error term for variable j, Σ is the variance matrix for the error-term vector ε, and e_i is the selection vector with one as the i^{th} element and zero otherwise.

Ultimately, the total spillover (TS), directional spillover received by asset i from j ($DS_{i\leftarrow j}$), directional spillover transmitted to j by i ($DS_{i\rightarrow j}$), and net spillover (NS) indices were calculated as the following:

$$TS(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{2.4}$$

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{2.5}$$

$$DS_{i\rightarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(N)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(H)}{N} \times 100 \tag{2.6}$$

$$NS_i(H) = DS_{i\rightarrow j}(H) - DS_{i\leftarrow j}(H) \tag{2.7}$$

2.3.2 Safe Haven Analysis

We adopted the estimation framework introduced by Baur and Lucey (2010) and Baur and McDermott (2010) to examine the hedge and safe haven properties of clean energy indices for dirty and clean cryptocurrencies. Similar to Akhtaruzzaman et al. (2021), Peng (2020), Ratner and Chiu (2013), and some other papers mentioned earlier, we started by using a DCC-GARCH model proposed by Engle (2002) to estimate the correlation of underlying asset pairs.

The estimation comprises two steps. The first is to estimate a GARCH(1,1) model. Let r_t be the $N \times 1$ vector of pairs of return series r_{1t} and r_{2t}, given the information set I_{t-1}:

$$\begin{gathered} r_t = \mu_t + \epsilon_t, \\ h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}, \end{gathered} \tag{2.8}$$

where ϵ is the vector of residuals.

Secondly, we estimate the DCC parameter. Let H_t be the conditional covariance matrix of r_t. We had assumed r_t to be normally distributed with a zero mean, so we wrote H_t as the following:

$$\begin{gathered} H_t = D_t R_t D_t, \\ D_t = diag\ [h_{1t}^{1/2},\ h_{2t}^{1/2}], \\ R_t = diag[Q_t]^{-1/2}\ Qt\ diag[Q_t]^{-1/2}, \end{gathered} \tag{2.9}$$

where R_t denotes the matrix of time-varying conditional correlations, Q_t is the positive definite matrix of $q_{12,t}$, and h_t is the conditional standard deviations (SDs). Then we could get the estimated DCC model as:

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}^T + b Q_{t-1}, \tag{2.10}$$

where a and b are non-negative scalars satisfying $a + b < 1$, and $\bar{Q}$ is the unconditional variance matrix of standardised residuals u_t. We could thereby obtain the dynamic conditional correlations series $\rho_{12,t}$ as:

$$\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t}\ q_{22,t}}. \tag{2.11}$$

With the dynamic conditional correlations between cryptocurrencies and clean energy indices, we can proceed to examine the safe haven property of clean energy against cryptocurrencies' extreme negative movements. Following the studies of Ratner and Chiu (2013) and Peng (2020) among others, the dynamic conditional correlation DCC_t were regressed on dummy variables representing the extreme returns of assets as follows:

$$DCC_{ij,t} = c_0 + c_1 D(r_{crypto_i} q_{10}) + c_2 D(r_{crypto_i} q_5) + c_3 D(r_{crypto_i} q_1), \tag{2.12}$$

where $D(...)$ are dummy variables that capture extreme negative returns of a cryptocurrency at the 10%, 5%, and 1% quantiles of the distribution. According to the definition of safe haven in Baur and Lucey (2010), clean energy is a weak hedge for an individual cryptocurrency if c_0 is insignificantly different from zero, or a strong hedge if c_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain market condition if any of c_1, c_2 or c_3 are non-positive (significantly negative).

Alternatively, a similar approach to the Equation 2.12 is to regress DCC_t on the lagged extreme conditional volatility of dirty or clean cryptocurrency index which is proxied for market uncertainty, motivated by Baur and McDermott (2010):

$$DCC_{ij,t} = c_0 + c_1 D(v_{crypto} q_{90,t-1}) + c_2 D(v_{crypto} q_{95,t-1}) + c_3 D(v_{crypto} q_{99,t-1}), \tag{2.13}$$

where the dummy variables c_1, c_2 and c_3 here are equal to one if the conditional volatility at $t-1$ exceeds the 90%, 95% and 99% quantiles, respectively. This allowed us to examine the safe haven property of clean energy against cryptocurrencies during extreme market uncertainty.

To investigate the other way around that whether cryptocurrencies are a safe haven for clean energy stocks in times of extreme negative markets and uncertainty, we simply replaced with clean energy data on the right hand side for Equation 2.12 and 2.13, respectively.

2.4 Data

We collected daily closing price data for five major dirty cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Bitcoin Cash (BCH), Ethereum Classic (ETC) and Litcoin (LTC), as well as five clean cryptocurrencies, Cardano (ADA), Ripple (XRP), IOTA (MIOTA), Stellar (XLM), and Nano (NANO) from CoinMarketCap[9], spanning from 1 January 2018 to 17 September 2021 [10].

As we introduced and explained earlier in Section 2.1, the dirty cryptocurrencies are all built on PoW algorithms for consensus, which results in massive energy consumption in activities such as mining and transactions, while clean cryptocurrencies are built on different classes of energy-efficient consensus, including but not limited to PoS, PoA, Ripple Protocol, Stellar Protocol, etc.

[9] https://www.coinmarketcap.com.

[10] Our selection took into account the market capitalisation, data availability of closing price and market capiptalisation, and recent online media attention. We chose BCH and ETC in addition to BTC, ETH, and LTC as these two cryptos have been the largest PoW players following LTC for years, both are listed in the top 6 by market cap. Although DOGE was the third largest PoW crypto, we did not consider it as: 1. it was originally designed as a meme coin without other uses; 2. Its energy consumption is arbitrary due to its relatively complicated mining mechanism; 3. It has been highly influenced/boosted by Musk's social media comments. The selection of clean cryptocurrencies was not as straightforward as choosing dirty cryptocurrencies. The first issue was the data availability. The data of closing price and market cap should be available from January 1, 2018, so some other top players such as Solana, Polkadot, Avalanche, etc, were not considered as they came to the market much later. BNB was not considered as it shares a completely different nature as a derivative of the Binance Exchange, historically built on Ethereum blockchain technology, and began to support staking in 2020. MIOTA and NANO are chosen as they have been the most frequently discussed and compared to the dirty cryptos and even other clean players regarding energy consumption in more recent period (e.g., see https://www.trgdatacenters.com/most-environment-friendly-cryptocurrencies/, https://www.leafscore.com/blog/the-9-most-sustainable-cryptocurrencies-for-2021/ (retrieved in September of 2021), and https://www.thetimes.co.uk/money-mentor/article/eco-friendly-cryptocurrencies/). Although they might have become smaller players (compared to other cryptos we used) in recent months, historically, MIOTA ranked as 10^{th} largest, and NANO ranked as the 20^{th} among all as of January 7, 2018 (e.g., see the historical snapshot of CoinMarketCap data at https://coinmarketcap.com/historical/20180107/). Additionally, NANO is, to the best of our knowledge, one of the very few and earliest cryptos that explicitly address the "eco-friendly" characteristic, which can be seen from its description on CoinMarketCap website and from their official website's title *Nano | Eco-friendly & feeless digital currency*, which makes it a ideal representative of clean cryptos to attract potential environmentally conscious investors.

We further created two value-weighted indices of the dirty and clean cryptocurrencies, respectively named as DCRYPT and CCRYPT to track the overall performance of the two distinct cryptocurrency groups. Next, clean energy indices sourced from Bloomberg were used to represent the performance of the clean energy industry. We not only used the S&P Global Clean Energy Index (SPGTCED) and WilderHill Clean Energy Index (ECO) which tracks the overall performance of global or U.S. clean energy sectors, but also selected several indices from NASDAQ OMX Green Economy Index Family to track the performance of individual clean energy generation subsectors, partly following the literature of Pham (2019)[11]. Specifically, we used the NASDAQ OMX Bio/Clean Fuels Index (GRNBIO), Fuel Cell Index (GRNFUEL), Renewable Energy Index (GRNREG), Geothermal Index (GRNGEO), Solar Energy Index (GRNSOLAR), and Winde Energy Index (GRNWIND). The description of each clean energy index is provided in Table 2.1. To account for the general stock market performance, we collected the data for the S&P 500 Index (SP500) from Bloomberg. Finally, we collected the London P.M. gold fixing price (GOLD) from Federal Reserve Economic Data.[12] Note that all data were sourced in U.S. dollars and transformed to their first-differenced natural logarithms before use. Table 2.2 summaries the statistics for the log returns in percentage [13]. All return series are stationary and are not normal distributed based on Augmented Dickey–Fuller (ADF) test and Jarque-Bera (JB) test, respectively.

[11] We focus on clean energy generation subsectors in this paper.

[12] `https://fred.stlouisfed.org/series/GOLDPMGBD228NLBM`.

[13] The number of observations used in spillover analysis is less than that in safe haven analysis as we included gold in the spillover analysis which has slightly fewer trading days than the stock markets.

Table 2.1: Description of clean energy indices

Index name	Description
S&P Global Clean Energy Index	SPGTCED tracks the performance of world top 100 companies in clean energy sectors from both developed and emerging markets.
WilderHill Clean Energy Index	ECO is the first index that tracks the performance of top clean energy companies traded on the NASDAQ.
NASDAQ OMX Bio/Clean Fuels Index	GRNBIO tracks the performance of companies operating in plant-based fuel generation sector.
NASDAQ OMX Renewable Energy Index	GRNREG tracks the performance of companies operating in renewable energy generation sectors, such as solar, wind, geothermal, and fuel cells.
NASDAQ OMX Geothermal Index	GRNGEO tracks the performance of companies operating in geothermal power generation sector.
NASDAQ OMX Fuel Cell Index	GRNFUEL tracks the performance of companies operating in fuel cell energy sector.
NASDAQ OMX Solar Index	GRNSOLAR tracks the performance of companies operating in solar energy generation sector.
NASDAQ OMX Wind Index	GRNWIND tracks the performance of companies operating in wind energy generation sector

2.5 Results

2.5.1 Spillover Effects

2.5.1.1 Return Spillovers

We used an optimal lag length of 1 selected by the Akaike Information Criterion (AIC) for the VAR model to calculate the TS, DS, NS for the return series. Following Saeed et al. (2021), Aharon et al. (2021), Zeng et al. (2020), Diebold and Yılmaz (2012), and many other studies, we set a 200-day rolling window size and a 10-day ahead forecast horizon.

As shown in Table 2.3, the average dynamic total return connectedness from

Table 2.2: Descriptive statistics of returns (%)

	Mean	Min	Max	Std.Dev	Skewness	Kurtosis	ADF	JB
SPGTCED	0.089	-12.498	11.035	1.697	-0.888	10.900	-7.257***	4949.7***
ECO	0.119	-16.239	13.399	2.415	-0.657	6.733	-7.230***	1911.1***
GRNBIO	0.051	-18.193	13.394	2.272	-1.380	13.061	-6.645***	7230.9***
GRNFUEL	0.177	-18.028	21.617	3.829	0.180	3.735	-20.283***	572.7***
GRNREG	0.071	-15.256	8.930	1.319	-1.632	25.452	-7.535***	26707***
GRNGEO	0.015	-13.390	18.255	2.186	0.686	11.250	-9.351***	5212.6***
GRNSOLAR	0.106	-19.334	12.049	2.548	-0.704	6.551	-8.259***	1823.7***
GRNWIND	0.074	-10.982	7.720	1.584	-0.276	4.651	-16.126***	891.8***
BTC	0.128	-46.473	20.305	4.750	-1.156	11.468	-13.594***	5554.2***
ETH	0.153	-55.071	35.365	6.258	-0.796	8.834	-20.648***	3271.1***
ETC	0.052	-50.779	35.865	7.143	-0.441	7.293	-7.421***	2191.5***
BCH	-0.141	-56.140	42.082	7.447	-0.350	8.936	-20.230***	3262.0***
LTC	-0.025	-44.901	29.062	6.224	-0.668	7.122	-21.313***	2132.5***
ADA	0.121	-50.371	32.209	7.238	0.002	4.197	-20.127***	716.3***
XRP	-0.083	-55.040	62.668	7.405	0.238	12.606	-30.085***	6457.8***
XLM	-0.042	-41.004	55.932	7.283	0.667	9.026	-22.001***	3379.6***
MIOTA	-0.085	-54.333	33.224	7.478	-0.528	6.744	-20.483***	1892.5***
NANO	-0.176	-61.455	54.654	9.113	0.028	8.112	-14.095***	2672.2***
DCRYPT	0.136	-47.692	19.470	4.917	-1.266	11.057	-13.579***	5222.2***
CCRYPT	0.027	-41.826	55.388	6.780	0.036	9.146	-14.665***	3396.4***
SP500	0.053	-12.765	8.968	1.361	-1.117	18.298	-9.018***	13248.0***
GOLD	0.031	-5.265	5.133	0.913	-0.453	5.478	-12.866***	1203.9***

Note: *** indicates the significance level of 1%.

January 2018 to September 2021 is 63.25%, which is about medium-high level. From Figure 2.1, we can observe that there was a notable increase in total connectedness of around 25% in the April of 2020, which can be explained by the increased correlations between assets at that time from DCCs plots (D). However, if we dig into the total connectedness table, we can see that the the average total spillovers between either of the cryptocurrency markets and clean energy markets are relatively low during the period, despite the fact that SPGTCED and ECO are the two largest spillover transmitters (101.96% and 101.86%). The FROM connectedness between clean energy indices and cryptocurrency indices is much lower than that between clean energy and general stock markets (SP&500), and are at the same level of that between clean energy and gold. The TO connectedness shows that cryptocurrency market transmits more information to gold than to clean energy markets on average. Gold market is the most isolated as it is the smallest spillover receiver (28.65%)/transmitter (14.14%), followed by the dirty cryptocurrency (50.01%/37.9%) and clean cryptocurrency (48.64%/41.16%).

Table 2.3: Average dynamic total return connectedness

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	71.35	2.73	3.14	2.67	3.25	1.63	1.49	3.78	2.39	3.08	3	1.49	28.65
SP500	1.14	25.51	10.41	13.21	8.32	5.15	5.06	11.53	12.25	3.83	1.96	1.66	74.49
SPGTCED	1.06	9.58	21.83	15.00	7.11	6.51	4.79	13.06	11.14	7.43	1.27	1.23	78.17
ECO	0.81	12.16	14.56	21.61	7.97	8.84	4.74	9.72	13.84	3.31	1.17	1.28	78.39
GRNBIO	1.62	10.53	10.34	11.7	33.97	4.96	4.03	7.17	8.63	3.29	2.06	1.7	66.03
GRNFUEL	0.88	7.92	10.44	14.52	5.51	37.41	2.47	7.32	7.58	3.55	1.18	1.23	62.59
GRNGEO	1.5	8.02	9.24	8.52	5.55	3.03	43.25	8.22	6.05	3.3	1.84	1.48	56.75
GRNREG	1.41	10.64	13.7	10.29	5.24	4.91	4.48	23.11	11.72	11.54	1.68	1.29	76.89
GRNSOLAR	1.01	12.51	12.29	15.34	6.7	4.98	4.02	12.65	24.26	3.27	1.58	1.4	75.74
GRNWIND	1.48	6.18	13.04	6.07	3.71	3.82	2.73	18.63	4.92	37.33	1.2	0.88	62.67
DCRYPT	2.03	2.93	2.49	1.98	2.78	1.5	1.66	3.27	2.39	1.44	49.99	27.53	50.01
CCRYPT	1.19	2.73	2.33	2.57	2.78	2.01	1.25	2.55	2.32	0.9	28.02	51.36	48.64
TO OTHERS	14.14	85.92	101.96	101.86	58.92	47.33	36.72	97.9	83.22	44.93	44.96	41.16	759.03
Inc. OWN	85.49	111.42	123.79	123.47	92.89	84.75	79.97	121.01	107.47	82.26	94.95	92.53	TOTAL
NET	-14.51	11.42	23.79	23.47	-7.11	-15.25	-20.03	21.01	7.47	-17.74	-5.05	-7.47	63.25

Figure 2.1: Dynamic total return connectedness

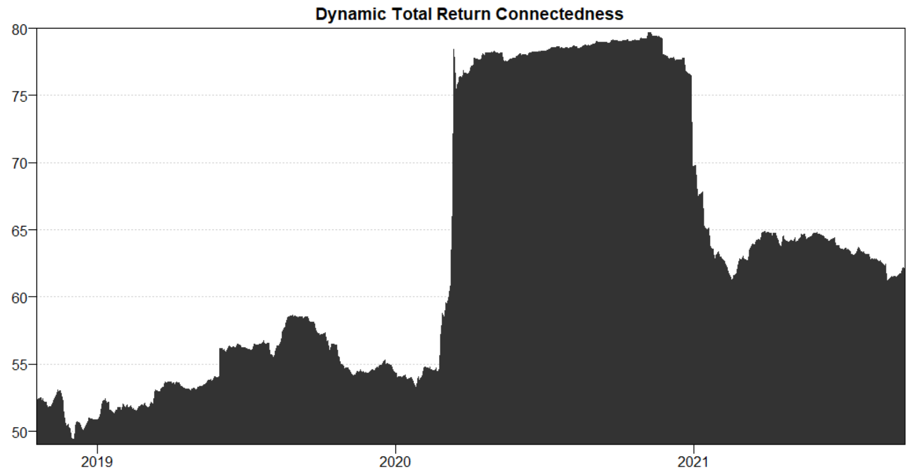


Figure 2.2 depicts the dynamic directional return spillovers received by one market from other markets over time. Clearly, S&P500 and most of the clean energy markets heavily are affected by other markets as they continue receiving the highest spillover effects during the whole period. Clean energy markets are greater spillover receivers than cryptocurrency markets, while gold is the smallest receiver at both the beginning and the end. All market received much more spillovers from other markets in 2020 than in other periods.

Figure 2.2: Dynamic directional return connectedness FROM others

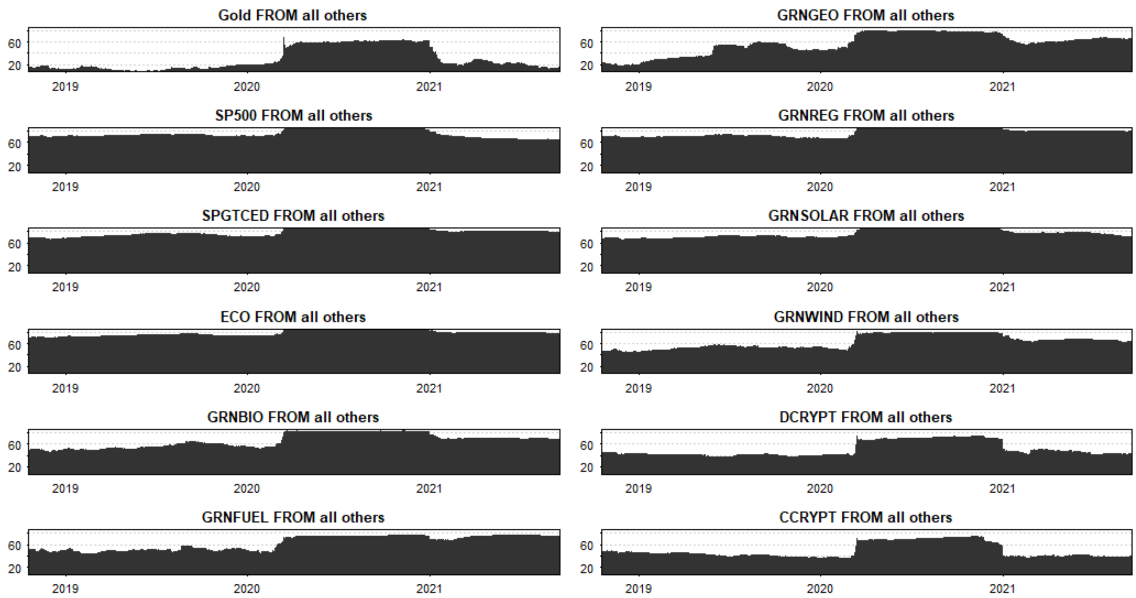
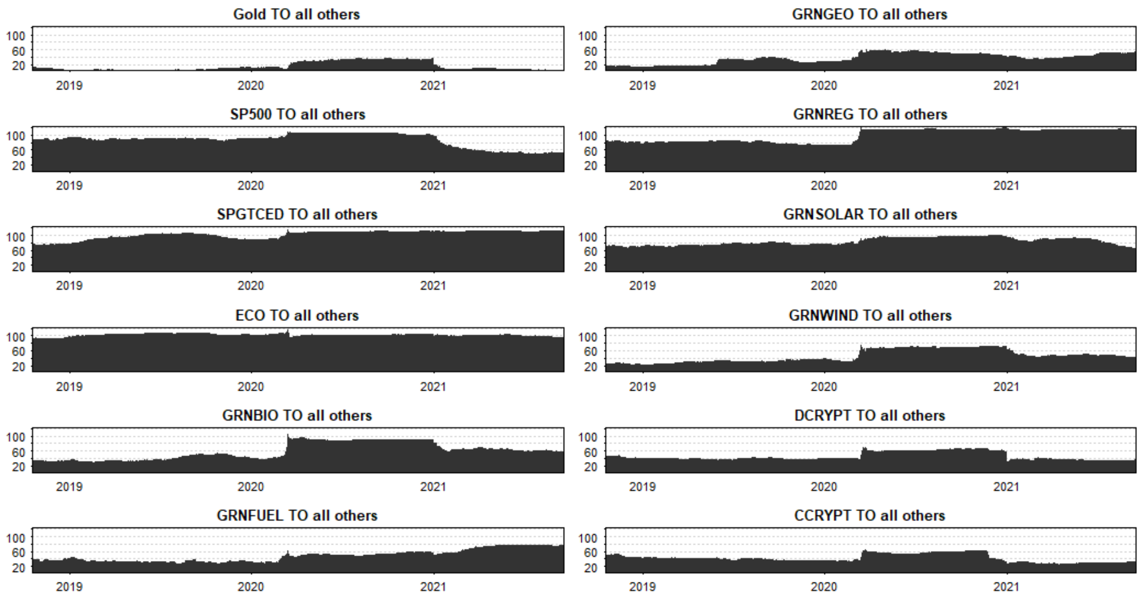


Figure 2.3 presents the dynamic directional return spillovers of one market transmitted to other markets. General clean energy indices such as SPGTCED and ECO have higher spillover effects to others than most of the other subsector indices. S&P500 had relatively high spillover effects to others until the early 2021. Dirty cryptocurrencies slightly higher spillover effects to others than clean cryptocurrency and gold markets. Gold, similar to previous results, has the least spillover effect to others at all time.

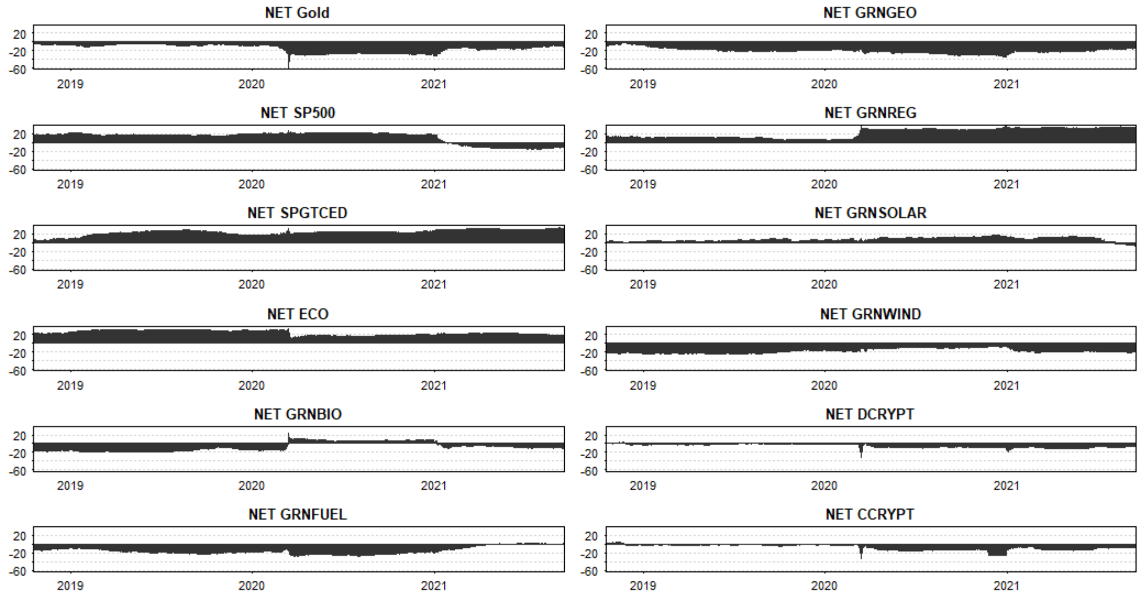
Figure 2.3: Dynamic directional return connectedness TO others



If look at the net spillovers (Figure 2.4), we can easily tell that both of the gold, dirty and clean cryptocurrency markets have been spillover receivers during the whole sample period. General market (S&P500) has received much more spillovers from other markets since 2021. More interestingly, the role of clean energy indices play in terms of spillovers varied from sectors to sectors. Half of the clean energy indices are spillover transmitter in the whole period, including SPGTCED, ECO, GRNREG, and GRNSOLAR, while GRNFUEL, GRNGEO, and GRNWIND are spillover receivers. GRNBIO switched from receivers to transmitters in the April of 2020 and then switched back from 2021 onward.

Figure 2.5 and Figure 2.6 are the net pairwise directional return connectedness for dirty and clean cryptocurrency indices, respectively. The net spillovers from dirty cryptocurrency to clean cryptocurrency was negative at the beginning, and turned

Figure 2.4: Total net return connectedness

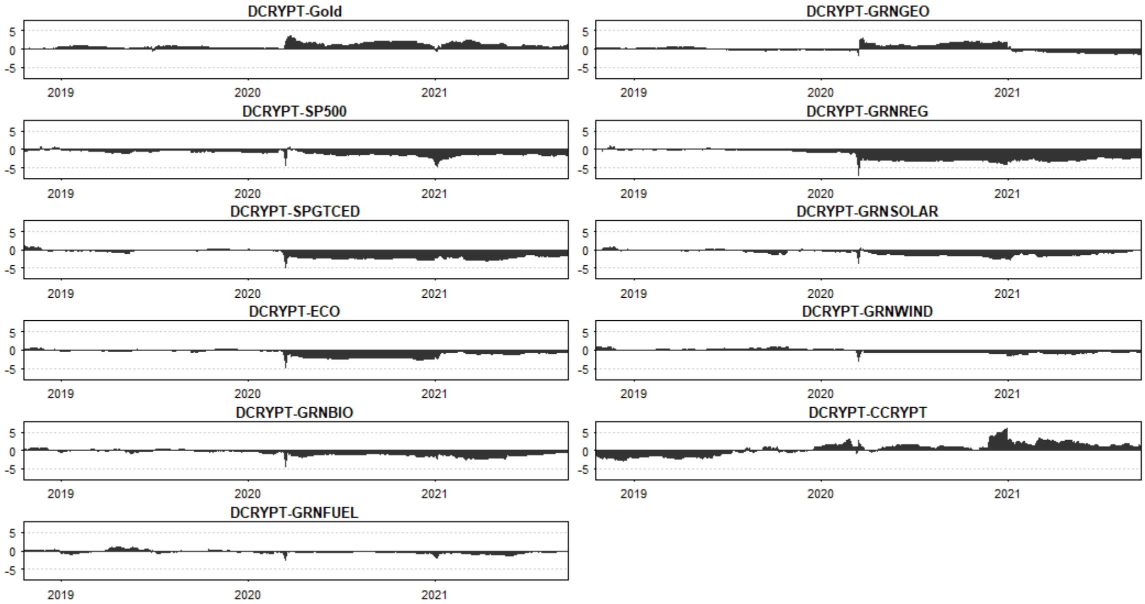


positive from the mid of 2019, which means that dirty cryptocurrency has regained the market dominance from clean cryptocurrency. Generally, both CCRYPT and DCRYPT are spillover receivers of the general stock market and most of the clean energy markets. Both DCRYPT and CCRYPT are transmitters for gold.

2.5.1.2 Volatility Spillovers

The volatility series were estimated using standard GARCH(1,1) model (E). We chose an optimal lag order of 4 based on the AIC and same other settings to calculate the TS, DS, and NS for the volatility series. As recorded in Table 2.4, the average dynamic total connectedness of volatilities from January 2018 to September 2021 is 64.12%, which is slightly higher than that of returns. Figure 2.7 presents the time-varing dynamic total volatility spillovers among different markets. It can observed that there was a even sharper increase in total connectedness between volatilities than returns in the April of 2020 when the correlations between markets increased at the same time (D). If we zoom in total spillovers table, we can see that the the average total spillovers between either of the cryptocurrency market and clean energy markets are still relatively low during the period, but are higher than the that observed in return connectedness. SPGTCED and ECO are the largest transmitters, followed by GRNREG and S&P500. Half of the clean energy markets

Figure 2.5: Net pairwise directional return connectedness for DCRYPT



are larger receivers than the general stock market. The cryptocurrency and the gold market generally are involved the least in the volatility transmission. The level of FROM and TO connectedness between clean energy indices and cryptocurrency indices are slightly higher than that of return connectedness, but are still slightly lower than that between clean energy and gold on average. Gold market remains as the most isolated market as it is the smallest spillover receiver (43.02%) and transmitter (26.09%) again.

Figure 2.6: Net pairwise directional return connectedness for CCRYPT

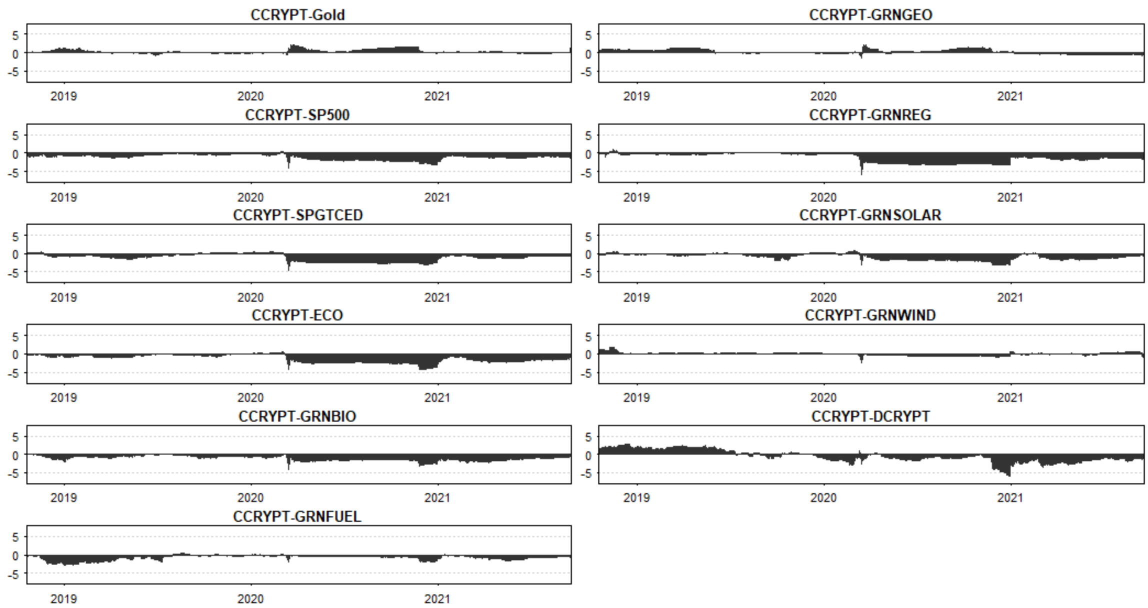


Table 2.4: Average dynamic total volatility connectedness

	Gold	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	56.98	4.58	5.88	4.1	4.21	1.88	2.48	5.62	3.68	4.02	2.93	3.63	43.02
SP500	2.82	30.78	10.56	10.2	8.83	4.5	4.54	11.87	6.55	5	2.15	2.21	69.22
SPGTCED	2.5	9.36	23.9	12.67	8.49	4.24	7.12	12.75	8.34	5.85	2.63	2.16	76.1
ECO	2.94	12.51	15.23	21.57	9.53	5.24	5.56	10.13	8.2	4.68	2.36	2.05	78.43
GRNBIO	2.35	10.34	10.29	7.8	32.52	2.5	7.12	8.71	4.94	6.76	3.31	3.34	67.48
GRNFUEL	1.64	7.97	8.99	10.79	4.49	45.92	5.72	4.61	3.31	2.92	2.15	1.5	54.08
GRNGEO	3.94	6.52	10.55	7.21	7.41	2.33	39.23	6.85	5.86	4.3	2.85	2.95	60.77
GRNREG	2.11	11.81	14.14	8.41	6.94	4.82	4.71	24.6	9.5	8.06	2.68	2.22	75.4
GRNSOLAR	2.44	10.76	12.38	11.77	7.77	3.06	3.84	13.7	25.29	4.26	2.8	1.93	74.71
GRNWIND	2.05	4.09	11.15	5.94	5.07	4.38	6.38	14.63	5.4	34.64	3.62	2.64	65.36
DCRYPT	1.99	3.17	4.68	3.66	5.46	1.7	2.29	4.86	4.15	5.52	45.87	16.65	54.13
CCRYPT	1.31	3.05	4.99	4.13	4.89	3.31	2.85	5	3.03	2.84	15.35	49.26	50.74
TO others	26.09	84.17	108.84	86.69	73.09	37.97	52.62	98.72	62.97	54.2	42.8	41.28	769.43
Inc. own	83.07	114.96	132.73	108.25	105.62	83.88	91.85	123.33	88.26	88.85	88.67	90.54	TOTAL
NET	-16.93	14.96	32.73	8.25	5.62	-16.12	-8.15	23.33	-11.74	-11.15	-11.33	-9.46	64.12

Figure 2.7: Dynamic total volatility connectedness

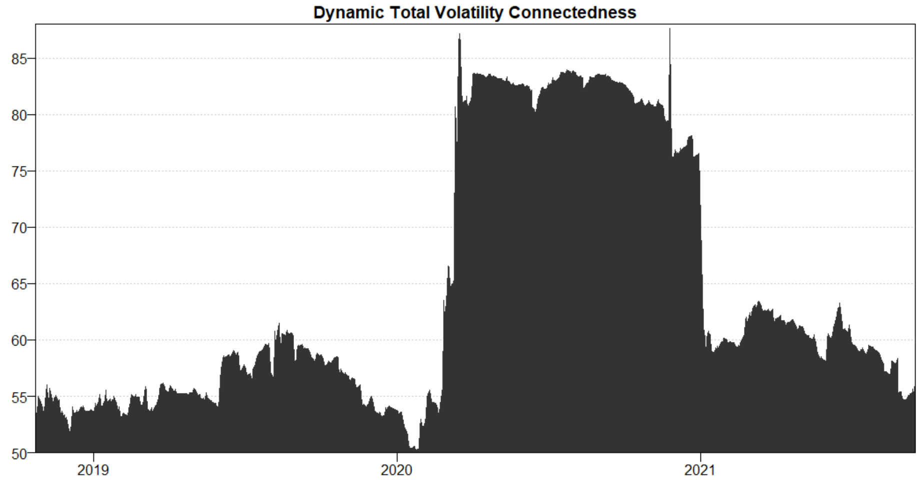


Figure 2.8 depicts the dynamic directional volatility spillovers received by one market from other markets over time. This time, the two major clean energy indices SPGTCED and ECO are the largest receivers. Most of the other clean energy subsectors share similar pattern, but not for the case in GRNFUEL which is more volatile. Clean cryptocurrency received more spillovers than dirty cryptocurrency before the mid of 2020, but has received much less afterwards. All market received much more spillovers from other markets in 2020 than in other periods.

Figure 2.8: Dynamic directional volatility connectedness FROM others

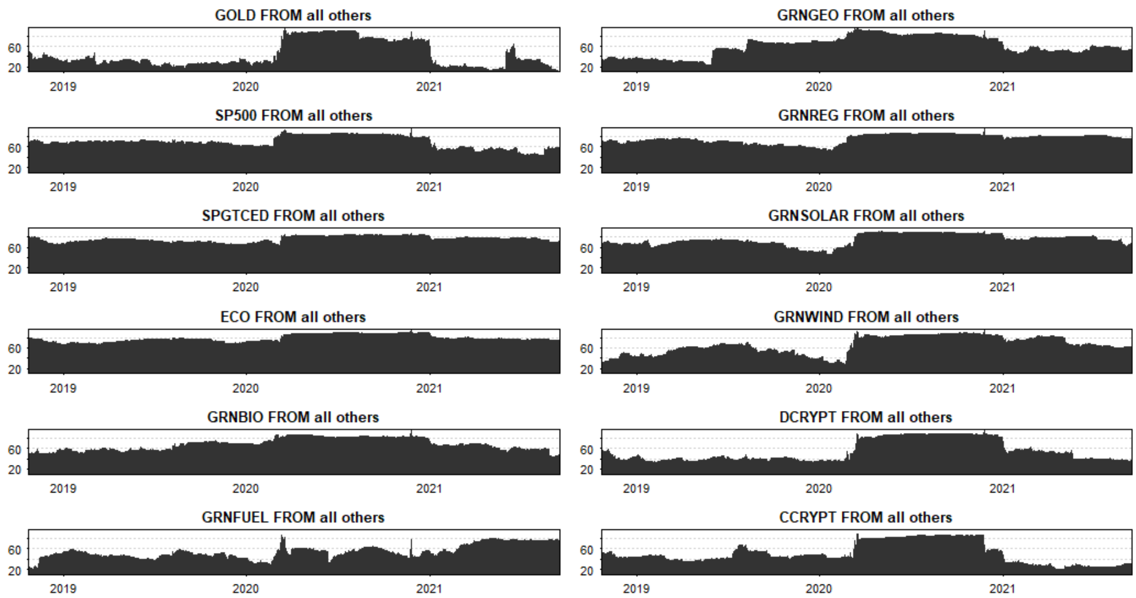
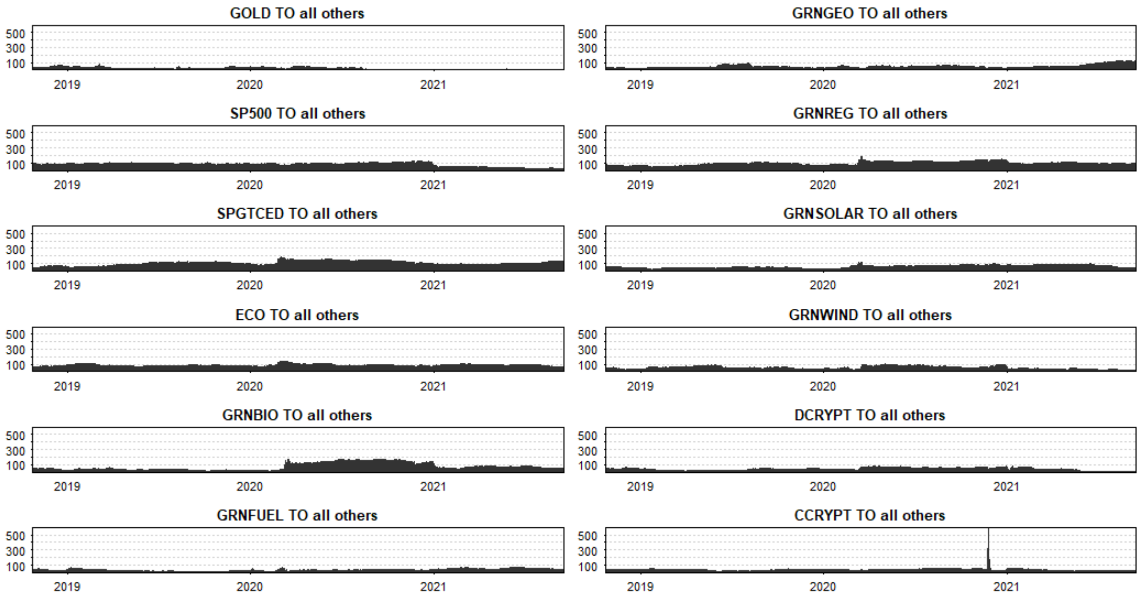


Figure 2.9 presents the dynamic directional volatility spillovers of one market transmitted to other markets. S&P500 and some of the clean energy indices have relatively higher spillover effects to others than from the others. Dirty cryptocurrency conveys slightly higher spillover effects to others than clean cryptocurrency and gold on average. Gold, similar to previous result, has the least spillover effects to others at all time. One important feature is that the clean cryptocurrency once had a extremely large spillover effect to other markets near the end of year 2020.

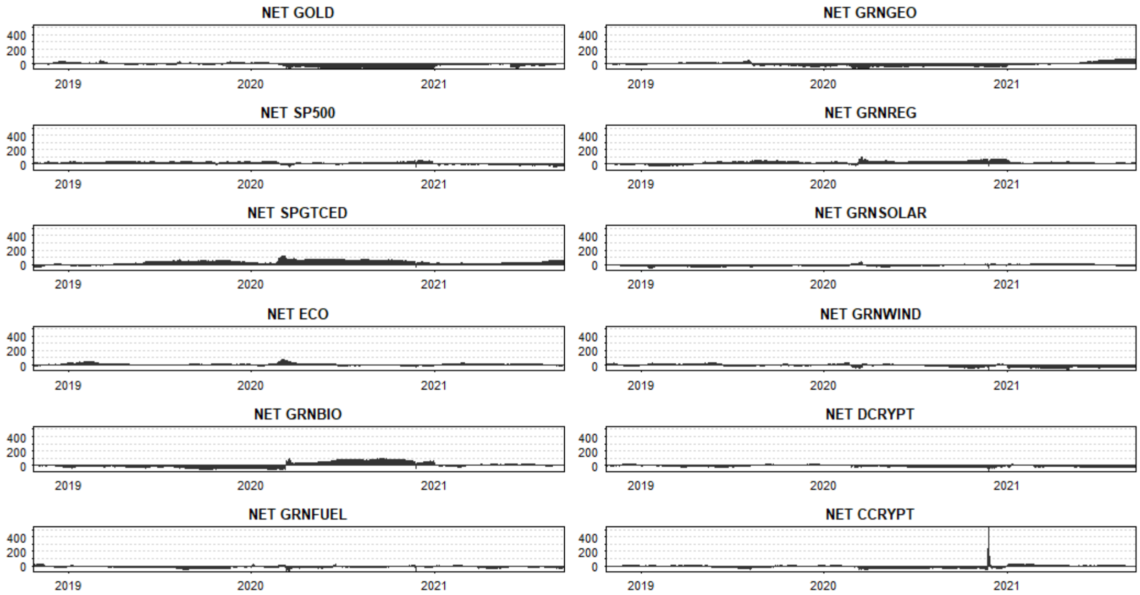
Figure 2.9: Dynamic directional volatility connectedness TO others



The plots of net volatility spillovers show quite a different picture to those of returns (Figure 2.10). Gold is no longer a all time receiver as it was a transmitter before 2020 April. S&P500 and major clean energy indices such as SPGTCED and ECO still can be considered as transmitters during the whole sample period. Other clean energy subsectors vary from type to type. They have been switching between receiver and transmitter at different time. Dirty cryptocurrency generally can be classified as a receiver after 2020 April. Clean cryptocurrency is a receiver at most of the time, but it transmitted very large spillovers once in December of 2020.

Figure 2.11 and Figure 2.12 are the net pairwise directional volatility connectedness for dirty and clean cryptocurrency indices, respectively. Surprisingly, the net spillover from dirty to clean cryptocurrency was positive, but has become negative following a extreme negative shock at the end of 2020. This tells us that when clean

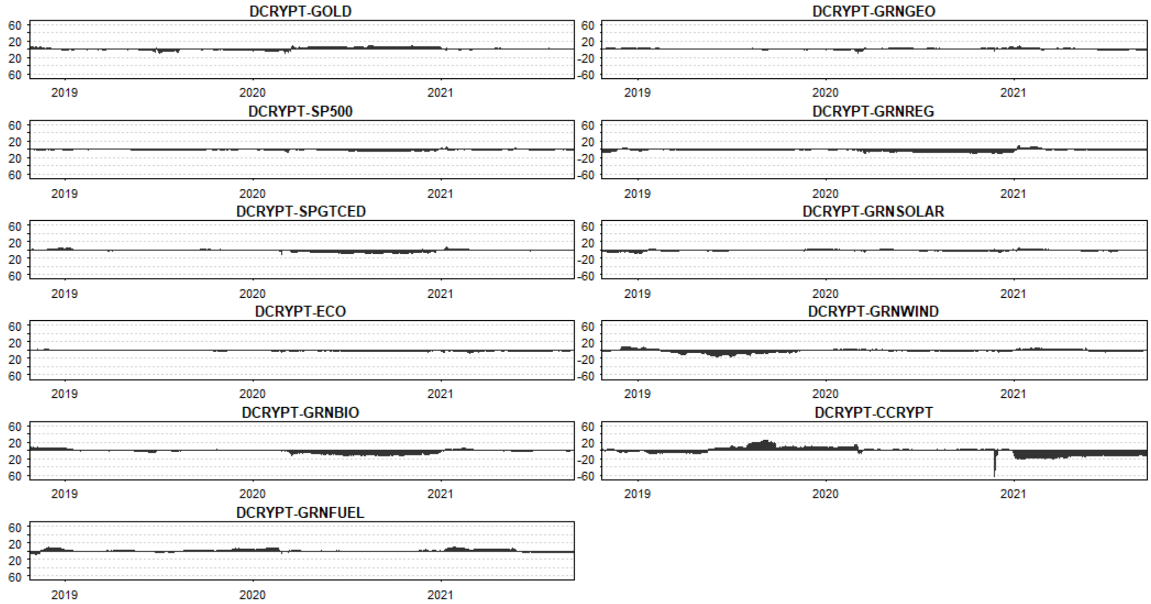
Figure 2.10: Total net volatility connectedness



cryptocurrency is experiencing high volatility, the dirty cryptocurrency market get affected. In addition, the net volatility spillover from dirty cryptocurrency to gold has become quite negative from 2020 April to December, which suggests that investments have been somehow transferred from dirty cryptocurrency to gold market when the former is experiencing high uncertainty. Another interesting pattern is that clean cryptocurrency had a extreme volatility spillover effect to all other market near the end of 2020, which has decayed rapidly. Similar to previous findings, the net spillovers between cryptocurrencies and clean energy are different and there is no unified pattern among them.

Overall, the return and volatility connectedness between clean energy and general market or between clean energy subsectors are more pronounced than that between clean energy and cryptocurrencies, which suggests that investor in the market have not really linked the clean energy and cryptocurrencies together regardless of whether the cryptocurrency is dirty or clean.

Figure 2.11: Net pairwise directional volatility connectedness for DCRYPT



2.5.2 Safe Haven Analysis

2.5.2.1 Dynamic Conditional Correlations

Table 2.5 lists the average DCC coefficients between clean energy indices and the two groups of cryptocurrencies. All mean DCC coefficients are universally positive. The time-varing DCCs between clean energy indices and cryptocurrencies are in the D. From D.1 to D.8, it can be observed that large variations in correlations appeared around the April of 2020 for most pairs, except for GRNFUEL versus NANO and GRNGEO versus ETC. The dynamic correlations between GRNFUEL and both ETC and NANO and that between GRNGEO and both ETC and IMOTA are lower, but more stable than the other pairs. Complemented by Table 2.5, we see that the correlations between clean energy indices and cryptocurrencies are positive in most of the time, regardless of cryptocurrency types, which implies that the clean energy indices might not have direct hedge potentials for both types of cryptocurrency during the periods under study and in the near future. Moreover, clean energy stocks react heterogeneously to cryptocurrencies and there is no differentiated patterns between clean energy stocks and the two cryptocurrency groups.

Figure 2.12: Net pairwise directional volatility connectedness for CCRYPT

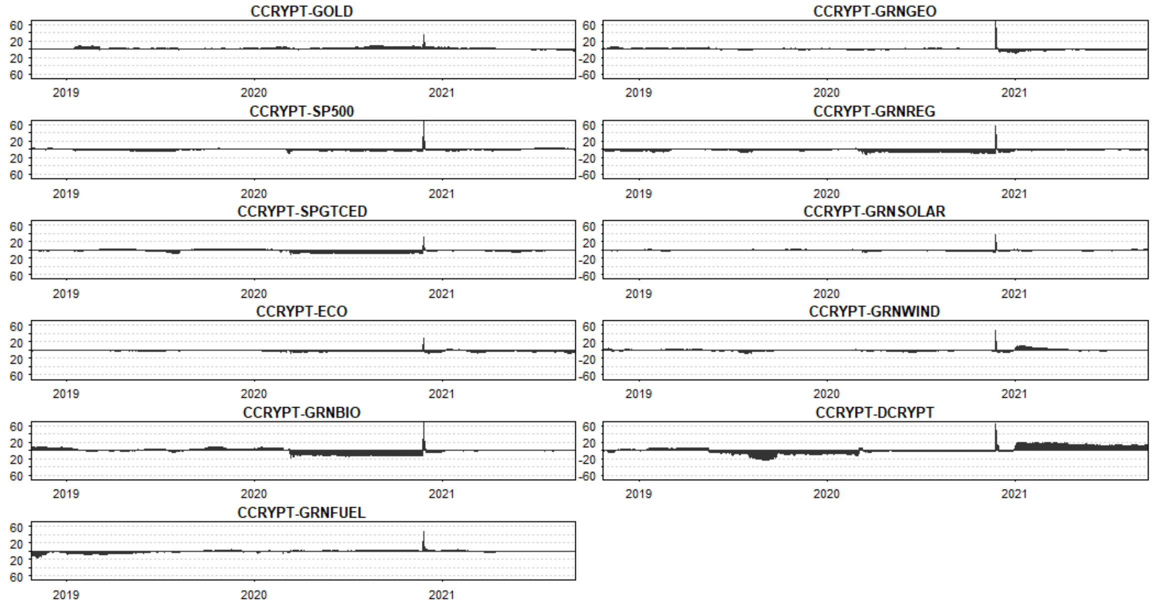


Table 2.5: DCCs between clean energy indices and cryptocurrencies

	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNREG	GRNGEO	GRNSOLAR	GRNWIND
BTC	0.1572	0.1186	0.1370	0.0990	0.1491	0.0874	0.1088	0.1188
ETC	0.1301	0.1079	0.0852	0.0709	0.1260	0.0722	0.0956	0.0883
BCH	0.1338	0.1028	0.0908	0.0791	0.1250	0.0764	0.0799	0.0868
LTC	0.1464	0.1309	0.1206	0.0979	0.1561	0.0646	0.1115	0.1194
ETH	0.1493	0.1309	0.1244	0.1103	0.1425	0.0672	0.1007	0.1234
ADA	0.1605	0.1399	0.1354	0.1064	0.1588	0.1121	0.1331	0.0817
MIOTA	0.1530	0.1432	0.1456	0.1093	0.1557	0.1226	0.1396	0.0925
XRP	0.1348	0.1519	0.1195	0.1334	0.1271	0.0595	0.1043	0.0688
XLM	0.1743	0.1620	0.1607	0.1112	0.1713	0.0988	0.1385	0.0964
NANO	0.1601	0.1642	0.0998	0.1166	0.1526	0.0716	0.1353	0.0973

2.5.2.2 Return Analysis

Table 2.6 summarises the results of the hedge and safe haven properties of clean energy indices in extreme bearish cryptocurrency market conditions. All the hedge ratios (θ_0) in Table 2.6 are significantly positive, which confirms that none of the clean energy indices can be a direct hedge for either types of cryptocurrencies during the studied period. The θ_1 for most of the panels are negative and some of which are significant, which indicates that clean energy indices can be weak or even strong safe havens for cryptocurrencies in the 10% quantile during the period, with very few exceptions.In terms of θ_2 and θ_3, the results are more spotty. It suggests that clean energy can also be a weak safe haven for cryptocurrency in 5% and 1% quantiles, but it depends very much on which clean energy and cryptocurrency are used.

Reversing the relationship in Table 2.7, we see that the results for θs are not uniformed. Cryptocurrency, regardless of types, seems to be a weak safe haven for GRNSOLAR in the 10% quantile as all θ_1 for GRNSOLAR are insignificantly negative in all panels. Most of the cryptocurrecies are weak havens for GRNGEO at 10% except for BTC which is a strong safe haven, and XRP, MIOTA, and NANO which are not safe havens for GRNGEO in the 10% quantile at all. For θ_2 and θ_3, we can only see few of cryptocurrencies are safe havens for clean energy stocks, such as ETC which acts as safe havens for most clean energy subsectors in various quantiles. Clearly, the results are even more spotty than the reverse, and we can not clearly say that cryptocurrencies are general safe havens for clean energy stocks and we cannot distinguish the difference between types.

Overall, we found that clean energy can be generally viewed as a safe haven for the extreme returns of either dirty or clean cryptocurrencies in the 10% quantiles; clean energy can be a safe haven for them in the 5% and 1% quantiles as well, but it really depends on the selection of underlying assets. Most of the cryptocurrencies are not evident as general safe havens for clean energy stocks. Given the ecological footprint of dirty cryptocurrencies that is perhaps a comforting finding. The portfolio suggestion that arises from this is that investors with significant exposure to (in particular, from an ecological perspective, dirty) cryptocurrencies can choose clean energy stocks for safe haven benefits and environmental responsibility.

Table 2.6: Results of hedge and safe haven analysis of clean energy indices for daily cryptocurrency extreme returns

	Hedge (θ_0)	10% quantile (θ_1)	5% quantile (θ_2)	1% quantile (θ_3)
Panel A :SPGTCED				
BTC	0.1574***	*-0.0052*	0.0080	*-0.0098*
ETC	0.1299***	*-0.0034*	0.0065	0.0147
BCH	0.1339***	*-0.0031*	0.0040	0.0017
LTC	0.1461***	*-0.0002*	0.0053	0.0043
ETH	0.1495***	*-0.0098*	0.0119	0.0143
ADA	0.1610***	*-0.0032*	*-0.0064*	0.0080
MIOTA	0.1534***	***-0.0486****	0.0184**	0.0105
XRP	0.1368***	*-0.0163*	*-0.0052*	*-0.0047*
XLM	0.1744***	0.0002	*-0.0027*	0.0003
NANO	0.1604***	***-0.0132****	0.0157**	0.0189
Panel B: ECO				
BTC	0.1194***	*-0.0164*	0.0208	*-0.0210*
ETC	0.1076***	*-0.0017*	0.0043	0.0196
BCH	0.1035***	*-0.0009*	*-0.0137*	0.0031
LTC	0.1323***	0.0007	*-0.0067*	*-0.0055*
ETH	0.1317***	*-0.0055*	*-0.0066*	0.0090
ADA	0.1408***	*-0.0028*	*-0.0136*	0.0027
MIOTA	0.1444***	*-0.0196*	0.0137	*-0.0045*
XRP	0.1529***	*-0.0168*	0.0097	0.0234
XLM	0.1625***	*-0.0053*	*-0.0007*	0.0081
NANO	0.1652***	***-0.0155****	0.0086	0.0085
Panel C: GRNBIO				
BTC	0.1372***	*-0.0107*	0.0205	*-0.0114*
ETC	0.0863***	*-0.0183*	0.0123	0.0042
BCH	0.0921***	*-0.0155*	*-0.0042*	0.0363
LTC	0.1203***	0.0011	0.0012	0.0113
ETH	0.1250***	*-0.0128*	0.0064	0.0387
ADA	0.1357***	*-0.0066*	0.0009	0.0307
MIOTA	0.1471***	***-0.0397*****	0.0475**	0.0017

Table 2.6 continued from previous page

XRP	0.1205***	*-0.0211*	0.0127	0.0409
XLM	0.1605***	*-0.0122*	0.0361	*-0.0354*
NANO	0.1008***	***-0.0265***	0.0282*	0.0229
Panel D: GRNFUEL				
BTC	0.0991***	*-0.0088*	0.0056	0.0296
ETC	0.0727***	***-0.0254***	0.0220	*-0.0400*
BCH	0.0788***	*-0.0037*	0.0099	0.0065
LTC	0.0972***	0.0025	0.0108	*-0.0090*
ETH	0.1105***	*-0.0027*	*-0.0010*	0.0101
ADA	0.1073***	*-0.0038*	*-0.0094*	*-0.0027*
MIOTA	0.1096***	***-0.0218***	0.0381***	0.0011
XRP	0.1337***	*-0.0055*	0.0111	*-0.0251*
XLM	0.1121***	*-0.0052*	*-0.0095*	0.0105
NANO	0.1167***	*-0.0020*	0.0025	*-0.0004*
Panel E: GRNREG				
BTC	0.1501***	*-0.0220*	0.0251	*-0.0030*
ETC	0.1266***	*-0.0120*	0.0049	0.0374
BCH	0.1272***	*-0.0277*	0.0074	0.0218
LTC	0.1570***	*-0.0069*	*-0.0029*	*-0.0024*
ETH	0.1445***	***-0.0327****	0.0138	0.0569
ADA	0.1604***	*-0.0118*	*-0.0109*	0.0154
MIOTA	0.1570***	***-0.0306***	0.0320	0.0090
XRP	0.1299***	***-0.0265***	*-0.0024*	*-0.0004*
XLM	0.1719***	*-0.0067*	*-0.0041*	0.0181
NANO	0.1543***	***-0.0293*****	0.0182	0.0301
Panel F: GRNGEO				
BTC	0.0875***	*-0.0041*	0.0040	0.0096
ETC	0.0722***	*-0.0000*	0.0000	0.0000
BCH	0.0764***	*-0.0015*	*-0.0008*	0.0180**
LTC	0.0644***	*-0.0011*	0.0060	0.0049
ETH	0.0673***	*-0.0052*	*-0.0011*	0.0466***
ADA	0.1119***	0.0009	0.0032	0.0077
MIOTA	0.1225***	*-0.0022*	0.0050**	0.0044
XRP	0.0595***	*-0.0015*	0.0014	0.0092

Table 2.6 continued from previous page

XLM	0.0983***	0.0056	*-0.0026*	*-0.0015*
NANO	0.0720***	***-0.0116****	0.0138***	0.0149*
Panel G: GRNSOLAR				
BTC	0.1095***	*-0.0114*	0.0115	*-0.0173*
ETC	0.0981***	***-0.0319****	0.0143	*-0.0052*
BCH	0.0819***	*-0.0161*	*-0.0146*	0.0345
LTC	0.1119***	*-0.0011*	*-0.0043*	*-0.0122*
ETH	0.1017***	*-0.0108*	*-0.0025*	0.0217
ADA	0.1335***	0.0006	*-0.0118*	0.0133
MIOTA	0.1409***	***-0.0260****	0.0239*	0.0007
XRP	0.1064***	***-0.0326****	0.0160	0.0337
XLM	0.1385***	*-0.0070*	0.0129	0.0028
NANO	0.1369***	***-0.0239****	0.0125	0.0134
Panel I: GRNWIND				
BTC	0.1196***	*-0.0139*	0.0082	0.0206
ETC	0.0883***	*-0.0009*	*-0.0088*	0.0501**
BCH	0.0871***	*-0.0042*	0.0022	0.0027
LTC	0.1193***	*-0.0030*	0.0090	*-0.0046*
ETH	0.1236***	***-0.0091****	0.0067	0.0315***
ADA	0.0828***	*-0.0087*	*-0.0062*	0.0126
MIOTA	0.0932***	***-0.0183****	0.0216**	0.0028
XRP	0.0694***	*-0.0063*	0.0051	*-0.0172*
XLM	0.0971***	*-0.0054*	*-0.0065*	0.0162
NANO	0.0981***	***-0.0147****	0.0119	0.0066

Notes:
1. Equation 2.12 is used. Table shows the relationship between each clean energy index (each panel) as a safe haven and various cryptocurrencies;
2.. Clean energy is a weak hedge for an individual cryptocurrency if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain market condition if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative);
3. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

Table 2.7: Results of hedge and safe haven analysis of cryptocurrencies for daily clean energy extreme returns

	Hedge (θ_0)	10% quantile (θ_1)	5% quantile (θ_2)	1% quantile (θ_3)
Panel A: BTC				
SPGTCED	0.1532***	0.0224**	0.0306***	0.0142
ECO	0.1145***	0.0234*	0.0175	0.0865**
GRNBIO	0.1327***	*-0.0016*	0.0649***	0.1138***
GRNFUEL	0.0961***	0.0190*	0.0046	0.0460*
GRNGEO	0.0872***	***-0.0098****	0.0213*	0.0076
GRNREG	0.1414***	0.0485***	0.0406	0.0777*
GRNSOLAR	0.1062***	*-0.0095*	0.0053*	0.0778*
GRNWIND	0.1170***	*-0.0013*	0.0291**	0.0424*
Panel B: ETC				
SPGTCED	0.1290***	0.0090*	*-0.0003*	0.0180
ECO	0.1082***	***-0.0196*****	0.0210*	0.0549***
GRNBIO	0.0807***	0.0073	0.0345	0.1872***
GRNFUEL	0.0702***	0.0137	*-0.0093*	*-0.0237*
GRNGEO	0.0722***	*-0.0000*	0.0000	0.0000
GRNREG	0.1245***	0.0107	*-0.0079*	0.0798***
GRNSOLAR	0.0948***	*-0.0098*	0.0214	0.0653
GRNWIND	0.0873***	0.00533	0.0089	*-0.0045*
Panel C: BCH				
SPGTCED	0.1318***	0.0112**	0.0173**	0.0070
ECO	0.0991***	0.0236**	0.0134	0.0590*
GRNBIO	0.0853***	0.0036	0.0695**	0.1533***
GRNFUEL	0.0762***	0.0266**	0.0009	0.0188
GRNGEO	0.0725***	0.0032	0.0161***	0.0011
GRNREG	0.1186***	0.0426**	0.0265	0.0796**
GRNSOLAR	0.0770***	0.0000	0.0433*	0.0696*
GRNWIND	0.0861***	0.0024	0.0070	0.0146
Panel D: LTC				
SPGTCED	0.1454***	0.0026	0.0073	0.0296***
ECO	0.1304***	0.0061	0.0057	0.0584***

Table 2.7 continued from previous page

GRNBIO	0.1171***	0.0027	0.0299*	0.1666***
GRNFUEL	0.0974***	0.0071	*-0.0131*	0.0421**
GRNGEO	0.0644***	*-0.0032*	0.0087	0.0125
GRNREG	0.1538***	0.0114	0.0109	0.0625***
GRNSOLAR	0.1105***	*-0.0088*	0.0269**	0.0480**
GRNWIND	0.1185***	*-0.0012*	0.0145**	0.0146
Panel E: ETH				
SPGTCED	0.1468***	0.0092	0.0255**	0.0251
ECO	0.1282***	0.0168***	-0.0007	0.1026***
GRNBIO	0.1205***	0.0074	0.0385*	0.1194***
GRNFUEL	0.1091***	0.0133*	*-0.0021*	*-0.0067*
GRNGEO	0.0669***	*-0.0077*	0.0208***	0.0019
GRNREG	0.1363***	0.0307*	0.4150	0.1029**
GRNSOLAR	0.0984***	*-0.0020*	0.0319*	0.0879**
GRNWIND	0.1226***	*0.0003*	0.0095*	0.0245***
Panel F: ADA				
SPGTCED	0.1594***	*-0.0012*	0.0160*	0.0365**
ECO	0.1381***	0.0106	*-0.0020*	0.0835***
GRNBIO	0.1322***	0.0042	0.0255	0.1411***
GRNFUEL	0.1057***	0.0140*	*-0.0154*	0.0107
GRNGEO	0.1120***	*-0.0081*	0.0173**	0.0035
GRNREG	0.1561***	0.0058	0.0275	0.0677***
GRNSOLAR	0.1320***	*-0.0041*	0.0176	0.0631***
GRNWIND	0.0798***	0.0022	0.0227*	0.0506**
Panel G: MIOTA				
SPGTCED	0.1510***	0.0094	0.0179**	0.0146
ECO	0.1398***	0.0243**	0.0046	0.0682**
GRNBIO	0.1412***	0.0012	0.0572***	0.1318***
GRNFUEL	0.1068***	0.0232**	0.0010	0.0192
GRNGEO	0.1219***	0.0022	0.0086***	*-0.0001*
GRNREG	0.1510***	0.0291**	0.0242	0.0527*
GRNSOLAR	0.1386***	*-0.0060*	0.0226*	0.0443**
GRNWIND	0.0906***	0.0046	0.0187*	0.0472***
Panel H: XRP				

Table 2.7 continued from previous page

SPGTCED	0.1325***	*-0.0077*	0.0508***	0.0544*
ECO	0.1465***	0.0303*	0.0219	0.1210***
GRNBIO	0.1155***	0.0085	0.0342*	0.1330***
GRNFUEL	0.1313***	0.0280*	*-0.0258*	0.0665*
GRNGEO	0.0589***	0.0022	0.0071	0.0021***
GRNREG	0.1235***	0.0093	0.0354*	0.0870***
GRNSOLAR	0.1012***	*-0.0034*	0.0485*	0.0963**
GRNWIND	0.0678***	*-0.0005*	0.0160**	0.0225*
Panel I: XLM				
SPGTCED	0.1728***	0.0020	0.0207***	0.0221**
ECO	0.1580***	0.0144	0.0386**	0.0650**
GRNBIO	0.1559***	0.0111	0.0375*	0.0172***
GRNFUEL	0.1085***	0.0270***	*-0.0007*	0.0053
GRNGEO	0.0988***	*-0.0044*	0.0072	0.0065
GRNREG	0.1661***	0.0292**	0.0307*	0.0697***
GRNSOLAR	0.1358***	*-0.0024*	0.0449***	0.0678**
GRNWIND	0.0950***	0.00723	0.0096	0.0260**
Panel J: NANO				
SPGTCED	0.1588***	0.0063	0.0076	0.0286**
ECO	0.1613***	0.0152*	0.0176	0.0479**
GRNBIO	0.0973***	0.0015	0.0191	0.1367***
GRNFUEL	0.1161***	0.0040***	0.0006	*-0.0027*
GRNGEO	0.0713***	0.0005	0.0049	0.0009
GRNREG	0.1477***	0.0135	0.0512***	0.0907***
GRNSOLAR	0.1334***	*-0.0038*	0.0337**	0.0578**
GRNWIND	0.0960***	*-0.0020*	0.0293***	0.0066

Notes:

1. Modified Equation 2.12 is used. Table shows the relationship between each cryptocurrency index (each panel) as a safe haven and various clean energy indices;

2. A cryptocurrency is a weak hedge for clean energy subsector index if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. A cryptocurrency serves as a weak (strong) safe haven for a clean energy subsector index under certain market condition if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative);

3. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

2.5.2.3 Uncertainty Analysis

Table 2.8 summarise the results of the hedge and safe haven properties of clean energy indices for cryptocurrencies in periods of increased crypto market uncertainty. All hedge coefficients (θ_0) in Table 2.8 are significantly positive, which confirms that clean energy indices can not be a direct hedge for either types of cryptocurrencies during the times of increased market uncertainty. Although the results of θ_1 coefficients are spotty, most of them are positive, which indicates that clean energy indices are not safe havens for either types of cryptocurrency during high market uncertainty (90% threshold). For θ_2, most of them for dirty cryptocurrencies are negative and some of which are significant, which suggests that most of the clean energy indices are weak or strong safe havens for dirty cryptocurrencies on the 95% threshold of volatility. Exceptions are GRNFUEL which is not a safe haven for BTC and ETH, GRNREG which is not a safe haven for LTC, GRNGEO which is not a safe haven for ETC, and GRNWIND which is not a safe haven for ETH. Finally, regarding θ_3, we can see that coefficients for most of the panels are positive, except for some of which in Panel E and F, which indicates that more than half of the clean energy indices are not safe havens for either dirty or clean cryptocurrencies during extreme uncertainty (99% threshold). Exceptions are GRNREG which is a weak safe haven for NANO on the 99 99% threshold; and GRNGEO which is a weak safe haven for clean cryptocurrencies on the 99% threshold.

Table 2.9 presents the results of the hedge and safe haven properties of dirty and clean cryptocurrencies in periods of increased clean energy market uncertainty. We find that none of the cryptocurrencies is a safe haven on the 90% threshold. Interestingly, we notice that some of the cryptocurrencies are strong safe havens for GRNFUEL on the 95% threshold of volatility, including ETC, BCH, ETH, ADA, XLM. ETC is also a weak haven for ECO and GRNWIND. LTC is a a weak safe haven for GRNGEO and NANO is for GRNWIND on the 99% threshold. BTC, MIOTA, and XRP are not safe havens for clean energy at all. Similar to the previous analysis on returns, these spotty and inconsistent results suggest that cryptocurrencies in regardless types are not a appropriate safe haven choice for clean energy stocks.

Overall, we conclude that clean energy is more likely to be a safe haven for dirty cryptocurrencies than clean cryptocurrencies in the periods of increased market uncertainty, depending on the choice of underlying assets while the reverse is not the case, cryptocurrencies not showing consistent safe haven properties for clean energy stocks.

Table 2.8: Results of hedge and safe haven analysis of clean energy indices in periods of extreme dirty and clean cryptocurrency volatility proxied for market uncertainty

	Hedge (θ_0)	90% threshold (θ_1)	95% threshold (θ_2)	99% threshold (θ_3)
Panel A: SPGTCED				
BTC	0.1553***	0.0191*	*-0.0184*	0.0898***
ETC	0.1285***	0.0197	***-0.0286****	0.0976***
BCH	0.1450***	0.0097*	***-0.0138****	0.0775***
LTC	0.1477***	0.0168***	***-0.0233****	0.0846***
ETH	0.1472***	0.0136*	*-0.0134*	0.1340***
ADA	0.1599***	-0.0050	0.0181**	0.0172
MIOTA	0.1508***	0.0151**	0.0107	0.0139
XRP	0.1337***	-0.0109	0.0356*	0.0370
XLM	0.1734***	0.0010	0.0137**	0.0138
NANO	0.1580***	-0.0001	0.0359***	0.0214*
Panel B: ECO				
BTC	0.1162***	0.0147	*-0.0242*	0.2111***
ETC	0.1055***	0.0277***	***-0.0356****	0.1386***
BCH	0.1019***	0.0102	***-0.0383****	0.1694***
LTC	0.1308***	0.0065	*-0.0136*	0.1138***
ETH	0.1301***	*-0.0000*	*-0.0260*	0.2012***
ADA	0.1382***	*-0.0033*	0.0289**	0.0542**
MIOTA	0.1383***	0.0260**	0.0312*	0.0630**
XRP	0.1457***	0.0174	0.0664**	0.1112***
XLM	0.1576***	0.0168	0.0399**	0.0731**
NANO	0.1607***	0.0103	0.0357***	0.0584***
Panel C: GRNBIO				
BTC	0.1336***	0.0251	*-0.0262*	0.2142***
ETC	0.0790***	0.0435***	*-0.0151*	0.2459***
BCH	0.0875***	0.0234	*-0.0345*	0.2558***
LTC	0.1158***	0.0282**	*-0.0048*	0.2173***
ETH	0.1209***	0.0229	*-0.0162*	0.1997***

Table 2.8 continued from previous page

ADA	0.1329	0.0056	0.0282*	0.0461*
MIOTA	0.1401***	0.0350**	0.0273	0.0579*
XRP	0.1155***	0.0074	0.0452**	0.0883***
XLM	0.1558***	0.0074	0.0702***	0.0646*
NANO	0.0962***	0.0033	0.0517***	0.0655**
Panel D:				
GRNFUEL				
BTC	0.0947***	0.0111	0.0172	0.2087***
ETC	0.0701***	*-0.0079*	*-0.0072*	0.1828***
BCH	0.0768***	0.0059	*-0.0072*	0.1959***
LTC	0.0965***	0.0045	*-0.0135*	0.1549***
ETH	0.1087***	*-0.0070*	0.0050	0.1346***
ADA	0.1065***	***-0.0191****	0.0265**	0.0471**
MIOTA	0.1041***	0.0274***	0.0284**	0.0967***
XRP	0.1272***	0.0142	0.0740***	0.1045***
XLM	0.1096***	*-0.0020*	0.0251*	0.0585***
NANO	0.1159***	0.0029**	0.0050***	0.0092***
Panel E: GRNREG				
BTC	0.1441***	0.0347*	*-0.0169*	0.2361***
ETC	0.1238***	0.0120	***-0.0215****	0.2001***
BCH	0.1224***	0.0108	*-0.0186*	0.2355***
LTC	0.1536***	0.0076	0.0041	0.1499***
ETH	0.1385***	0.0159	*-0.0102*	0.2786***
ADA	0.1577***	*-0.0056*	0.0290*	0.0205
MIOTA	0.1532***	0.0178	0.0117	0.0110
XRP	0.1274***	*-0.0224*	0.0317	0.0287
XLM	0.1689***	0.0101	0.0245	0.0061
NANO	0.1494***	0.0062	0.0507***	*-0.0007*
Panel F: GRNGEO				
BTC	0.0867***	0.0033	*-0.0126*	0.0955***
ETC	0.0722***	0.0000	0.0000	0.0000***
BCH	0.0754***	0.0026	*-0.0011*	0.0750***
LTC	0.0643***	0.0030	***-0.0100****	0.0518***
ETH	0.0664***	0.0025	*-0.0108*	0.1088***

Table 2.8 continued from previous page

ADA	0.1100***	0.0202***	0.0036	*-0.0095*
MIOTA	0.1218***	0.0077***	*-0.0001*	*-0.0020*
XRP	0.0589***	0.0051	0.0034	*-0.0108*
XLM	0.0977***	0.0105***	0.0032	*-0.0154*
NANO	0.0708***	*-0.0021*	0.0258***	***-0.0207****
Panel G:				
GRNSOLAR				
BTC	0.1063***	0.0185	*-0.0380*	0.2462***
ETC	0.0943***	0.0061	***-0.0296***	0.2133***
BCH	0.0798***	0.0045	*-0.0522*	0.2300***
LTC	0.1097***	0.0097	*-0.0139*	0.1446***
ETH	0.0996***	0.0023	*-0.0316*	0.2345***
ADA	0.1304***	0.0103	0.0269**	0.0316*
MIOTA	0.1370***	0.0134	0.0160	0.0360
XRP	0.1003***	0.0038	0.0566**	0.0799*
XLM	0.1334***	0.0224*	0.0477***	0.0457
NANO	0.1327***	0.0076	0.0400***	0.0426*
Panel I: GRNWIND				
BTC	0.1164***	0.0031	*-0.0075*	0.2458***
ETC	0.0862***	0.0094	*-0.0146*	0.1841***
BCH	0.0859***	0.0007	*-0.0049*	0.1095***
LTC	0.1176***	0.0087*	*-0.0062*	0.1220***
ETH	0.1213***	0.0073**	0.0009	0.1295***
ADA	0.0808***	*-0.0048*	0.0211	0.0266
MIOTA	0.0909***	0.0064	0.0157	0.0096
XRP	0.0685***	*-0.0019*	0.0063	0.0207*
XLM	0.0961***	0.0008	0.0044	0.0090
NANO	0.0955***	0.0011	0.0339***	0.0010

Notes:
1. Equation 2.13 is used; Table shows the relationship between each clean energy index (each panel) as a safe haven and various cryptocurrencies under extreme uncertainty;
2. Clean energy is a weak hedge for an individual cryptocurrency under extreme uncertainty if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain level of uncertainty if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative);
3. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

Table 2.9: Results of hedge and safe haven analysis of cryptocurrencies in periods of extreme clean energy market uncertainty

	Hedge (θ_0)	90% threshold (θ_1)	95% threshold (θ_2)	99% threshold (θ_3)
Panel A: BTC				
SPGTCED	0.1477***	0.0924***	0.0006	0.0170
ECO	0.1035***	0.1312***	0.0239	0.0757**
GRNBIO	0.1186***	0.1436***	0.0694***	0.0546
GRNFUEL	0.0900***	0.0653***	0.0194	0.1249***
GRNGEO	0.0842***	0.0228***	0.0124	0.0235*
GRNREG	0.1289***	0.1706***	0.0371	0.1266***
GRNSOLAR	0.0933***	0.0986***	0.0938***	0.0857**
GRNWIND	0.1129***	0.0256***	0.0595***	0.0369*
Panel B: ETC				
SPGTCED	0.1281***	0.0118**	0.0106	0.0258**
ECO	0.1045***	0.0302***	0.0102	*-0.0126*
GRNBIO	0.0663***	0.1311***	0.0880***	0.1266***
GRNFUEL	0.0668***	0.0502***	***-0.0358****	0.0876***
GRNGEO	0.0722***	0.0000	0.0000***	0.0000***
GRNREG	0.1206***	0.0303***	0.0034	0.1364***
GRNSOLAR	0.0873***	0.0326***	0.0756***	0.1196***
GRNWIND	0.0856***	0.0119	0.0353***	*-0.0309*
Panel C: BCH				
ECO	0.0901***	0.1179***	0.0094	0.0429
GRNBIO	0.0680***	0.1873***	0.0631***	0.0808*
GRNFUEL	0.0719***	0.0813***	***-0.0374****	0.0873***
GRNGEO	0.0740***	0.0112***	0.0208***	0.0223***
GRNREG	0.1085***	0.1224***	0.0590***	0.1295***
GRNSOLAR	0.0647***	0.1100***	0.0709***	0.0620
GRNWIND	0.0848***	0.0053	0.0271***	0.0048
Panel D: LTC				
SPGTCED	0.1438***	0.0126***	0.0186***	0.0326***
ECO	0.1239***	0.0665***	0.0160	0.0578***
GRNBIO	0.1059***	0.0898***	0.0830***	0.1421***

Table 2.9 continued from previous page

GRNFUEL	0.0943***	0.0229***	0.0064	0.0985***
GRNGEO	0.0623***	0.0160***	0.0140**	*-0.0013*
GRNREG	0.1475***	0.0499***	0.0459***	0.1297***
GRNSOLAR	0.1036***	0.0326***	0.0748***	0.0856***
GRNWIND	0.1169***	0.0128***	0.0235***	0.0005
Panel E: ETH				
SPGTCED	0.1423***	0.0490***	0.0230**	0.0883***
ECO	0.1186***	0.1004***	0.0241	0.0926***
GRNBIO	0.1075***	0.1365***	0.0487***	0.0814**
GRNFUEL	0.1068***	0.0401***	***-0.0254****	0.0728***
GRNGEO	0.0649***	0.0103*	0.0187**	0.0332***
GRNREG	0.1243***	0.1167***	0.0920***	0.1748***
GRNSOLAR	0.0885***	0.059***	0.1125***	0.1064***
GRNWIND	0.1209***	0.0135***	0.0105*	0.0540***
Panel F: ADA				
SPGTCED	0.1559***	0.0258***	0.0191**	0.1012***
ECO	0.1313***	0.0638***	0.0249**	0.0899***
GRNBIO	0.1218***	0.0893***	0.0657***	0.1242***
GRNFUEL	0.1042***	0.0278***	***-0.0230****	0.0567***
GRNGEO	0.1096***	0.0056	0.0356***	0.0106
GRNREG	0.1491***	0.0440***	0.0749***	0.1471***
GRNSOLAR	0.1256***	0.0201**	0.0871***	0.1051***
GRNWIND	0.0737***	0.0337***	0.0646***	0.1311***
Panel G: MIOTA				
SPGTCED	0.1478***	0.0350***	0.0179**	0.0759***
ECO	0.1318***	0.1001***	0.0126	0.0678**
GRNBIO	0.1272***	0.1468***	0.0570***	0.0760**
GRNFUEL	0.1034***	0.0437***	0.0087	0.1089***
GRNGEO	0.1214***	0.0055***	0.0099***	0.0087**
GRNREG	0.1432***	0.0777***	0.0663***	0.1323***
GRNSOLAR	0.1315***	0.0448***	0.0580***	0.0646***
GRNWIND	0.0853***	0.0287***	0.0664***	0.0944***
Panel H: XRP				
SPGTCED	0.1245***	0.0806***	0.0120	0.1588***

Table 2.9 continued from previous page

ECO	0.1361***	0.1317***	0.0288	0.1156***
GRNBIO	0.1030***	0.1279***	0.0534***	0.0924***
GRNFUEL	0.1250***	0.0457***	0.0374*	0.1884***
GRNGEO	0.0580***	0.0069**	0.0129***	0.0144**
GRNREG	0.1143***	0.0701***	0.0808***	0.1669***
GRNSOLAR	0.0898***	0.0761***	0.1108***	0.1315***
GRNWIND	0.0654***	0.0160***	0.0310***	0.0255**
Panel I: XLM				
SPGTCED	0.1691***	0.0405***	0.0141***	0.0444***
ECO	0.1481***	0.1237***	0.021	0.0508**
GRNBIO	0.1431***	0.1190***	0.0854***	0.1323***
GRNFUEL	0.1054***	0.0699***	***-0.0288****	0.0305
GRNGEO	0.0969***	0.0086**	0.0169***	0.0102
GRNREG	0.1567***	0.1151***	0.0388**	0.1029***
GRNSOLAR	0.1261***	0.0696***	0.0866***	0.1051***
GRNWIND	0.0915***	0.0269***	0.0331***	0.0561***
Panel J: NANO				
SPGTCED	0.1574***	0.0112**	0.0237***	0.0349***
ECO	0.1549***	0.0850***	0.0051	0.0502***
GRNBIO	0.0867***	0.0925***	0.0532***	0.1141***
GRNFUEL	0.1154***	0.0100***	0.0014	0.0090***
GRNGEO	0.0710***	*-0.0041*	0.0179***	0.0124
GRNREG	0.1381***	0.1014***	0.0520***	0.1627***
GRNSOLAR	0.1255***	0.0564***	0.0658***	0.0738***
GRNWIND	0.0939***	0.0148*	0.0447***	*-0.0256*

Notes:

1. Modified Equation 2.13 is used; Table shows the relationship between each cryptocurrency index (each panel) as a safe haven and various clean energy indices under extreme uncertainty;

2. A cryptocurrency is a weak hedge for a clean energy subsector index under extreme uncertainty if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. A cryptocurrency serves as a weak (strong) safe haven for a clean energy subsector index under certain level of uncertainty if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative).

3. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

2.6 Robustness Check

We further considered using a time-varying parameter VAR model (TVP-VAR) proposed by Antonakakis et al. (2020) to examine the robustness of previous results of spillover analysis sections. The TVP-VAR approach has advantages over the DY (rolling window VAR) approach, suggested by Antonakakis et al. (2020) that it does not require a rolling window size to be biasedly assigned and it avoids losing observations as it introduces a time-varing variance-covariance matrix by adopting the Kalman filter with forgetting factors assigned during the estimation step.

The TVP-VAR model with p lags is defined as the following:

$$\begin{aligned} y_t &= \Phi_t z_{t-1} + \epsilon_t & \epsilon_t \mid I_{t-1} \sim N(0, \Sigma_t), \\ vec(\Phi_t) &= vec(\Phi_{t-1}) + e_t & e_t \mid I_{t-1} \sim N(0, E_t), \end{aligned} \tag{2.14}$$

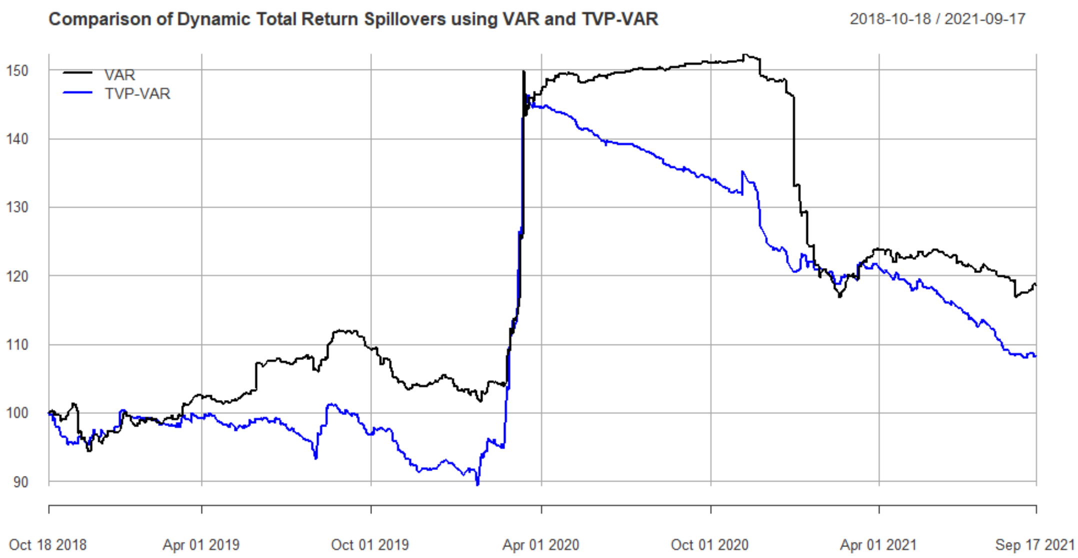
where y_t represents $m \times 1$ vector of endogenous variables, while z_{t-1} represents $pm \times 1$ vector of lagged y_t from $t-p$ to $t-1$. ϵ_t and e_t are vectors of error terms. I_{t-1} denotes all known information until $t-1$. Σ_t and E_t are time-varying variance-covariance matrices.

Following Antonakakis et al. (2020), we initiated the Kalman filter using the Minnesota prior, followed by using the benchmark decay factors of (0.99, 0.99) in the estimation step to calculate the time-varing coefficients and variance-covariance matrices. Subsequently, the time-varing coefficients and the time-varing variance-covariance matrices were introduced to the step of generalized forecast error variance decomposition in the DY approach so that we could calculate the spillover indicies TS, $DS_{i \leftarrow j}$, $DS_{i \rightarrow j}$, and NS.

F.1 and G.1 list the average dynamic total return and volatility connectedness, respectively. F.1 to F.6 are plots of dynamic return connectedness results, while G.1 to G.6 are plots of dynamic volatility connectedness results. By using the TVP-VAR model, we avoided the loss of the first 200 observations. We show that there was a decaying return connectedness from 2018 to 2019 and same for the volatility connectedness but from 2018 to 2020, which were probably due to the collapse in crypto market started in the January of 2018. The major differences between the results of using the DY and TVP-VAR models happens in the period from 2020 April till the year end. To better illustrate the difference, we dropped the first 200 results of total connectedness obtained using the TVP-VAR model, and scale both results obtained by DY and TVP-VAR models to 100 at the start. Figure 2.13 and 2.14 compare the dynamic total return and volatility connectedness using VAR and TVP-

VAR approaches, respectively. Both show a drastic increase in the total spillovers approaching the April of 2020. However, while using the VAR approach the high level of spillovers lasted for nearly a year before collapsing at the beginning of 2021, the spillover calculated using the TVP-VAR model has been decaying after the peak. This is not surprising as the DY approach is more sensitive to outliers than the TVP-VAR method as the latter is smoothed by a Kalman filter. Overall, both approaches provided qualitatively similar information and our findings remain robust.

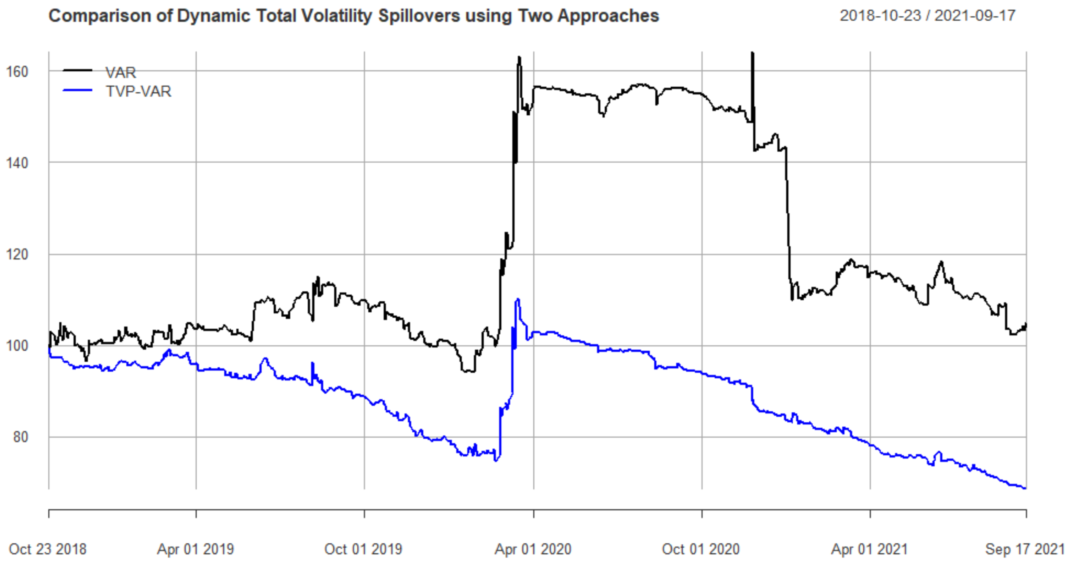
Figure 2.13: Dynamic total return spillovers using VAR and TVP-VAR



2.7 Conclusion

Renewable energies and cryptocurrencies are both great innovations. Unlike the former which are more positively regarded and are good choices for carbon-neutral portfolios, the latter have received much more negative comments for the energy consumption and pollution issues. In fact, there are increasing number of cryptocurrencies that are not energy-hungry, depending on what its underlying consensus is. What the relationships and whether there are co-movements between renewable energy (sectoral) stocks and (different) cryptocurrencies are unclear. Therefore, one of the objectives of this paper is to investigate the financial integration between

Figure 2.14: Dynamic total volatility spillovers using VAR and TVP-VAR



the renewable energy stocks and cryptocurrencies. To achieve this, we followed previous studies such as Corbet and Yarovaya (2020) and Schinckus (2021), among others, to distinguish cryptocurrencies from the sustainability perspective. We employed a popular spillover measure by Diebold and Yılmaz (2012) to calculate the spillover indices across several selected markets. Overall, we found that the return and volatility connectedness between clean energy and cryptocurrencies is much lower than that between clean energy and the general equity market or between clean energy subsectors, which suggests that clean energy markets are more associated with the general market, while cryptocurrencies are more isolated and act as a separate asset class. To some extent, our results support the findings of Ji et al. (2018) which claimed the isolation of Bitcoin market. Clearly, investors in the financial market have not to date really linked clean energy and either types of cryptocurrencies together, and they appear to hold cryptocurrencies based on the intrinsic or expected value of cryptocurrencies and not based on their fundamental differences in transaction mechanisms or energy acquisition channels, which offers the potentials of using clean energy as a hedge for cryptocurrencies in the future. However, investors should be also aware that clean energy stocks do not homogeneously react to the movements of other markets such as cryptocurrencies in our case, while Pham (2019) discovered similar evidence in the clean energy-crude oil relationship. This suggests that investors need to consider the own characteristics of different clean energy indices/stocks and cryptocurrencies and manage their portfolio at a disaggregate level. Policy makers need to aware that single policy would not affect all clean energy markets to the same extent, instead they need to carefully research the distinctive characteristics of each sub-market before the implementation. The current weak connectedness between cryptocurrency markets and other markets also provides opportunities for further integration of these markets.

Moreover, past research such as Naeem and Karim (2021) and Pham et al. (2021) suggested that green investments such as clean energy could be used as diversification or hedge tool for cryptocurrency investors. However, in this paper, we show that the time-varing dynamic conditional correlations between clean energy indices and cryptocurrencies is mostly positive, regardless of cryptocurrency types, which implies that clean energy indices might not be a direct hedge for either dirty and clean cryptocurrencies.

Furthermore, we tested the hedge and safe haven properties of clean energy indices in spells of extreme falling crypto markets and extreme crypto market uncertainty and the reverse based on the framework proposed by Baur and Lucey (2010) and Baur and McDermott (2010). We confirmed our previous finding that clean energy stocks have not yet become an effective direct hedge for cryptocurrencies. However, we find compelling evidence that clean energy *can* can be viewed as a safe haven for both dirty or clean cryptocurrencies at the 10% quantiles of negative returns, in general; it can be a safe haven in the 5% and 1% quantiles as well, depending on the selection of underlying assets. In addition, clean energy is more likely to be a safe haven for dirty cryptocurrencies than for clean cryptocurrencies in periods of increased market volatility, subject to the selection of underlying assets as well. In contrast, cryptocurrency asset is not a universal safe haven for clean energy stocks. We believe that retail investors or institutional managers who have used or are seeking to use clean energy stocks to hedge cryptocurrencies would find this study beneficial for their investments and portfolio constructions. As we see more investors, especially from institutions, are pouring their money into the crypto market, investing in clean energy stocks seems to be a valuable decision. While cryptocurrencies have a significant negative ecological impact this can be perhaps mitigated by investors in these assets also choosing clean energy assets, which supports companies undergoing sustainable actions as well as the market growth, while also receiving the safe haven benefits for encountering cryptocurrency extreme risks in return. In other words, portfolio stability and ecological protection are not necessarily incompatible.

Ethereum, the second largest cryptocurrency in the market, has finally really started its transition to Ethereum 2.0 since late 2022, which will gradually abandon its current power-hungry PoW consensus and move forward with energy-efficient PoS instead. We would like to see more dirty cryptocurrencies follow the steps of Ethereum. Apparently, current policy of promoting sustainability is not appealing enough for cryptocurrency founders as investors seem to be indifferent to investing in dirty and clean cryptocurrencies, or somewhat slightly in favour of dirty cryptos. We see that clean cryptocurrencies have been conveying volatility shocks to dirty cryptos since 2021, but dirty cryptos are still dominating the crypto market being the return transmitters. Policy makers should create incentives for the transition of dirty cryptocurrencies from PoW consensus mechanism to energy-efficient non PoW consensus, and for the investors, especially the institutional investors, to invest more in cleaner cryptocurrencies rather than the dirty ones. The development of green energy and green cryptocurrencies has brought significant environmental benefits compared to fossil energy and dirty cryptocurrencies. Restrictions and legal constraints of energy use in crypto-mining are still weak. Greater efforts should be made by the society to promote greener industry and investment, and arouse the environmental awareness of investors and companies of dirty cryptocurrencies.

APPENDIX D

DCCs between clean energy indices and cryptocurrencies over time

Figure D.1: DCCs between SPGTCED and cryptocurrencies

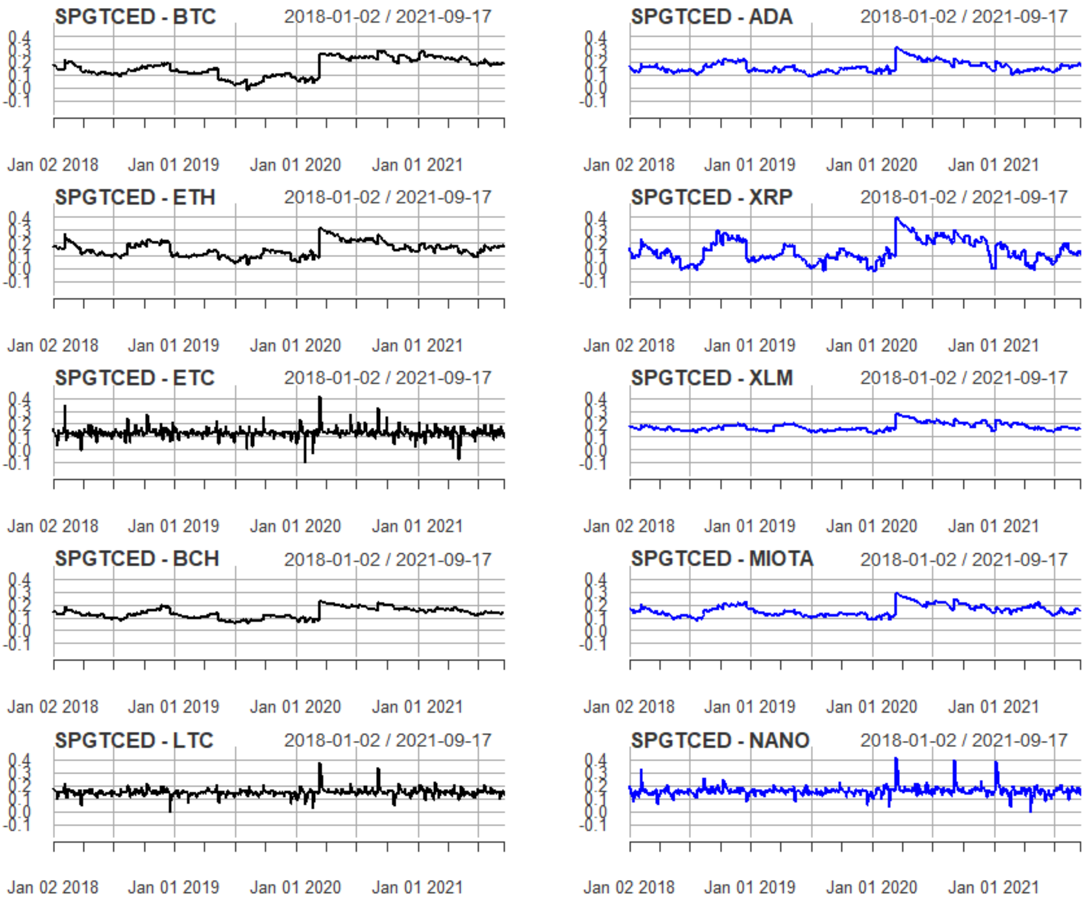


Figure D.2: DCCs between ECO and cryptocurrencies

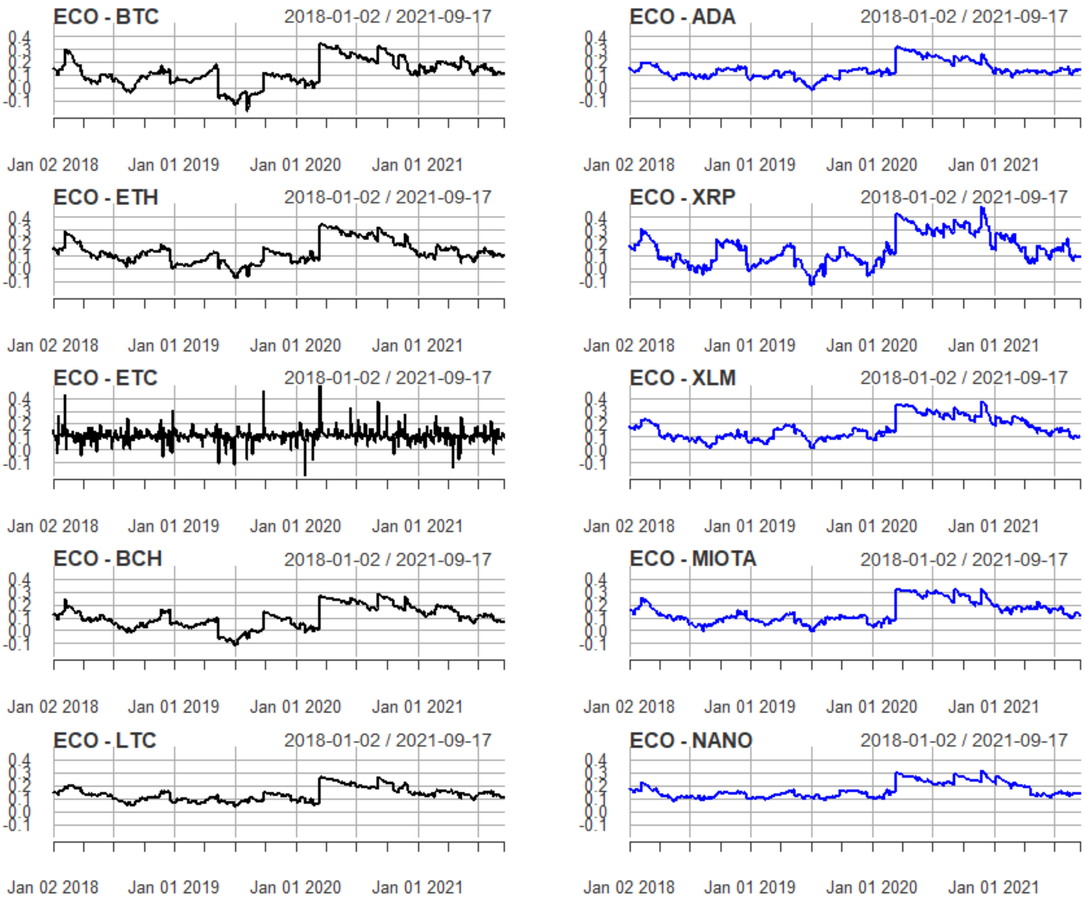


Figure D.3: DCCs between GRNBIO and cryptocurrencies

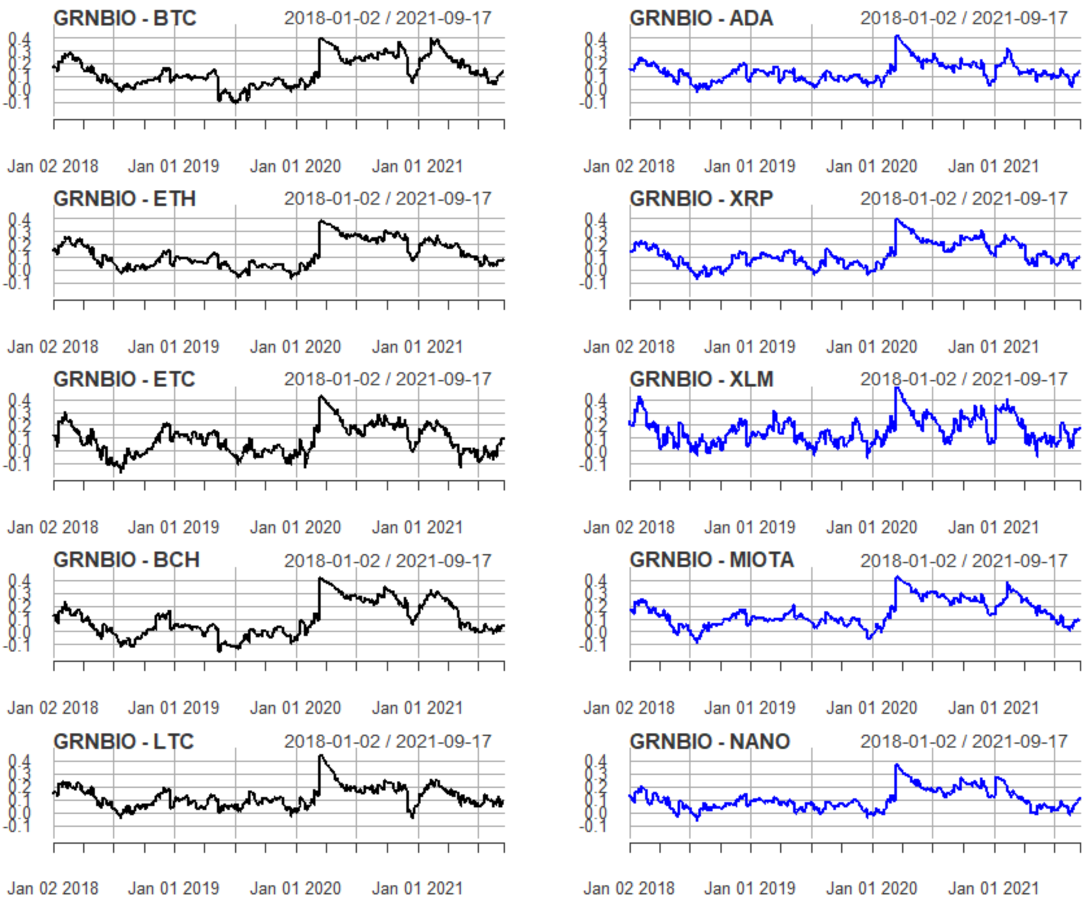


Figure D.4: DCCs between GRNFUEL and cryptocurrencies

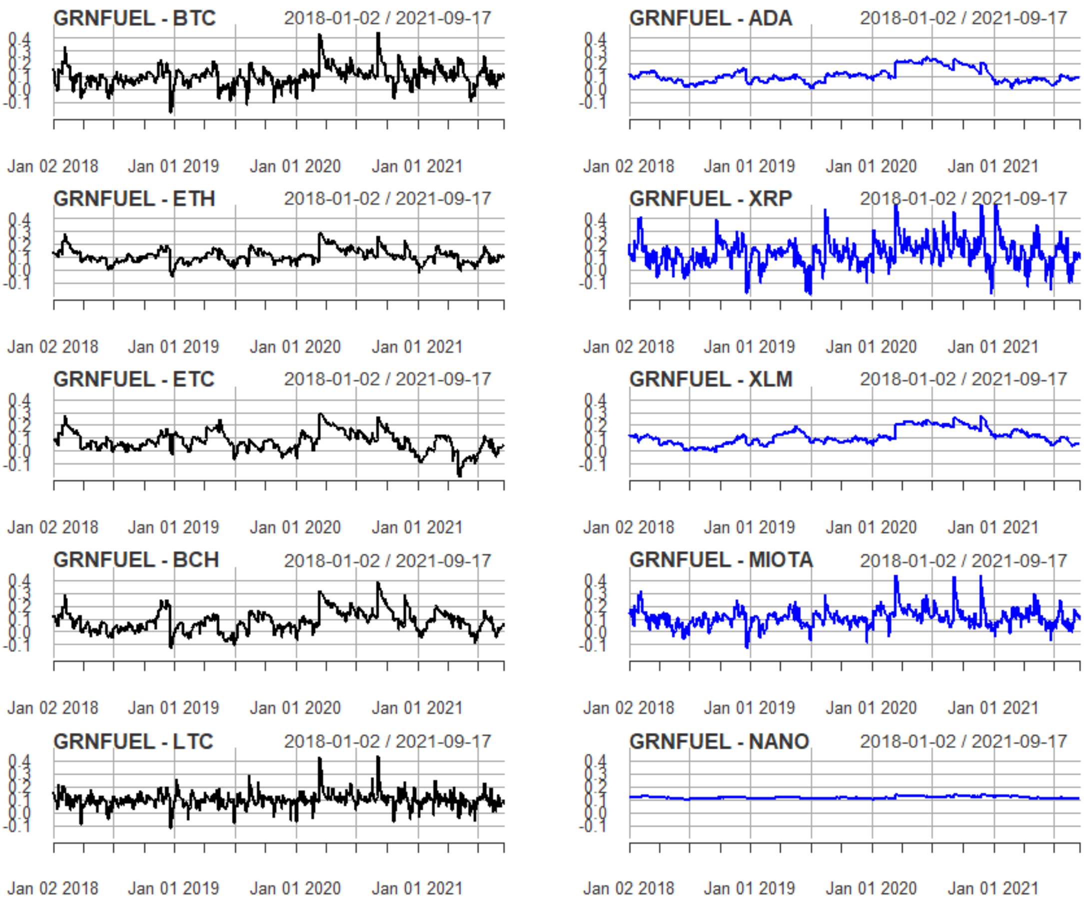


Figure D.5: DCCs between GRNREG and cryptocurrencies

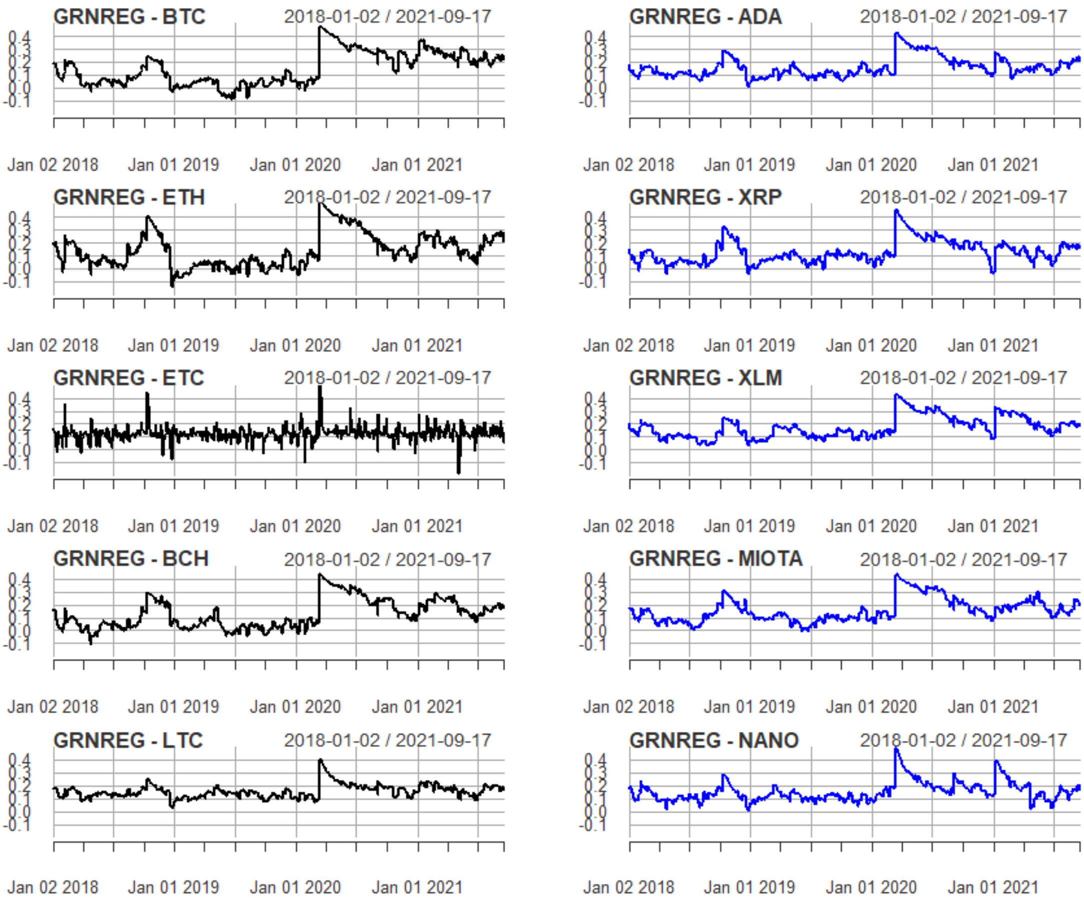


Figure D.6: DCCs between GRNGEO and cryptocurrencies

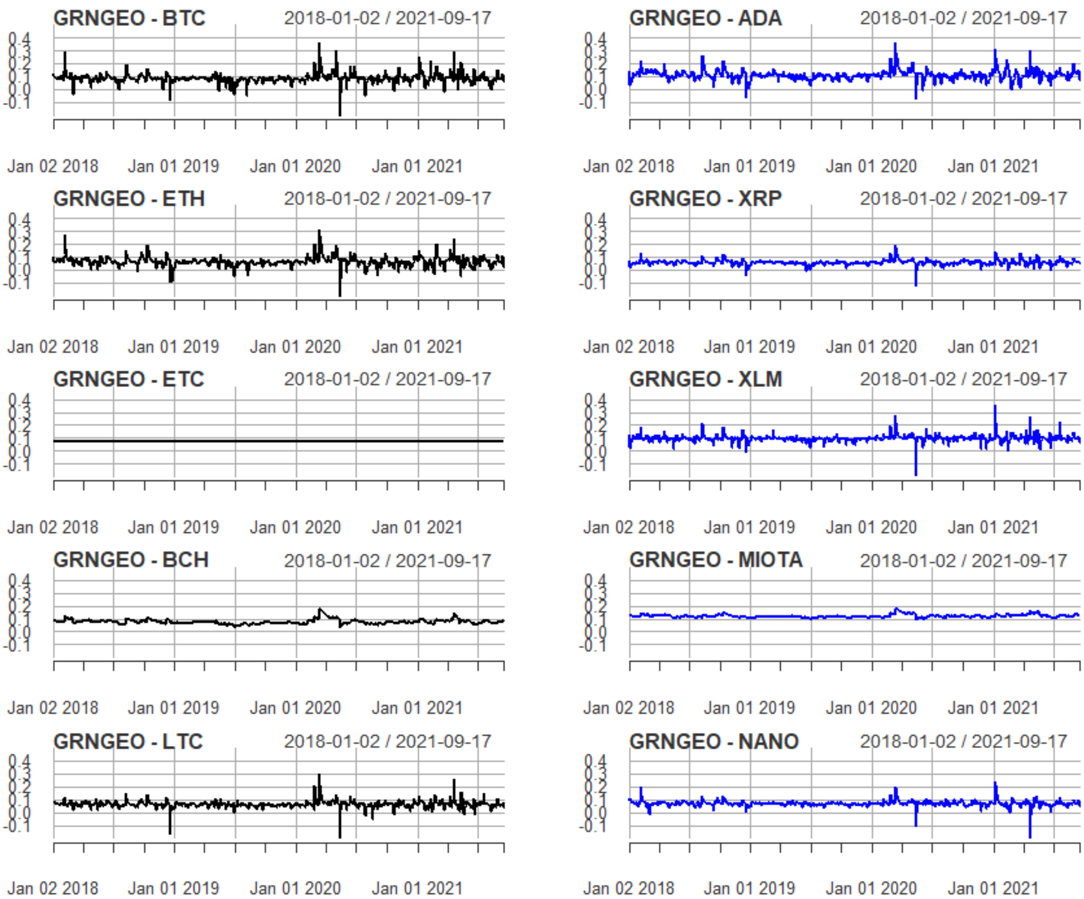


Figure D.7: DCCs between GRNSOLAR and cryptocurrencies

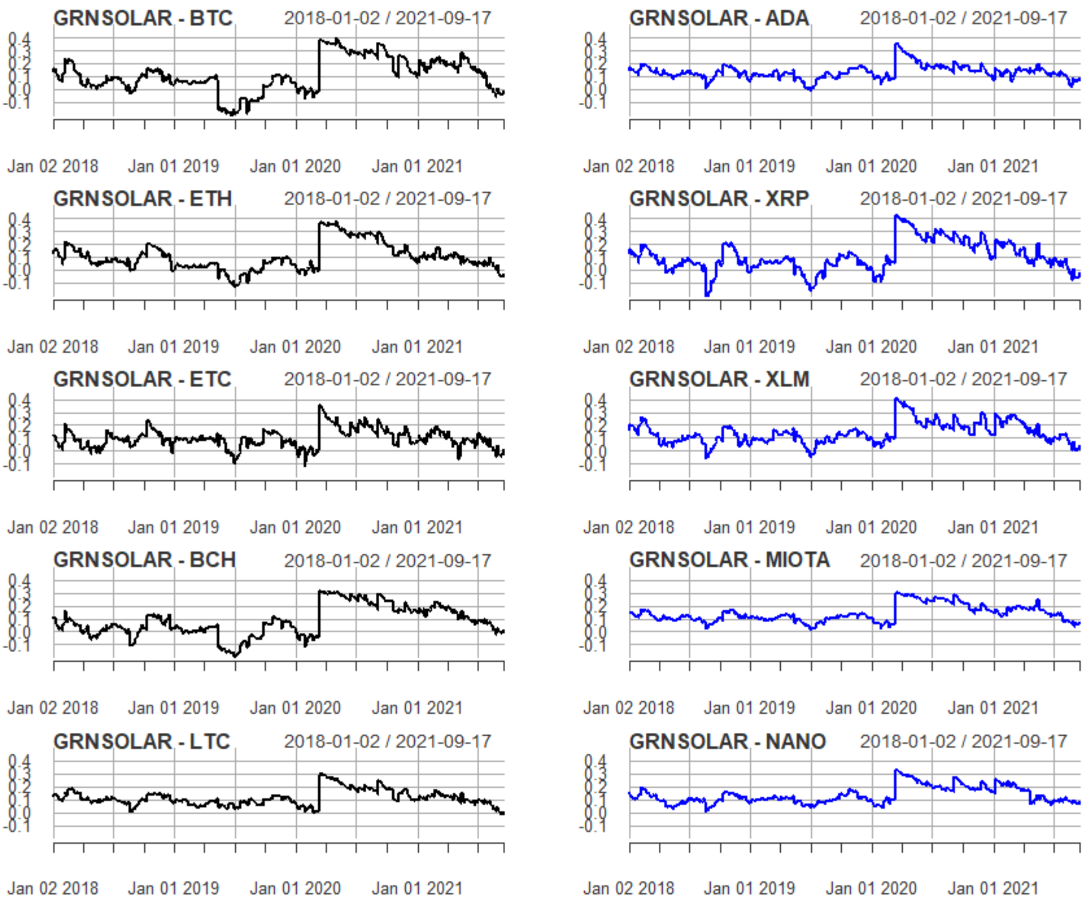
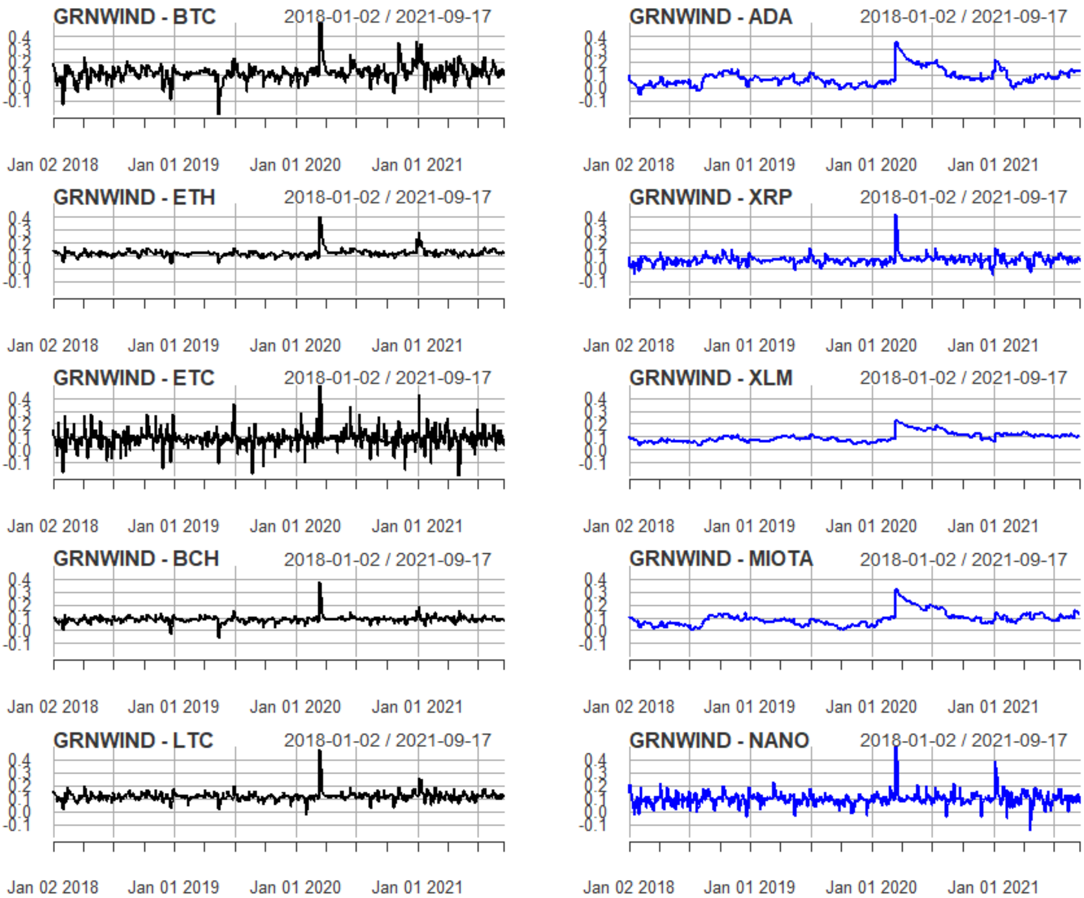


Figure D.8: DCCs between GRNWIND and cryptocurrencies



APPENDIX E

ESTIMATION RESULTS OF GARCH(1,1) MODEL IN VOLATILITY SPILLOVER ANALYSIS

Table E.1: Estimation results of GARCH(1,1) model

	μ	ω	α	β	Log-Likelihood
SPGTCED	0.0008**	0.0000***	0.1537***	0.8447***	2731.232
ECO	0.0008	0.0000***	0.0946***	0.9001***	2343.399
GRNBIO	0.0007	0.0000***	0.1364***	0.8268***	2380.133
GRNFUEL	0.0008	0.0000**	0.0647***	0.9309***	1861.709
GRNREG	0.0007**	0.0000**	0.1562***	0.8391***	3005.217
GRNGEO	0.0006	0.0000***	0.3488***	0.6854***	2368.953
GRNSOLAR	0.0010	0.0000***	0.1018***	0.8599***	2215.170
GRNWIND	0.0010**	0.0000*	0.0972***	0.8646***	2617.024
DCRYPT	0.0015	0.0003***	0.1343***	0.7439***	1505.958
CCRYPT	-0.0024	0.0004***	0.1942***	0.7526***	1230.797
SP500	0.0011***	0.0000***	0.2907***	0.6967***	3027.870
Gold	0.0001	0.0000**	0.0631***	0.9271***	3136.461

Note:
1. Volatility clustering are captured as the coefficients α and β for all series are significantly positive and their sum are closed to one.
2 . ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

APPENDIX F

Return spillovers analysis using TVP-VAR

Table F.1: Average dynamic total return connectedness using TVP-VAR

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
Gold	67.33	2.79	4.27	3.32	3.72	1.46	1.88	4.96	3	3.57	2.39	1.31	32.67
SP500	1.16	25.69	10.17	13.18	8.64	5.09	5.14	11.64	12.67	3.74	1.56	1.32	74.31
SPGTCED	1.28	9.07	21.99	15.23	7.3	6.92	4.79	13.17	10.59	7.44	1.19	1.03	78.01
ECO	0.91	11.46	14.78	21.98	8.23	9.36	4.59	9.81	13.5	3.33	0.96	1.08	78.02
GRNBIO	1.71	10.75	10.51	12.2	33.34	5	3.77	7.89	9.01	3.12	1.46	1.24	66.66
GRNFUEL	0.7	7.24	10.92	15.35	5.59	36.99	2.75	7.26	7.53	3.4	1.12	1.17	63.01
GRNGEO	1.29	8.06	9.2	8.62	5.05	3.27	44.21	8.55	5.89	3.32	1.48	1.06	55.79
GRNREG	1.75	10.43	13.72	10.38	5.74	4.86	4.64	22.92	11.64	11.35	1.43	1.13	77.08
GRNSOLAR	1.09	12.47	11.95	15.31	7.01	5.23	3.82	12.7	24.87	3.31	1.14	1.08	75.13
GRNWIND	1.76	5.91	13.05	6.51	3.8	4.22	3.14	18.28	4.98	36.3	1.17	0.87	63.7
DCRYPT	1.74	2.76	2.49	2.02	2.45	1.42	1.88	3.03	2.23	1.36	50.21	28.43	49.79
CCRYPT	1	2.54	2.23	2.51	2.44	1.74	1.28	2.41	2.13	0.81	29.06	51.86	48.14
TO others	14.39	83.49	103.31	104.62	59.96	48.56	37.68	99.71	83.17	44.75	42.95	39.73	762.32
Inc. own	81.73	109.18	125.29	126.61	93.3	85.55	81.89	122.62	108.03	81.05	93.16	91.59	TOTAL
NET	-18.27	9.18	25.29	26.61	-6.7	-14.45	-18.11	22.62	8.03	-18.95	-6.84	-8.41	63.53

Figure F.1: Dynamic total return connectedness (TVP-VAR)

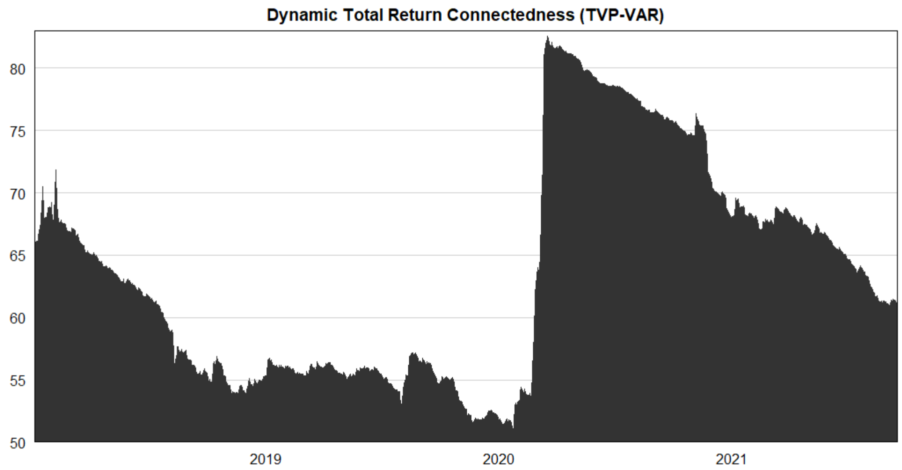


Figure F.2: Dynamic directional return connectedness FROM others (TVP-VAR)

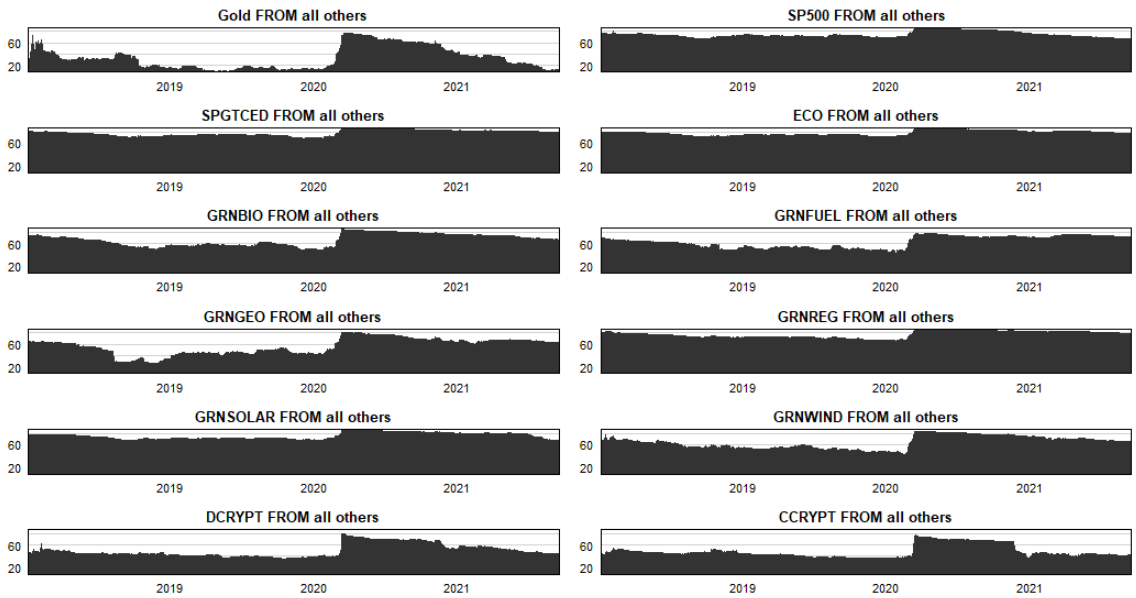


Figure F.3: Dynamic directional return connectedness TO others (TVP-VAR)

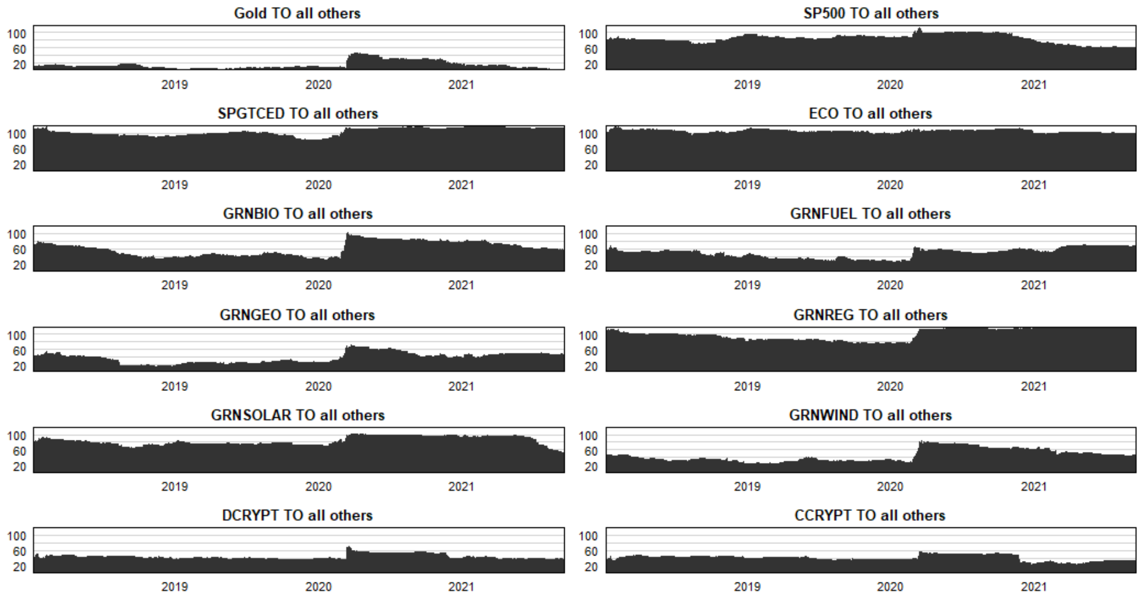


Figure F.4: Total net return connectedness (TVP-VAR)

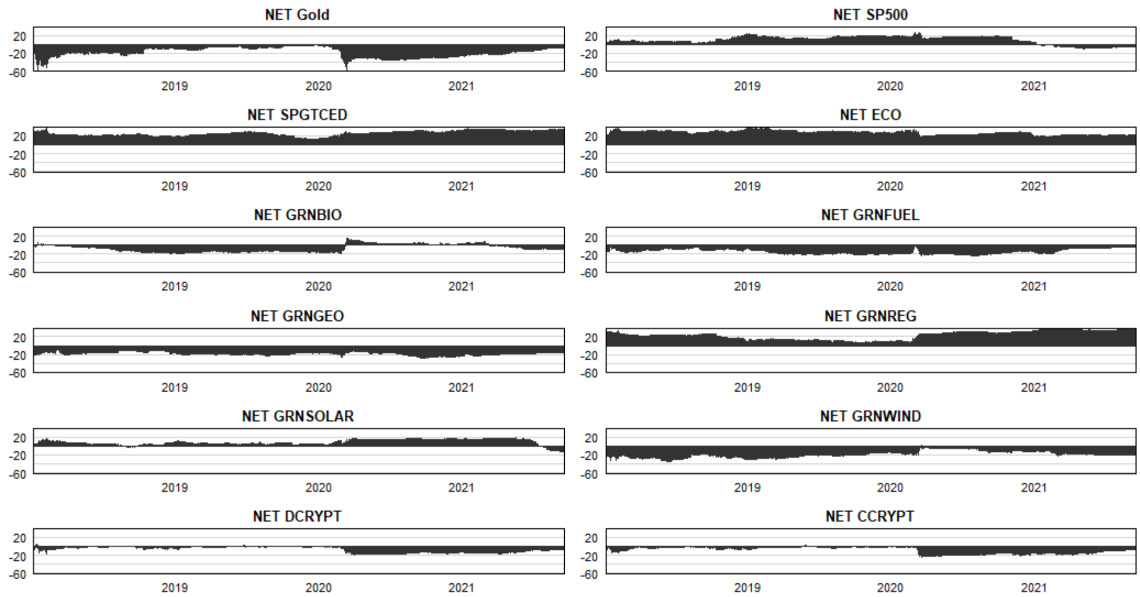


Figure F.5: Net pairwise directional return connectedness for DCRYPT (TVP-VAR)

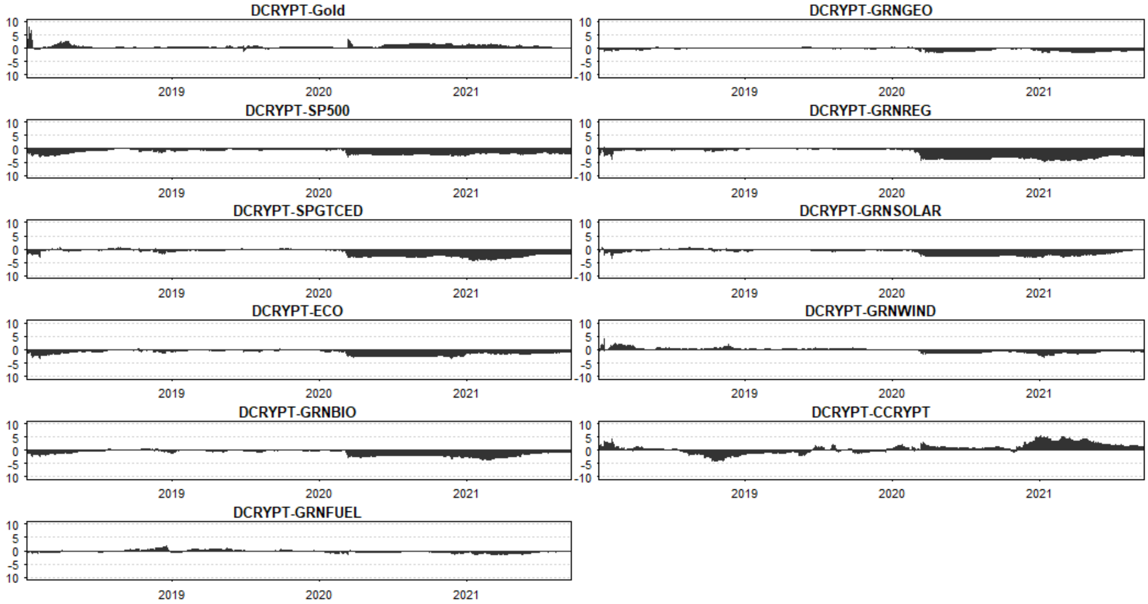
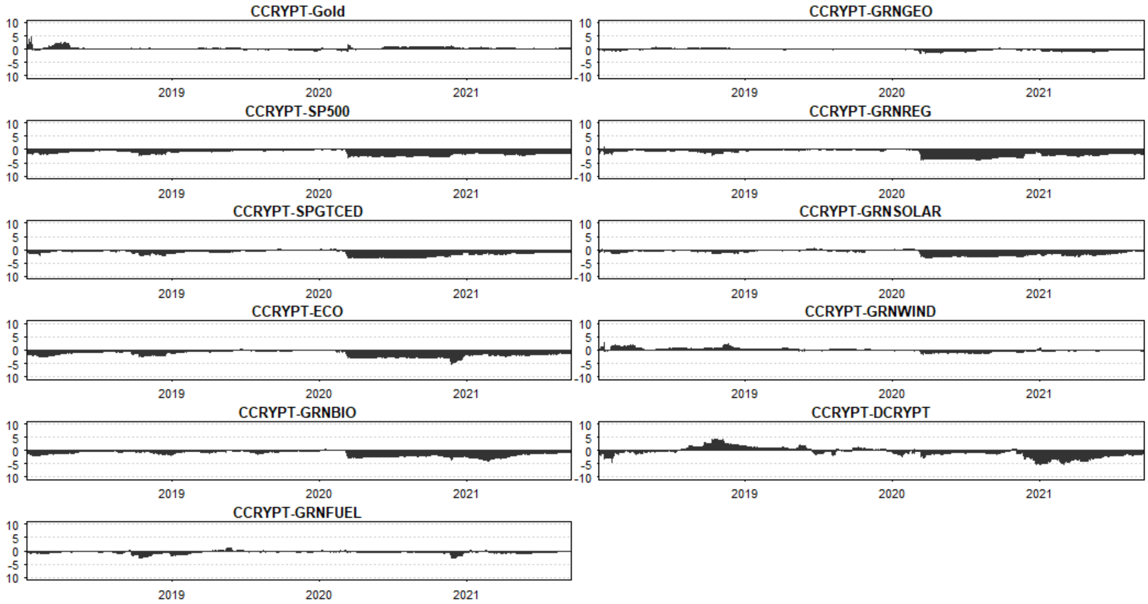


Figure F.6: Net pairwise directional return connectedness for CCRYPT (TVP-VAR)



APPENDIX G

VOLATILITY SPILLOVERS ANALYSIS USING TVP-VAR

Table G.1: Average dynamic total volatility connectedness using TVP-VAR

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	35.43	4.21	9.7	10.1	6.18	5.5	2.95	9.13	6.86	6.05	1.92	1.96	64.57
SP500	3.49	25.84	10.81	9.49	11.11	4.57	3.14	13.17	9.48	5.7	2.35	0.87	74.16
SPGTCED	4.78	7.54	18.39	14.03	10.05	7.37	4.82	12.94	10.39	6.87	1.66	1.14	81.61
ECO	4.95	7.97	14.75	17.72	10.6	7.95	4.27	11.47	10.73	6.45	1.74	1.39	82.28
GRNBIO	4.38	10.38	11.74	10.95	21.48	4.53	5.08	12.2	8.78	6.08	2.75	1.66	78.52
GRNFUEL	3.96	4.32	12.98	12.32	6.51	33.73	4.72	8.5	5.33	6.1	0.7	0.84	66.27
GRNGEO	4.23	6.53	11.26	9.87	8.33	4.49	30.87	8.78	6.81	5.86	1.48	1.48	69.13
GRNREG	4.36	9.11	13.96	11.06	9.38	6.72	3.97	18.27	10.01	8.74	2.86	1.56	81.73
GRNSOLAR	4.41	9.38	13.03	12.99	9.72	5.13	3.45	13.23	18.36	6.11	2.64	1.55	81.64
GRNWIND	4.05	4.63	12.9	10.56	7.09	6.75	4.62	15.25	7.63	21.05	3.18	2.29	78.95
DCRYPT	2.51	3.65	3.74	3.56	4.73	1.47	1.07	6.77	4.05	5.2	45.79	17.46	54.21
CCRYPT	1.36	1.66	3.21	3.82	3.04	2.47	1.4	4.6	2.48	2.76	17.92	55.27	44.73
TO OTHERS	42.48	69.4	118.08	108.74	86.74	56.95	39.48	116.05	82.54	65.91	39.22	32.2	857.79
Inc. OWN	77.91	95.24	136.47	126.46	108.22	90.68	70.35	134.32	100.91	86.96	85	87.47	TOTAL
NET	-22.09	-4.76	36.47	26.46	8.22	-9.32	-29.65	34.32	0.91	-13.04	-15	-12.53	71.48

Figure G.1: Dynamic total volatility connectedness (TVP-VAR)

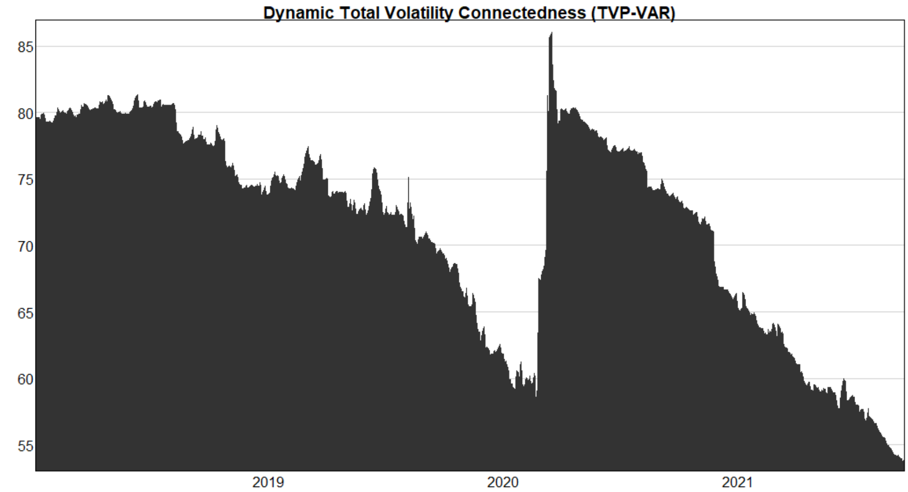


Figure G.2: Dynamic directional volatility connectedness FROM others (TVP-VAR)

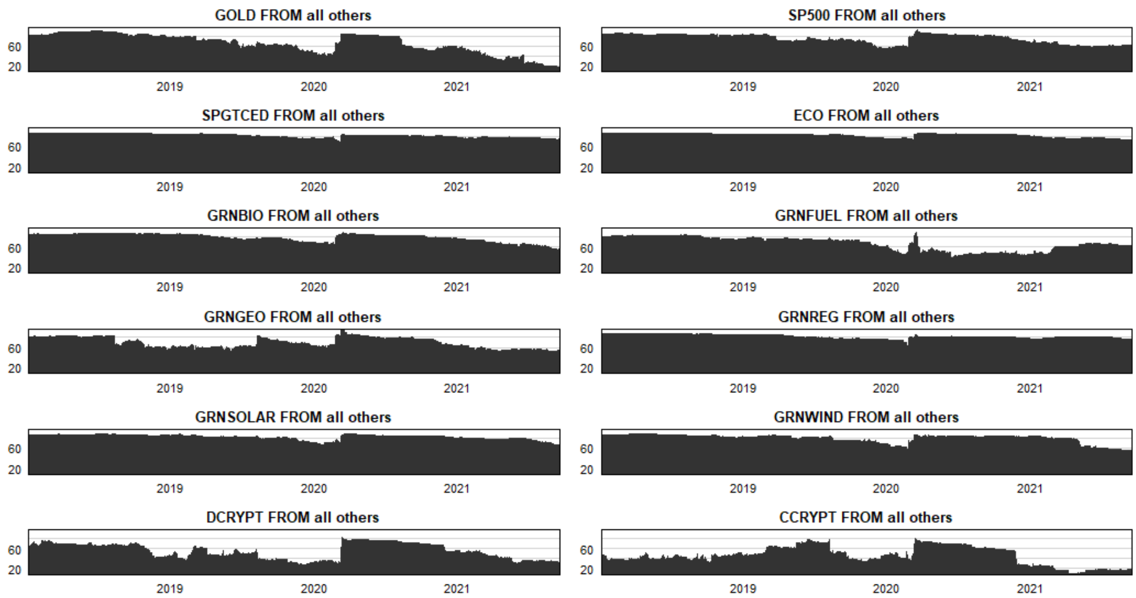


Figure G.3: Dynamic directional volatility connectedness TO others (TVP-VAR)

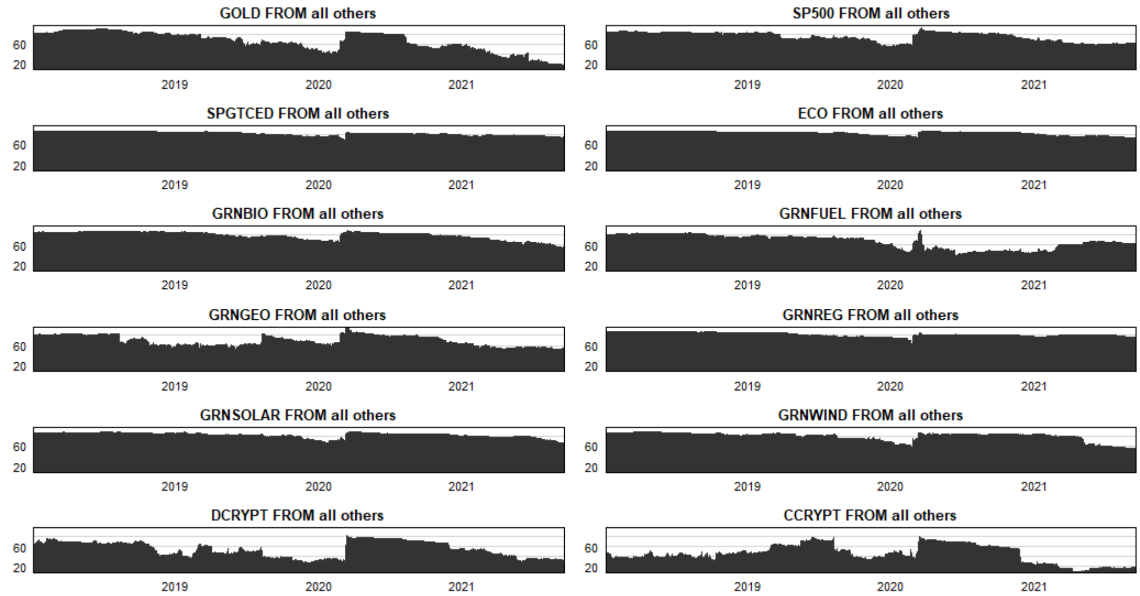


Figure G.4: Total net volatility connectedness (TVP-VAR)

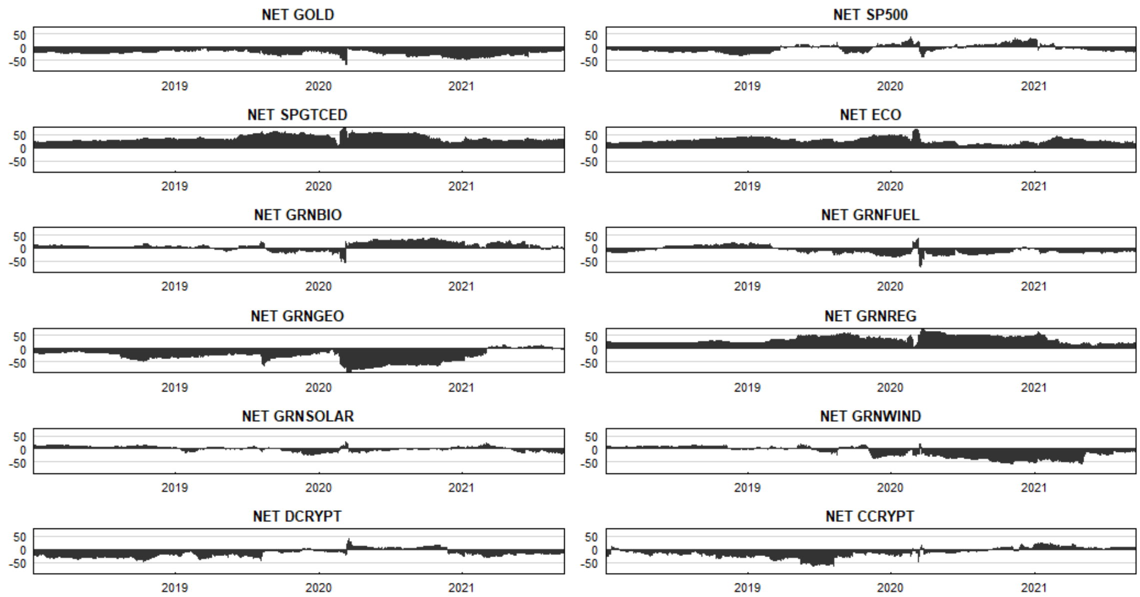


Figure G.5: Net pairwise directional volatility connectedness for DCRYPT (TVP-VAR)

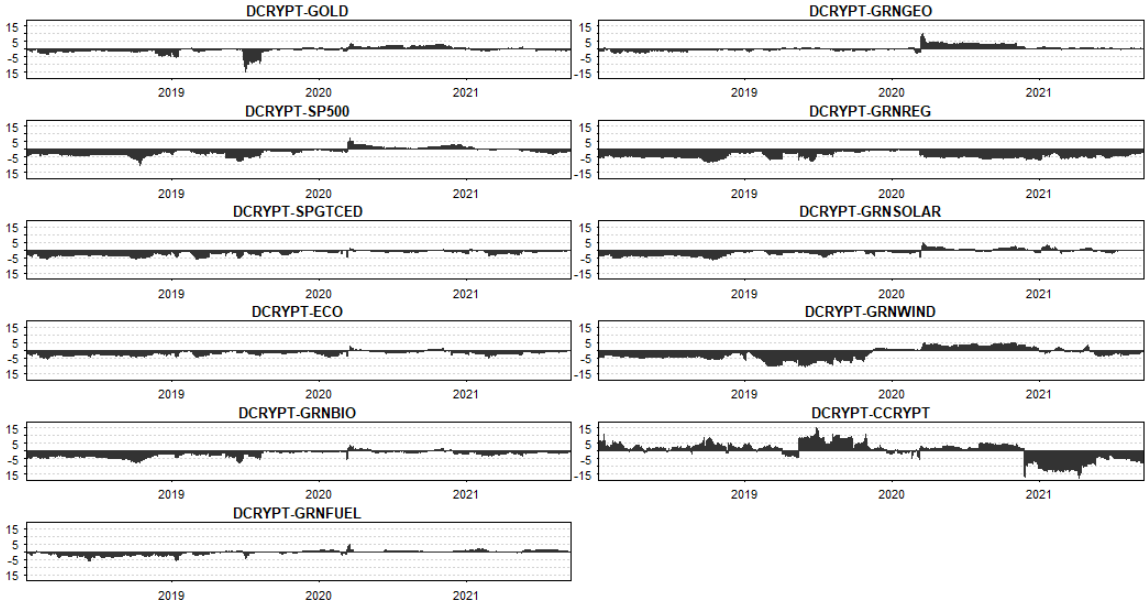
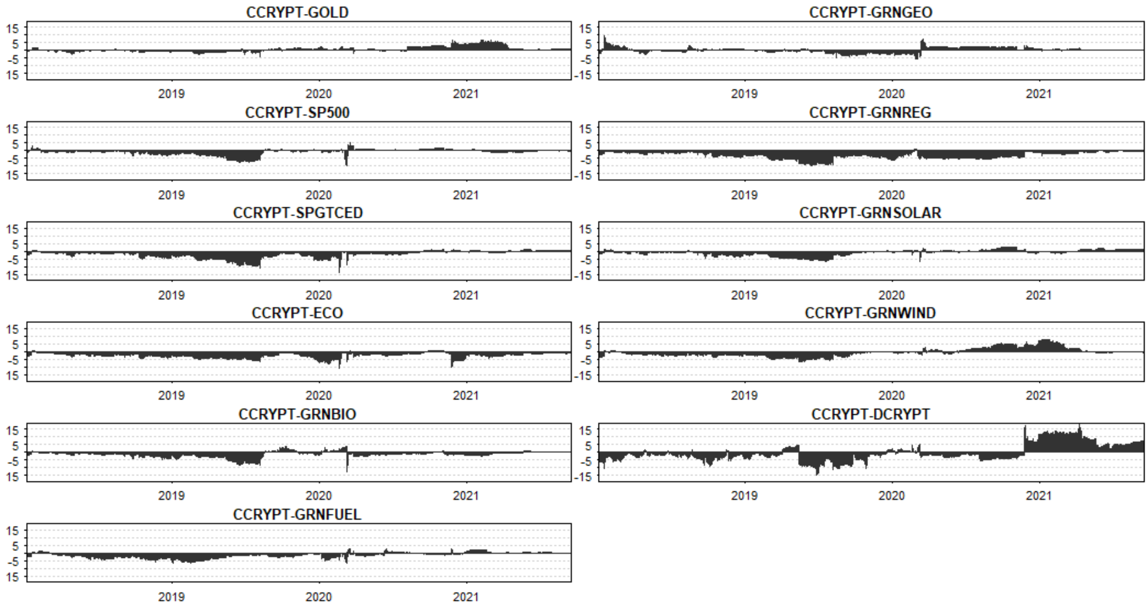


Figure G.6: Net pairwise directional volatility connectedness for CCRYPT (TVP-VAR)



CHAPTER 3

An Examination of Herding in Emerging Assets

3.1 Herd Behaviour in Cryptocurrencies

3.1.1 Introduction

It has only been 14 years since the birth of Bitcoin, the first decentralised virtual currency, and as of the time of writing (November 2022), there are more than 20,000 kinds of crypto products in circulation, and the total market capitalisation is worth more than 800 billion U.S. Dollar [1]. These disruptive currencies are built on innovative block-chain technology and most of them support numerous fascinating applications such as smart contracts, file storage and secure transactions, among others.

Investing in cryptocurrencies can be extremely rewarding, and this is one of the most attractive features to investors. Taking Bitcoin as an example, it had once reached a peak price of over 64,000 USD in 2021 from literally nearly zero face value when it was launched. Such high value of this type of assets brings extremely volatile nature in return as we see the current price of Bitcoin went back down to around 17,050 USD. The high uncertainty in the cryptocurrency market always raises concerns about price bubbles and necessitates more sophisticated trading skills. In this overall context, investors are very likely to react differently if they

[1] Obtained from CoinMarketCap at `https://www.coinmarketcap.com` on Nov 30, 2022.

trade with their own beliefs, according to rational asset pricing models. However, similar to many other financial markets, the presence of herd trading in the crypto market can still be reasonably expected. This refers to investors who tend to follow the actions or mimic the trading decisions of others, which can be either completely irrational or somewhat rational [Bikhchandani and Sharma (2001)].

Past studies treat all cryptocurrencies as the same, but these assets are intrinsically actually different, especially from a sustainability perspective [Corbet et al. (2021), Gallersdörfer et al. (2020)]. The energy consumption of activities related to conventional cryptocurrencies that use Proof-of-Work (PoW) as underlying consensus, such as Bitcoin and Ethereum, is huge and has attracted much negative commentary [2]. Gallersdörfer et al. (2020) estimated the energy consumption of top 20 Proof-of-Work (PoW) based cryptocurrencies beyond Bitcoin. Even by modelling in a conservative way, their estimates of these cryptos are all exceptionally high. Both Corbet et al. (2021) and Gallersdörfer et al. (2020) suggested that future regulators and practitioners should distinguish between cryptocurrencies that are built on energy-intensive or energy-efficient algorithms. In fact, there exist a number of energy-efficient cryptocurrencies at present, such as Cardano, Ripple, and IOTA which have or had been the top 10 cryptocurrencies by market capitalisation and with more being developed. The estimated energy consumption of Cardano, XRP, IOTA is 0.5479, 0.0079, and 0.00011 KWh per transaction, respectively, significantly lower compared to that of Bitcoin—707 KWh per transaction [3]. With policy globally leaning towards greater environmentally conscious actions, more environmentally conscious investors are perhaps likely to switch from energy-intensive cryptocurrencies to altcoins that are more sustainable.

In this study, we attempt to discover market dynamics of two distinct types of cryptocurrencies based on their fundamental difference in energy consumption and efficiency, termed black ("dirty") and green ("clean"), from a narrow perspective—herding – to establish if there are different patterns. This adds to the behavioural finance literature on cryptocurrency market from a novel angle. If clean cryptocurrencies display different market characteristics from dirty ones, it shows different market efficiency and manipulation level, and this might provide opportunities for investors or regulators to consider usage level of cleaner cryptocurrencies. If the two markets display similar dynamics then, given the larger size of the dirty

[2] https://digiconomist.net/bitcoin-energy-consumption and https://digiconomist.net/ethereum-energy-consumption.

[3] https://www.trgdatacenters.com/most-environment-friendly-cryptocurrencies.

market it is likely that the still predominantly and at least retail crypto investors will, at the margin, prefer trading dirty cryptocurrencies.

The remainder of this paper is structured as follows. We review some past literature in Section 3.1.2. We describe the methodology and data in Section 3.1.3 and 3.1.4, respectively. We discuss the results in Section 3.1.5, followed by Section 3.1.6 where we check the robustness of previous results. Finally, we conclude and address implications of our study in Section 3.1.7.

3.1.2 Literature Review

A number of papers have investigated the presence of herd behaviour in the cryptocurrency market as well as its possible driving forces. Poyser (2018) is the first study analysing herd behaviour in cryptocurrency market. They examined the largest 100 cryptocurrencies by market capitalisation using static regression model and Markov-switching model. Their results suggest that the herding in cryptocurrencies depends on market states. Bouri et al. (2019) examined the herding phenomenon among 14 leading cryptocurrencies using both static and rolling window regression models. Their follow-up analysis suggest that herding in the market is time-changing. Youssef (2020) also investigated the presence of the time-varying behaviour. They discovered several factors that might affect the magnitude of herding, including the crypto-market volatility and trading volume, the U.S. stock index price return, the strength of the U.S. dollar, gold price, and the economic policy uncertainty. Amirat and Alwafi (2020) studied the behaviour of 20 largest cryptocurrencies with the use of a MarketVector Index Solution (MVIS) CryptoCompare Digital Assets 100 Index as a proxy for the crypto market. Their results showed that herding is time-varying, and that consumer comfort among the Americans might be related to the phenomenon.

Current empirical results are not always consistent due to differences in constructing the market portfolio, assets under investigation and time frames. For example, Vidal-Tomás et al. (2019) discovered the existence of herding in cryptocurrency market downturns from 2015 to 2017 using 65 cryptocurrencies. However, their results of using equal-weighted portfolio are not consistent to value-weighted approach until they excluded the largest cryptocurrency—Bitcoin. Similarly, Kallinterakis and Wang (2019) found significant herding of top 296 cryptocurrencies from December 2013 to July 2018 using equal-weighted portfolio, but the herding was insignificant and vanished after using value-weighted portfolio with and without Bitcoin, respectively. Stavroyiannis and Babalos (2019), on the other hand, believed that herding did not exist in the cryptocurrency market using a time-varying parameter regression model. Moreover, while Bouri et al. (2019) suggested economic policy uncertainty might lead to such behaviour, Youssef (2020) argued that economic policy uncertainty reduced the herding intensity.

3.1.3 Methodology

We tested the existence of herd behaviour in the clean and dirty cryptocurrency markets using both cross-sectional standard deviation of returns (CSSD) approach introduced in Christie and Huang (1995) and the cross-sectional absolute deviation of returns (CSAD) approach proposed in Chang et al. (2000).

Christie and Huang (1995) suggested that the degree of the dispersion of asset returns in a market portfolio can be used to detect whether herding exists in that market, which is calculated as:

$$CSSD_{m,t} = \sqrt{\frac{\sum_{i=1}^{N}\left(r_{i,t} - r_{m,t}\right)^2}{N-1}}, \tag{3.1}$$

where N is the number of cryptocurrencies in the clean or dirty crypto portfolio, $R_{i,t}$ is the logarithmic return of individual cryptocurrency i in the respective portfolio at time t, $R_{m,t}$ is the portfolio return, representing the market return, at time t.

As suggested by Christie and Huang (1995), herd effects in the market usually lead to low return dispersions of returns as returns are clustering, but low return dispersions are not necessarily attributable to herding. Hence, it is hard to verify the presence of herds with the use of the return dispersion (CSSD) during normal market, but it is reasonable to test the presence of herding under market stress as rational investors should be sensitive to outliers and react differently to the market condition, causing the dispersion to increase. In other words, herding should exist if low dispersion presents during extreme market movements. We followed Christie and Huang (1995) to examine the herd effects by testing the level of dispersions in extreme tails of return distribution:

$$CSSD_{m,t} = \alpha_0 + \alpha_1 D_{m,t}^{UT} + \alpha_2 D_{m,t}^{LT} + \epsilon_t, \tag{3.2}$$

where $D_{m,t}^{UT}$ and $D_{m,t}^{UT}$ are dummy variables with values of 1 if the market return at time t is in the upper or lower tails and 0 otherwise. A significantly negative coefficient α_1 or α_2 indicates the presence of herding during extreme up or down market condition, respectively.

The CSSD approach has drawbacks. For example, it has been criticised being too sensitive to outliers as it squares the difference between individual and market returns when calculating the dispersions. More importantly, and it has limited use in less extreme cases. To improve these, Chang et al. (2000) proposed a alternative metrics called the cross-sectional absolute deviation of returns to measure the dispersions, expressed as:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N} \left| r_{i,t} - r_{m,t} \right|}{N}, \tag{3.3}$$

A general quadratic regression of $CSAD_{m,t}$ on market returns was then built to discover the presence of herding behaviour in the full sample:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \epsilon_t, \tag{3.4}$$

As suggested by Chang et al. (2000), herd effects would lead to a non-linear relationship between $CSAD_{m,t}$ and the $R_{m,t}$ as the linear relationship predicted by the rational pricing model will no longer hold, which is inferred by a significantly negative coefficient γ_2.

Moreover, it is reasonable to assume that investors may react differently to upward and downward trends, so we divided the market into up and and down states to investigate the potential asymmetric herding behaviour in two market conditions following Chang et al. (2000):

$$CSAD_{m,t}^{UP} = \gamma_0 + \gamma_1 \left| R_{m,t}^{UP} \right| + \gamma_2 \left(R_{m,t}^{UP} \right)^2 + \epsilon_t, \tag{3.5}$$

$$CSAD_{m,t}^{DOWN} = \gamma_0 + \gamma_1 \left| R_{m,t}^{DOWN} \right| + \gamma_2 \left(R_{m,t}^{DOWN} \right)^2 + \epsilon_t, \tag{3.6}$$

where $\left| R_{m,t}^{UP} \right|$ and $\left| R_{m,t}^{DOWN} \right|$ are positive and negative market returns, respectively.

Since the dirty cryptocurrencies have been dominating the market for years especially Bitcoin and Ethereum which share much larger market capitalisation and greater attention than other folks and any clean cryptocurrencies, we further tested the possibility that clean cryptocurrency investors may tend to follow the dynamics of the dirty cryptocurrency market (γ_4) rather than their own (γ_2):

$$CSAD_{c,t} = \gamma_0 + \gamma_1 \left| R_{c,t} \right| + \gamma_2 R_{c,t}^2 + \gamma_3 CSAD_{d,t} + \gamma_4 R_{d,t}^2 \epsilon_t, \tag{3.7}$$

where subscription c refers to clean cryptocurrencies, while d is for dirty ones.

Additionally, similar to the methodology used in single market analysis, we tested the above relationship under asymmetric market conditions. For example, Equation 3.8 and 3.9 allow us to examine whether clean cryptocurrencies asymmetrically herd with the dirty cryptocurrencies (γ_4 and γ_5), and whether this is conditioned on the market status of dirty crypto market ($R_{d,t}^{UP}$ and $R_{d,t}^{DOWN}$).

$$\begin{aligned} CSAD_{c,t}^{UP} = {} & \gamma_0 + \gamma_1 \left| R_{c,t}^{UP} \right| + \gamma_2 (R_{c,t}^{UP})^2 + \gamma_3 CSAD_{d,t} + \gamma_4 D_c^{UP} (R_{d,t}^{UP})^2 \\ & + \gamma_5 D_c^{UP} (R_{d,t}^{DOWN})^2 + \epsilon_t \end{aligned} \tag{3.8}$$

$$\begin{aligned} CSAD_{c,t}^{DOWN} = {} & \gamma_0 + \gamma_1 \left| R_{c,t}^{DOWN} \right| + \gamma_2 (R_{c,t}^{DOWN})^2 + \gamma_3 CSAD_{d,t} \\ & + \gamma_4 D_c^{DOWN} (R_{d,t}^{UP})^2 + \gamma_5 D_c^{DOWN} (R_{d,t}^{DOWN})^2 + \epsilon_t \end{aligned} \tag{3.9}$$

where dummy variables $D_{c,t}^{UP}$ and $D_{c,t}^{DOWN}$ are equal to 1 when clean crypto market return at t is positive or negative, respectively.

3.1.4 Data

We manually collected daily closing price data for 6 major "dirty" (Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, Litcoin, and Monera) [4] and 12 "clean" cryptocurrencies (Cardano, Ripple, Polygon, Algorand, Stellar, VeChain, TRON, Cosmos, Hedera, Tezos, EOS, and IOTA) [5] ranked in the top 50 by market capitalisation

[4] Dogecoin was not selected because: 1. Dogecoin was originally created as a meme coin without other uses; 2. its energy consumption is debated as Dogecoin can be mined in parallel with other coins such as Litecoin without using additional power, which makes it actual energy consumption hard to define and estimate; 3. it has been clearly, highly and temporarily influenced/boosted by Musk's social media comments, which will distract the results of the other cryptocurrencies.

[5] The "clean" cryptos are selected based on the market capitalisation status as well as recent media attention. We first screened the most frequently discussed energy-efficient cryptos on the internet, examples are on `https://www.leafscore.com/blog/the-9-most-sustainable-cryptocurrencies-for-2021/` (retrieved in November of 2021), `https://finance.yahoo.com/news/15-environmentally-sustainable-cryptocurrencies-invest-224849569.html`, `https://www.thetimes.co.uk/money-mentor/article/eco-friendly-cryptocurrencies/`, etc. Second, we excluded cryptos that were not in top 50 or did not have a full two-year data when we conducted the analysis. In this process, Solana, Polkadot, Avalanche, Chia, and some others were not considered as they came to the market much later. Binance Coin was not selected as it shares a completely different nature as a derivative of the Binance Exchange, historically built on Ethereum blockchain, and began to support its own staking in 2020. IOTA was the last pick and the smallest player which ranked 48^{th} when we conducted this analysis. However, it ranked as 18^{th} largest cryptocurrency as of November 3, 2019.

[6] from CoinMarketCap, spanning from 1 November 2019 to 1 November 2021 [7]. Similar to the definition in the last chapter, the dirty cryptocurrencies are so termed based on their reliance on PoW algorithms for consensus which requires tremendous energy inflows to support mining and transaction activities, while clean cryptocurrencies are built on different kinds of energy-efficient consensus algorithms, including Proof-of-Stake (PoS), Proof-of-Authority (PoA), Ripple Protocol, Stellar Protocol, and some other alternatives. We calculated the respective value-weighted portfolio returns based on end of day market capitalisation of these assets.

3.1.5 Results

Table 3.1 reports the estimation results of herding using the CSSD approach using 5% extreme tails [8]. The α_1 and α_2 for both clean and dirty crypto portfolios are significantly positive, which indeed indicates that no herfing effect is found during the periods of extreme market movements in either of markets.

Table 3.1: Regression results of $CSSD_{m,t}$ on dummy variables of value-weighted average market return extremes

Market	α_0	α_1	α_2
	0.0427***	0.0478***	0.0210***
Clean crypto	(0.0000)	(0.0000)	(0.0000)
	0.0251***	0.0168***	0.0247***
Dirty crypto	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Equation 3.2.
2. *** denotes the rejection of the null hypothesis at the 1% significance level.

From the CSAD approach we obtained opposite results to those in the CSSD approach with respect to different types of cryptocurrencies as shown in Table 3.2. Specifically, herding behaviour only exists in the dirty cryptocurrency market, captured by a significantly negative coefficient of the $R^2_{m,t}$ term (-0.3048***).

[6] On 5 November 2021 when we retrieved the data.

[7] As we define "dirty" and "clean" cryptocurrencies based on their energy consumption, we prefer using coins than tokens as tokens using others' blockchain technology are not that comparable to coins such as Bitcoin on energy issues. We excluded stablecoins also because their volatilities are slight on a daily basis.

[8] Our results remain robust for 1% and 10% extreme tails, albeit the 1% sample is small. All results are available upon request.

Table 3.2: Regression results of $CSAD_{m,t}$ on unconditional value-weighted average market returns

Market	γ_0	γ_1	γ_2
Clean crypto	0.0228***	0.2160***	0.3641***
	(0.0000)	(0.0000)	(0.0009)
Dirty crypto	0.0124***	0.2598***	**-0.3048*****
	(0.0000)	(0.0000)	(0.0017)

Notes:
1. Equation 3.4 was used;
2. *** denotes the rejection of the null hypothesis at the 1% significance level.

Results from Table 3.3 confirms that the degree of herding varies from market conditions. Herding behaviour in dirty cryptocurrency market only presents in down markets as only the coefficient of $\left(R_{m,t}^{DOWN}\right)^2$ is significantly negative (-0.4350***). No evidence of herding is found in either rising and falling clean cryptocurrency markets as γ_2s are significantly positive, which is consistent with the previous results with the use of a generalised formula.

Table 3.3: Regression results of $CSAD_{m,t}$ on asymmetric value-weighted average market returns

Market	γ_0	γ_1	γ_2
Panel A: Positive market returns			
Clean crypto	0.0237***	0.2158***	0.9890***
	(0.0000)	(0.0000)	(0.0004)
Dirty crypto	0.0147***	0.0981*	0.9925*
	(0.0000)	0.0975	(0.0587)
Panel B: Negative market returns			
Clean crypto	0.0248***	0.0476	0.6666***
	(0.0000)	(0.1880)	(0.0000)
Dirty crypto	0.0117***	0.3141***	**-0.4350*****
	(0.0000)	(0.0000)	(0.0010)

Notes:
1. Equation 3.5 and 3.6 were used in Panel A and B, respectively;
2. *** and * denote the rejections of the null hypothesis at the 1% and 10% significance levels, respectively.

So far, evidence indicates that there are herds in dirty cryptocurrencies, but not in clean cryptocurrencies. However, interestingly, we found that the performance in dirty cryptocurrency market does affect investors' behaviour in clean cryptocurrency market. As presented in the Panel A of Table 3.4, although investors do not herd in clean cryptocurrencies as γ_2 is significantly positive (0.6927***), they herd with information provided in price movements of dirty cryptocurrency, captured by a negative and statistically significant coefficient γ_4 (-0.3852***). Specifically, if we look at the Panel B and C, we find that clean cryptocurrency investors only herd towards dirty crypto market when both markets are positively rewarded as only coefficient γ_4 in the Equation 3.8 is significantly negative (-1.6619***). We cannot conclude that clean crypto investors herd with the dirty crypto market when both markets are falling as γ_5 in the Equation 3.9 is negative but not statistically significant. Nevertheless, it can be observed that when the two markets diverge, the behaviour of clean crypto investors is more likely to be driven by the performance of dirty cryptocurrencies as the values of γ_5 (7.4689***) and γ_4 (3.2001**) are much larger than those of γ_2 (0.7762*** and 0.7358***) in Panel B and C, respectively.

Table 3.4: Regression results of $CSAD_{c,t}$ on unconditional and asymmetric value-weighted market returns

Market	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
Panel A: Unconditional market returns						
Clean crypto	0.0231***	0.1770***	0.6927***	0.0417	**-0.3852*****	
	(0.0000)	(0.0000)	(0.0000)	(0.3290)	(0.0001)	
Panel B: Positive market returns						
Clean crypto	0.0202***	0.2849***	0.7762***	0.1801***	**-1.6619*****	7.4689***
	(0.0000)	(0.0000)	(0.0032)	(0.0009)	(0.0000)	(0.0001)
Panel C: Negative market returns						
Clean crypto	0.0240***	0.0412	0.7358***	0.0255	3.2001**	-0.0852
	(0.0000)	(0.2919)	(0.0000)	(0.6831)	(0.0189)	(0.4389)

Notes:
1. Equation 3.7, 3.8, and 3.9 were used in Panel A, B and C, respectively;
2. *** and ** denote the rejections of the null hypothesis at the 1% and 5% significance levels, respectively.

3.1.6 Robustness check

We have shown a difference in herding patterns in dirty and clean cryptocurrency markets, taking into account the size effect [Kallinterakis and Wang (2019); Vidal-Tomás et al. (2019)] by using value-weighted portfolios . However, emphasizing weights on large participants may diminish the effects of noisy movements created by small ones. To ensure that our results are robust, we re-performed tests using equal-weighted portfolios of dirty and clean cryptocurrencies.

For the clean crypto market, results are consistent with previous findings when we employed the CSSD approach (Table 3.5). When we applied the CSAD approach, results became slightly different. Specifically, the γ_2 for clean cryptocurrency becomes negative (-0.1007) but not statistically significant (see Table 3.6). Such change results probably because the relation between $CSAD_{c,t}^{UP}$ and $R_{c,t}^{UP})^2$ is no longer significantly positive but insignificantly negative (-0.2259). Another minor difference is that the γ_2 and γ_4 in the Panel C of Table 3.8 are not statistically significant anymore.

Moreover, the signs of γ_2 and γ_5 are changed, which indicates the dispersions of clean crypto returns are affected by dirty crypto price movements which however makes sense as we have weakened the influence of larger participants on market returns. Regarding dirty crypto market, results are same.

Overall, we can draw the same conclusions in regard to herding regardless of using either equal-weighted or value-weighted portfolios as our market proxy.

Table 3.5: Regression results of $CSSD_{m,t}$ on dummy variables of equal-weighted average market return extremes

Market	α_0	α_1	α_2
Clean crypto	0.0395*** (0.0000)	0.0429*** (0.0000)	0.0228*** (0.0000)
Dirty crypto	0.0200*** (0.0000)	0.0302*** (0.0000)	0.0143*** (0.0000)

Notes:
1. Equation 3.2 was used.
2. *** denotes the rejection of the null hypothesis at the 1% significance level.

Table 3.6: Regression results of $CSAD_{m,t}$ on unconditional equal-weighted average market returns

Market	γ_0	γ_1	γ_2
	0.0219***	0.2344***	-0.1007
Clean crypto	(0.0000)	(0.0000)	(0.1990)
	0.0091***	0.2496***	**-0.2761*****
Dirty crypto	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Equation 3.4 was used;
2. *** denotes the rejection of the null hypothesis at the 1% significance level.

Table 3.7: Regression results of $CSAD_{m,t}$ on asymmetric equal-weighted average market returns

Market	γ_0	γ_1	γ_2
Panel A: Positive market returns			
	0.0212***	0.3341***	-0.2259
Clean crypto	(0.0000)	(0.0000)	(0.6210)
	0.0107***	0.1822***	0.8053**
Dirty crypto	(0.0000)	0.0002	(0.0137)
Panel B: Negative market returns			
	0.0219***	0.1269***	0.1354*
Clean crypto	(0.0000)	(0.0000)	(0.0946)
	0.0094***	0.1720***	**-0.1387****
Dirty crypto	(0.0000)	(0.0000)	(0.0140)

Notes:
1. Equation 3.5 and 3.6 were used in Panel A and B, respectively;
2. ***, ** and * denote the rejections of the null hypothesis at the 1% 5%, and 10% significance levels, respectively.

Table 3.8: Regression results of $CSAD_{c,t}$ on unconditional and asymmetric equal-weighted market returns

Market	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
Panel A: Unconditional market returns						
	0.0200***	0.1598***	0.8967***	0.2419***	-0.8952***	
Clean crypto	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	
Panel B: Positive market returns						
	0.0161***	0.2707***	1.2907**	0.4120***	-1.9123***	14.4398***
Clean crypto	(0.0000)	(0.0000)	(0.0102)	(0.0000)	(0.0000)	(0.0000)
Panel C: Negative market returns						
	0.0208***	0.1234***	-0.0319	0.0689	2.2970	0.1604
Clean crypto	(0.0000)	(0.0003)	(0.9196)	(0.3504)	(0.2118)	(0.5752)

Notes:
1. Equation 3.7, 3.8, and 3.9 were used in Panel A, B and C, respectively;
2. *** and ** denote the rejections of the null hypothesis at the 1% and 5% significance levels, respectively.

3.1.7 Conclusion

The environmental sustainability of cryptocurrencies is a subject of significant debate. We distinguished cryptocurrencies by their estimated energy consumption and analysed the market dynamics of both non-sustainable cryptocurrencies such as Bitcoin, Ethereum, Monera, etc and more sustainable cryptocurrencies including Cardano, Ripple, Stellar, etc, from the angle of herding. We found compelling evidence of herd behaviour in dirty cryptocurrencies following the approaches of Chang et al. (2000), which is asymmetric and more pronounced in down than in up markets. More interestingly, although we did not find herds present in clean crypto market themselves, we did find that clean crypto investors herd to dirty crypto markets, especially when both markets are positive. In other words, investors in clean cryptocurrencies tend to follow the actions of dirty crypto investors in up markets, even as the set of clean cryptocurrencies is expanding and a significant number of the most valuable cryptocurrencies are clean coins. These results are robust across value- and equal-weighted portfolios. Overall, findings suggest that policy efforts to shift investors towards cleaner cryptocurrencies may founder for so long as dirty cryptocurrencies remain dominant in size and salience.

3.2 Herd Behaviour in Chinese Renewable Energy Stocks

3.2.1 Introduction

Climate change is one of the greatest challenges nowadays, which has been threatening and disrupting the lives of humans and other creatures. Easing carbon emissions by reducing the use of fossil based energy is an effective approach to slowing down the global warming. Renewable energy sources as substitutes for fossil energy have received increasing policy support in the development because of its substantial benefits to the environment. Over the last twenty years, we have seen a booming growth in renewable energy usage. Even during the COVID-19 outbreaks, global adoption and market growth of renewable energy has been resilient and has continued to peak higher [Hannah Ritchie and Rosado (2020)]. As introduced in previous chapter, many financial service companies have created a wide range of clean energy related equity indices to capture the movements of publicly quoted clean energy related companies. Much research has emerged analysing their usefulness as portfolio components against conventional markets or products [examples include Shahbaz et al. (2021), Ahmad and Rais (2018), Kuang (2021), etc].

In this chapter, we move on to examine the investor behaviour in the Chinese renewable energy sector from the perspective of herding. Herding, again, refers to the behaviour whereby investors do not rely on their own analysis, mimic and follow others' trading actions in financial markets, which can easily push or drag price away from intrinsic values. There have been extensive studies of herding. See as examples in global equities [Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010), Zheng et al. (2015), Clements et al. (2017), Tan et al. (2008), etc], options [Bernales et al. (2020)], commodity [Demirer et al. (2015), Kumar et al. (2021), Youssef (2022a), Aytaç et al. (2018), Adrangi and Chatrath (2008), etc], and cryptocurrency markets [Bouri et al. (2019), Kallinterakis and Wang (2019), Vidal-Tomás et al. (2019), etc].

Evidence from many previous studies suggests that herding is subject to internal and external market conditions, and is thus intrinsically time-varying. Extant literature has shown that herding is asymmetric and the intensity varies between market states [Chang et al. (2000), Kizys et al. (2021), etc]. Some studies have suggested that herding may be more pronounced during periods of stress or heightened market uncertainty [for example, see Bikhchandani and Sharma (2000); Aharon (2021)]. Kizys et al. (2021) provided fresh evidence that investors tended to herd in stock markets during the first wave of Covid-19 as Covid-19 brought severe global economic uncertainty. Moreover, markets are interconnected [Chiou and Lee (2009); Choi and Hammoudeh (2010)]. Investors behaviour is likely to be affected by the performance of other associated markets [BenMabrouk and Litimi (2018); Youssef (2022b)]. For example, Balcilar et al. (2014) studied the impact of U.S. stock market and WTI oil volatilities on herd behaviour in Gulf Cooperation Council countries' stock markets. Economou et al. (2018), Youssef (2022b), and Youssef (2022a) analysed how external factors affect herd behaviour in stock, cryptocurrency, and commodity markets, respectively. Chiang and Zheng (2010) found that U.S market performance significantly influenced the behaviour in other global markets.

Despite this, there have been relatively few papers on herd effects at the sectoral level [BenMabrouk and Litimi (2018)], especially for renewable energy market. To the best of our knowledge, only three studies have paid attention to this emerging sectoral market, and only one has looked into the situation in China. This is remarkable when one considers that China has for years been the world leader in the renewable energy industry [Chiu (2017), Pan (2022)] as policy makers in China have treated it as a priority for socioeconomic development. China has committed to hit peak emissions before 2030 and finally achieve carbon neutrality by 2060. According to data released by Organisation for Economic Co-operation and Development (OECD), China has been the largest producer of two primary renewable energy sources, wind and solar energy, and the largest investors in the renewable energy industry internationally [9]. China also remains the largest producer and exporter of electric vehicles, accounting for more than 50% shares of global production and sales of electric vehicles [10]. The support and promotion from the Chinese government greatly stimulated the growth of these renewable energy companies. We believe that the emerging Chinese stock market is truly worth investigating. Historically, Chinese market has been criticised for having high infor-

[9] More information can be retrieved from their website https://data.oecd.org/energy/renewable-energy.htm.

[10] https://thedriven.io/2022/02/08/china-regains-dominance-of-global-ev-market-with-53-of-global-sales-in-2021/.

mation asymmetry and market manipulation rates, low governance transparency, and low quantity and quality of information disclosed by the companies. Besides, Geretto and Pauluzzo (2012) added that the current regulation for Chinese equity market is excessive, making the market even less efficient and accessible than the other mature markets, such as the United States. These problems exacerbate market inefficiency, and may lead to herding.

Our study therefore contributes to the literature in several ways. First, we add to the scant literature on herding behaviour in the Chinese renewable energy industry. We find compelling evidence that Chinese investors significantly herd in these stocks, which contradicts the findings by Shen (2018). Second, we document significant general stock market effects on such behaviour among Chinese investors. Third, we use both static and time-varying coefficient models and consider a size effect in calculating and verifying the results, which reinforces the methodological framework in this area. Finally, our study provides implications for the investors, analysts and regulators in the Chinese financial market. While China has ambitions to lead the global renewable energy production and investments, particular attention is required to stabilise the local financial market and improve the market efficiency.

The remainder of this paper is structured as follows. We review some past research in Section 3.2.2. We explain the methods in Section 3.2.3, followed by Section 3.2.4 where we describe the data. We discuss the results in Section 3.2.5 and present robustness checks in Section 3.2.6. Finally, we conclude and address implications of our study in Section 3.2.7.

3.2.2 Literature review

Numerous scholars have dedicated considerable effort to studying the behaviour of market participants and its impact on asset prices. One strand of literature focuses on the herding phenomenon. Despite the fact that the efficient market hypothesis [Samuelson (1965); Fama (1965, 1970)] is commonly applied as a heuristic in financial analysis, investors are observably likely to suppress their personal research base and simply copy the actions of others. Such behaviour, herding, can be either rational or completely irrational [Bikhchandani and Sharma (2000)]. There are different approaches to determining whether herd effects present, and our method derives from Christie and Huang (1995). Christie and Huang (1995) proposed that the dispersion level of asset returns in a market portfolio, measured by the cross-sectional standard deviation of returns (*CSSD*), can be used to detect the existence of herd effect in the market. They defined that if investors react individually based on their own views and do not herd around the market consensus, dispersion should be relatively high, according to rational asset pricing models. However, since their model based on the *CSSD* measure is linear, it can be interpreted as showing *co-movements* of returns instead of herding. In other words, herds are not necessarily attributes to low dispersions. Moreover, the conduct of this examination is restricted under extreme market circumstances, so it is unable to detect the behaviour in normal times. To improve this, Chang et al. (2000) suggested using the cross-sectional *absolute* deviation of returns (*CSAD*) to measure the dispersions and introduced a non-linear term to break rational asset pricing models and capture the presence of herding. The approach of Chang et al. (2000) is considered an improvement of the previous one and both of the two have been widely employed in later research in this area. Both models have been widely applied in research.

The literature offers a extensive list of studies on herding. For example, Chang et al. (2000) investigated asymmetric herd behaviour in international stock markets, where only in emerging markets such as South Korea and Taiwan it was significantly evidenced. Bernales et al. (2020) documented the presence of herding in the U.S. equity options market, and found that it was driven by increased volatility, position change, and information inflows. Bouri et al. (2019) studied the herd behaviour in the cryptocurrency market represented by 14 large coins and discovered that such behaviour is time-varying using a rolling window analysis. Demirer et al. (2015) analysed whether the volatility of the stock market has an impact on the herding phenomenon in the commodity market.

While most studies focus on the aggregated stock and commodity markets, some have examined equity sectors. For example, Litimi et al. (2016) examined the herding behaviour in U.S. listed companies across twelve NASDAQ sectors from 1985 to the end of 2013. The presence was only found in the public utilities and transportation sectors in general, albeit it might be induced in other sectors such as energy, health care, technology, etc by trading volume changes. Ukpong et al. (2021) paint a different picture by using ten Thompson Reuters Datastream sectors finding from 1990 to 2020 that herding was only found in financials, industrials and real estate. Similarly, Zheng et al. (2017) studied 10 sectors across 9 Asian markets and the US from 1993 to 2013. However, the number of studies on the renewable energy market is still rare, and their results are mixed. Shen (2018) applied tests on different energy sectors of the Chinese stock market. The author showed that herd behaviour presented in most sectors but *not* in the new energy and nuclear energy. Trück and Yu (2016) performed tests on 170 U.S. renewable energy companies that are included in indices. They showed that investors did not herd in most cases, except that the market was generally positive during a short period in 2008 when the oil market was experiencing sharp decreases. Chang et al. (2020), on the other hand, extended the works of Trück and Yu (2016) to the Europe and Asia markets and further analysed the dynamics in sub-periods of the 2008 global financial crisis, SARS, and COVID-19 by 2020 May end. Their results confirmed the absence of herd behaviour in the local renewable energy sector in these markets, and highlighted the external information from the oil and the fossil energy markets to the behaviour in renewable energy markets. Overall therefore the results to date are mixed.

3.2.3 Methodology

3.2.3.1 Base econometric models

Our initial and base econometric model for herd testing is the cross-sectional absolute deviation of returns (CSAD) approach by Chang et al. (2000), which has been already used in the previous essay.

We used the cross-sectional absolute deviation of returns in measuring the dispersions of the Chinese renewable energy stock returns, expressed as:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N} \left| r_{i,t} - r_{m,t} \right|}{N}, \tag{3.10}$$

where N is the number of renewable energy stocks, $R_{i,t}$ is the logarithmic return of individual renewable energy stock i on day t, $R_{m,t}$ is the average market return on day t.

Similarly, a general quadratic regression of $CSAD_{m,t}$ on variants of market returns was then built to uncover the presence of herding during the sample period (Eq. 3.11). Eq. 3.11 is a modification of previous Chang et al. (2000) approach as we included a $R_{m,t}$ term on the right-hand side following Chiang and Zheng (2010). This form enables us to account for asymmetric investor behavior in various market scenarios [11]. As suggested, the rational pricing model predicts a linear

[11] Please refer to Chiang and Zheng (2010) and Duffee (2001) for more details.

relationship between dispersions and returns and herding is detected when a non-linear relationship between $CSAD_{m,t}$ and the $R_{m,t}$ is found so that the dispersion of individual returns decreases or increases at a nonproportional rate towards the market returns during periods of high volatility. This is inferred by a significantly negative coefficient γ_3.

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \epsilon_t, \tag{3.11}$$

Additionally, to avoid serial correlation between variables, we added a one-day lagged dependent variable ($CSAD_{m,t-1}$) to Eq. 3.11 just as Eq. 3.12, following Yao et al. (2014) and Alhaj-Yaseen and Rao (2019). Besides, the statistical inference is based on Newey and West (1994) standard errors to further account for heteroskedasticity and serial autocorrelation in the error terms [12]. We followed Chiang and Zheng (2010) to test the presence of herd behaviour twice to ensure robustness; we first tried using a constraint, $\gamma_1 = 0$, to make equations more consistent with that in Chang et al. (2000), followed by a second test of easing the restriction.

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t, \tag{3.12}$$

Moreover, we analysed whether such behaviour is asymmetric under different market status using a nested model (Eq. 3.13), following Chang et al. (2000) and Chiang and Zheng (2010) [13]. We classified the market returns into positive and negative returns using dummy variables and evaluated the intensity of herd or anti-herd effect under the two market conditions.

$$\begin{aligned} CSAD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} \\ + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t \end{aligned} \tag{3.13}$$

where $D_{m,up}$ and $D_{m,down}$ are dummy variables with values of 1 if the return of the equally-weighted market portfolio at time t is positive and negative, respectively. A significantly negative coefficient γ_2 or γ_3 indicates that herding in renewable energy market exists in up or down market, respectively.

[12] Specifically, we used a Bartlett kernel based HAC covariance estimation using AR(1) prewhitened residuals and automatically selected bandwidth by Newey and West (1994).

[13] Check Alhaj-Yaseen and Rao (2019) and Kumar (2020) for more examples

The above econometric models examine the presence of herd effects in general, which presumes the persistence of parameter in the whole sample period. However, this is usually not the case for time series data. Thus, following the approach in Bouri et al. (2019) and Evrim Mandaci and Cagli (2022), we applied the multiple breakpoint test proposed by Bai and Perron (2003) on Eq. 3.12 to detect structural breaks in the full period, which allows us to re-estimate the coefficients for different short time periods based on the dates detected.

3.2.3.2 Time-varying autoregressive model

The Bai and Perron (2003) multiple breakpoint test mentioned in the last section can estimate break points by minimising the global sum of squared residuals. However, this method does not allow us to track the time-varying transition from herd to anti-herd and vice versa. We therefore employed the Time-Varying Autoregressive (TV-AR) model to verify again the results obtained using previous models.

As a starting point, we first introduce the $AR(p)$ model which is written as, in general:

$$y_t = \gamma_0 + \gamma_1 y_{t-1} + \ldots + \gamma_p y_{t-p} + \epsilon_t, \tag{3.14}$$

where p is the lag order of the dependent variable.

In above model (Eq. 3.14), y_t only depends on its own lags. However, there are other exogenous variables in our case, such as the $R_{m,t}$, $|R_{m,t}|$, $R^2_{m,t}$. Hence, we rewrite the equation as:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \gamma_1 x_{1t} + \ldots + \gamma_d x_{dt} + \epsilon_t, \tag{3.15}$$

The TV-$AR(p)$ model fits the $AR(p)$ model with time-varying coefficients. To calculate the coefficients, we view the TV-$AR(p)$ model as a special case of TV linear regression model which has a general form of:

$$y_t = \beta(z_t) X'_t + \epsilon_t, \quad t = 1, \ldots, T, \tag{3.16}$$

where y_t is the dependent variable, ϵ_t is the error term, X'_t is a vector of independent variables, and $\beta(z_t)$ is the vector of time-varying coefficents which is a function of z_t, a rescaled changing time period (t/T) or a random variable at time t. We combined both ordinary least squares estimator and the local polynomial kernel estimator (in our case, we used the Nadaraya–Watson estimator) to minimise the following [14]:

$$\left(\hat{\beta}(z_t), \hat{\beta}^{(1)}(z_t)\right) = \arg\min_{\theta_0,\theta_1} \sum_{t=1}^{T} \left[y_t - x_t^\top \theta_0 - (z_t - z) x_t^\top \theta_1\right]^2 K_b(z_t - z) \tag{3.17}$$

where b is the bandwidth, $K(\cdot)$ is the kernel function which in our case is the Triweight kernel for weights calculation.

Note that, for $TV\text{-}AR(p)$, the regressors in Eq. 3.16 also contain p lagged value of the response variable. We re-write the equation in a more intuitive way as:

$$\begin{aligned} y_t = \beta_0(z_t) + \beta_1(z_t) y_{t-1} + \ldots + \beta_p(z_t) y_{t-p} + \gamma_1(z_t) x_{1t} \\ + \ldots + \gamma_d(z_t) x_{dt} + \epsilon_t, \quad \text{for } t = 1, \ldots, T. \end{aligned} \tag{3.18}$$

For consistency, we used $p = 1$ so that our independent variables include a one-day lagged dependent variable ($CSAD_{m,t-1}$) and exogenous variables $R_{m,t}$, $\left|R_{m,t}\right|$, $R_{m,t}^2$. Ultimately, our model is specified below (Eq. 3.19).

$$\begin{aligned} CSAD_{m,t} = \gamma_0(z_t) + \gamma_1(z_t) R_{m,t} + \gamma_2(z_t) \left|R_{m,t}\right| + \gamma_3(z_t) R_{m,t}^2 \\ + \gamma_4(z_t) CSAD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1, \ldots, T. \end{aligned} \tag{3.19}$$

where all γ coefficients are time-varying.

3.2.4 Data

We collected daily price data and the year-end market capitalisation data for the constituents of the China Securities Index Co., Ltd. (CSI) New Energy Index. CSI company is a leading Chinese financial market index provider that is jointly funded and supported by the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The CSI has managed more than 5000 indices, providing benchmarks for domestic and international markets, with focus on China Mainland and Hong Kong markets. The CSI New Energy Index includes 80 major companies involved in renewable energy production, applications, storage and interaction devices, or other new energy service, which represents the overall performance of the Chinese renewable or new energy industry. We also collected the CSI 300 Index price data, a benchmark for the overall performance of the China A-share market, which tracks the top 300 Chinese companies in terms of market capitalisation and liquidity listed on either the Shanghai Stock Exchange or the Shenzhen Stock Exchange .

[14] See Casas and Fernandez-Casal (2019) for more clarifications

All data were sourced from Bloomberg Database, spanning from 5 January 2015 to 29 April 2022. Note that prices are denominated in the Chinese Yuan and were transformed to their first-differenced natural logarithms as log-returns before use.

3.2.5 Results

3.2.5.1 Full and sub- samples analysis

The coefficient estimates of general herd effects in the Chinese renewable energy market are reported in Table 3.9. As we mentioned earlier, we tested the presence of herd effect twice for robustness; we first imposed a constraint, $\gamma_1 = 0$, to make Eq. 3.12 more consistent with that in Chang et al. (2000) and then we eased the constraint for the second time. We found that herding does exist in the market as all γ_3 for $R^2_{m,t}$ are significantly negative (-3.2483*** when $\gamma_1 = 0$ and -3.7699*** when $\gamma_1 \neq 0$) in the full sample analysis, which contradicts the results reported by Shen (2018) who concluded that Chinese investors do not herd in the new energy industry, which is reasonable as they only analysed the market in 2015.

Table 3.9: Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{R_{m,t}}$	$\mathbf{\lvert R_{m,t}\rvert}$	$\mathbf{R^2_{m,t}}$	$\mathbf{CSAD_{m,t-1}}$
Full sample	0.0059***		0.3073***	**-3.2483******	0.5161***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
	0.0056***	-0.0365***	0.3332***	**-3.7699******	0.5256***
	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.12: $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

We continued to test the herding intensity in asymmetric market states. The coefficient estimates of asymmetric herd behaviour in the up and down Chinese renewable energy market are reported in Table 3.10. Consistent with previous results, the values of both herding coefficients γ_3 and γ_4 are negative and statistically significant, which implies the herding in Chinese renewable energy market has existed in the study period regardless of the market conditions. In addition, evidence show that the herd effects are generally more profound in the up (-4.1552***) than in the down (-3.6424***) conditions, which is consistent with the general findings of Chinese equity market by Chiang and Zheng (2010).

Table 3.10: Regression results of $CSAD_{m,t}$ on asymmetric renewable energy market returns

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{D_{up}R_{m,t}}$	$\mathbf{D_{down}R_{m,t}}$	$\mathbf{D_{up}R^2_{m,t}}$	$\mathbf{D_{down}R^2_{m,t}}$	$\mathbf{CSAD_{m,t-1}}$
Full sample	0.0056***	0.3136***	-0.3634***	**-4.1552*****	**-3.6424*****	0.5253***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.13: $CSAD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Given behaviour can be changing over time, we tested Eq. 3.12 for candidate breakdates using Bai and Perron (2003) approach. Five structural breaks were selected by most metrics, which are 07/03/2016, 10/04/2017, 26/06/2018, 22/11/2019, and 05/01/2021 (Appendix H.0.1) [15]. We then re-tested the presence of herding in different timeframe based on these breakpoints using the Eq. 3.12. Results are reported in Table 3.11. We found interesting evidence that significant herding only existed in the period from 05/01/2015 to 07/03/2016 (sub-sample 1) and 05/01/2021 to 29/04/2022 (sub-sample 6), where the intensity was stronger in the former than the latter period. These, again, contradict the results reported by Shen (2018) who concluded that Chinese new energy investors do not herd in 2015. There was no significant herding in the rest of periods. However, one might argue that in these period weak herding might exist as although Chang et al. (2000) did not propose the definition of weak herd behaviour, Zheng et al. (2017) and Bouri et al. (2019), among others, suggested, qualitatively, so-called weak herding is because it is less significant and/or having a lower negative herding coefficient.

[15] We note that the Chinese new energy industry had experienced sharp rises and falls in 2015 and early 2016 till the first breakdate. The market was bearish for a long time and kept trending lower from 2018 till early 2019, and started recovering in late 2019, which is close to our penultimate breakdate. After around our last breakdate which is the first day after the public holiday of the New Year's Day, the market has frequently spiked to new records, although fell sharply in the following month, recovered quickly and peaked in the fourth quarter of 2021 and started to fall.

Table 3.11: Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns in sub-samples

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{R_{m,t}}$	$\mathbf{\lvert R_{m,t} \rvert}$	$\mathbf{R^2_{m,t}}$	$\mathbf{CSAD_{m,t-1}}$
Sub-sample 1	0.0144***		0.2297***	**-2.8764*****	0.2714***
	(0.0000)		(0.0145)	(0.0019)	(0.0022)
	0.0132***	-0.0919***	0.3511***	**-4.8017*****	0.2976***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0003)
Sub-sample 2	0.0075***		0.2103**	-0.1899	0.3251***
	(0.0000)		(0.0106)	(0.9075)	(0.0000)
	0.0074***	-0.0292*	0.2233***	-0.4367	0.3294***
	(0.0000)	(0.0586)	(0.0074)	(0.8013)	(0.0000)
Sub-sample 3	0.0098***		0.3076***	-0.1264	0.1647***
	(0.0000)		(0.0000)	(0.8895)	0.0062
	0.0098***	0.0003	0.3074***	-0.1185	0.1645***
	(0.0000)	(0.9793)	(0.0000)	(0.8966)	0.0065
Sub-sample 4	0.0077***		0.0810**	-0.1744	0.4452***
	(0.0000)		(0.0276)	(0.7438)	(0.0000)
	0.0076***	-0.0286**	0.0954***	-0.5350	0.4453***
	(0.0000)	(0.0487)	(0.0087)	(0.3333)	(0.0000)
Sub-sample 5	0.0095***		0.2160***	-1.6491	0.4142***
	(0.0000)		(0.0013)	(0.1032)	(0.0000)
	0.0097***	0.0237	0.1868***	-1.1564	0.4124***
	(0.0000)	(0.1140)	(0.0014)	(0.1878)	(0.0000)
Sub-sample 6	0.0054***		0.2494***	**-2.7000*****	0.6414***
	(0.0000)		(0.0000)	(0.0001)	(0.0000)
	0.0054***	0.0097	0.2487***	**-2.6832*****	0.6394***
	(0.0000)	(0.4360)	(0.0000)	(0.0001)	(0.0000)

Notes:

1. Eq. 3.12: $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;

2. The range of sub-sample 1 is from 05/01/2015 to 07/03/2016; The range of sub-sample 2 is from 07/03/2016 to 10/04/2017; The range of sub-sample 3 is from 10/04/2017 to 26/06/2018; The range of sub-sample 4 is from 26/06/2018 to 22/11/2019; The range of sub-sample 5 is from 22/11/2019 to 05/01/2021; The range of sub-sample 6 is from 05/01/2021 to 29/04/2022.

3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Moreover, it is also essential to know that the tests following the Chang et al. (2000) framework only test for herding within the specific asset, or in our case, the industry, which is a particular type and strong form of herding Richards (1999). In other words, while the investors do not herding within the industry, we should allow the possibility of herd trading according to other markets' performance. In light of this, we focused on the period from 07/03/2016 - 05/01/2021 when no significant local herding was found, and we followed a common approach in literature such as Demirer et al. (2015), among others, to augment a term of squared returns of a particular market that we want to explore the impact of. Because we were curious about how investors were reacting to large price movements in the overall financial market, we used the squared returns of CSI 300 Index as a proxy for the Chinese equity market uncertainty to study the stock market effect in the herding context. The equation is written as follows:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{C300,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t, \tag{3.20}$$

where $R_{C300,t}$ is the logarithmic return of CSI 300 Index on day t.

The results using the Eq. 3.20 are presented in Table 3.12. Consistent with previous results, there was no within-industry herding from 07/03/2016 - 05/01/2021 as γ_3s are not significantly negative. Instead, the dispersion was found significantly negatively correlated to the squared returns of the general stock market (e.g., -2.3913***), which reveals that renewable energy investors still herd around the equity market in the absence of local herding.

Table 3.12: Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns incorporating the stock market effect

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{R_{m,t}}$	$\mathbf{\left\|R_{m,t}\right\|}$	$\mathbf{R^2_{m,t}}$	$\mathbf{R^2_{C300,t}}$	$\mathbf{CSAD_{m,t-1}}$
	0.0073***		0.2075***	0.0999	**-2.3913*****	0.4222***
	(0.0000)		(0.0000)	(0.8330)	(0.0000)	(0.0000)
	0.0072***	-0.0115	0.2144***	-0.0449	**-2.4313*****	0.4255***
	(0.0000)	(0.1786)	(0.0000)	(0.9301)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.20: $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{C300,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 07/03/2016 to 05/01/2021 when the local herding was absent;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

We further investigate the asymmetric impact of the overall stock market on the investor behaviour of renewable energy stocks by using dummy variables to capture the upturns and downturns of the general Chinese stock market (Eq. 3.21).

$$\begin{aligned} CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 D_{C300,up} R^2_{C300,t} \\ + \gamma_5 D_{C300,down} R^2_{C300,t} + \gamma_6 CSAD_{m,t-1} + \epsilon_t, \end{aligned} \tag{3.21}$$

where $D_{C300,up}$ and $D_{C300,down}$ are dummy variables with values of 1 if the return of the CSI 300 Index on day t is positive and negative, respectively.

Results of asymmetric stock market impact are presented in Table 3.13. We confirmed that the overall equity market performance had influenced the investors' self-confidence in renewable energy stocks. This phenomenon is more common during stock market ups than downs.

Table 3.13: Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns incorporating the asymmetric stock market effect

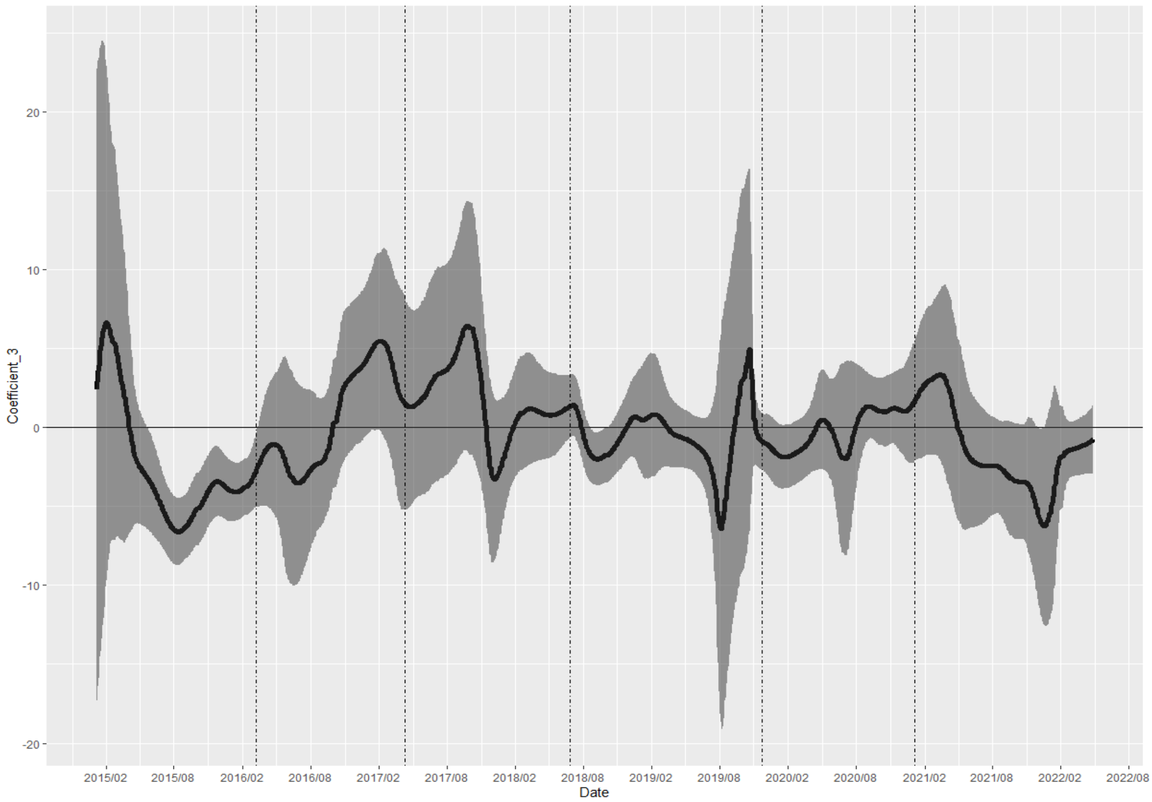
$\mathbf{CSAD_{m,t}}$	Const.	$\mathbf{R_{m,t}}$	$\mathbf{\lvert R_{m,t}\rvert}$	$\mathbf{R^2_{m,t}}$	$\mathbf{D_{C300,up}R^2_{C300,t}}$	$\mathbf{D_{C300,down}R^2_{C300,t}}$	$\mathbf{CSAD_{m,t-1}}$
	0.0071***		0.2384***	-0.5421	**-4.1258***	**-1.5658***	0.4227***
	0.0000		0.0000	0.3293	0.0000	0.0017	0.0000
	0.0072***	0.0049	0.2385***	-0.5435	**-4.2776***	**-1.4687***	0.4214***
	0.0000	0.5876	0.0000	0.3209	0.0000	0.0023	0.0000

Notes:
1. Eq. 3.21: $CSAD_{m,t} = \gamma_0+\gamma_1 R_{m,t}+\gamma_2\left|R_{m,t}\right|+\gamma_3 R^2_{m,t}+\gamma_4 D_{C300,up}R^2_{C300,t}+\gamma_5 D_{C300,down}R^2_{C300,t}+\gamma_6 CSAD_{m,t-1}+\epsilon_t$ was used;
2. The data range is from 07/03/2016 to 05/01/2021 when the local herding was absent;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

3.2.5.2 Time-varying Analysis

In this section, we present the results of time-varying herding coefficient. We first employed the Eq. 3.21, where the bandwidth was automatically selected by cross validation and the wild bootstrap 95% confidence levels were estimated after 30,000 runs based on Chen et al. (2018). Figure 3.1 plots the mean of the herding coefficient estimates over time ($\gamma_3(z_t)$) and their mean confidence intervals. The vertical dash lines are the breakdates detected as in Table H.0.1. The result is qualitatively similar to our previous results in Table 3.11, which confirms that herding in the Chinese renewable energy industry is indeed time-varying. From the plot, we can see that most of the herding coefficients in the sub-sample 1 and 6 are significantly negative, which confirms that strong form of herding within the industry happened during these periods, and was more intense in the former. Industry herding was also evidenced during other periods in a much weaker form, which is also consistent with our previous findings. Overall, we found that the herd effect is time-varying and is likely to persist.

Figure 3.1: Time-varying herding coefficient using Eq. 3.19

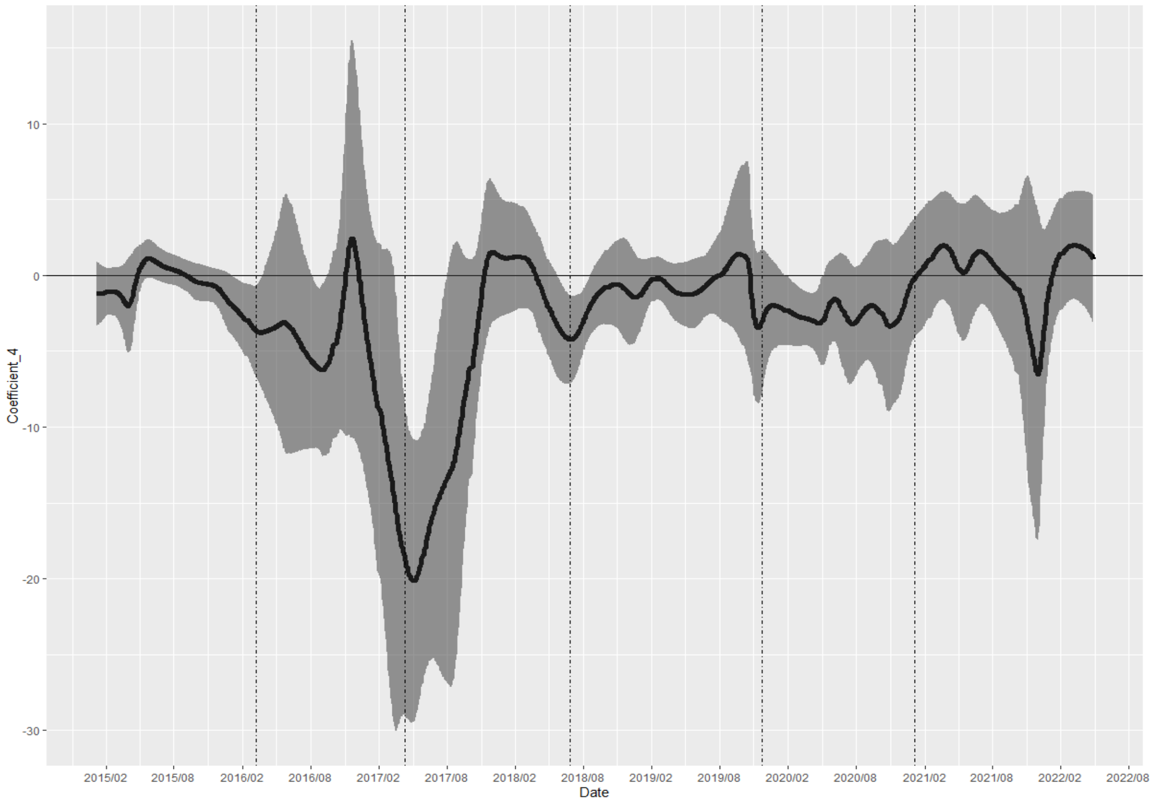


Furthermore, based on previous results of the potential impact of stock market performance on the herding behaviour (Table 3.12). We employed the Eq. 3.20 again, but this time we estimated it using the time-varying coefficients as follows (Eq. 3.22).

$$CSAD_{m,t} = \gamma_0(z_t) + \gamma_1(z_t)R_{m,t} + \gamma_2(z_t)\left|R_{m,t}\right| + \gamma_3(z_t)R^2_{m,t} + \gamma_4(z_t)R^2_{C300,t} + \gamma_5(z_t)CSAD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1,\ldots,T. \tag{3.22}$$

We plot the mean of the coefficient estimates of stock market effect over time ($\gamma_4(z_t)$) and their mean confidence intervals. Evidence confirms that the volatility of the stock market influences the behaviour in the renewable energy market, especially during the period from 07/03/2016 - 05/01/2021 (sub-sample 2-5). Combining with results from last section, we finally argue that investors tend to react to the overall performance of the stock market, either being overconfident when the large movements are positive, which is more likely as evidenced in Table 3.13, or feeling panic during periods of extreme price drops. Hence, they simply follow the market dynamics hoping to obtain better profits.

Figure 3.2: Time-varying herding coefficient using Eq. 3.22



3.2.6 Robustness check

3.2.6.1 Sized-based portfolios

In previous sections, we have presented the evidence of using equally-weighted market portfolio. However, one might suggest that small stocks may react differently to large stock portfolios in some cases [McQueen et al. (1996)]. Therefore, we applied similar approach by Chang et al. (2000) that we discretised the stocks into quantiles based on the market capitalization of each stock at the end of the year. Given our sample size [16], we specified the top 25% as the largest, 25%-75% as the medium, the last 25% as the smallest firms, and we reconstructed these portfolios each year. We then re-estimated the Eq. 3.12 and 3.13 for the industry herding using the new size-based portfolios, and empirical results are shown in Table 3.14 and 3.15, respectively. The new evidence still fully supports our previous results that Chinese investors do herd in the renewable energy market. The behaviour is generally more prevalent during upturns and among smaller stocks. Overall, our results remain robust taking into account the size effect.

Table 3.14: Regression results of $CSAD_{m,t}$ on sized-based unconditional renewable energy market returns

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{R_{m,t}}$	$\mathbf{\lvert R_{m,t}\rvert}$	$\mathbf{R^2_{m,t}}$	$\mathbf{CSAD_{m,t-1}}$
Panel A: Largest	0.0079***		0.2725***	**-2.4216*****	0.4080***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
	0.0078***	-0.0172*	0.2857***	**-2.7097*****	0.4109***
	(0.0000)	(0.0668)	(0.0000)	(0.0000)	(0.0000)
Panel B: Medium	0.0064***		0.3534***	**-4.0480*****	0.4584***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
	0.0062***	-0.0272*	0.3719***	**-4.3963*****	0.4649***
	(0.0000)	(0.0530)	(0.0000)	(0.0000)	(0.0000)
Panel C: Smallest	0.0069***		0.4299***	**-4.4046*****	0.3542***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
	0.0068***	-0.0140	0.4402***	**-4.5820*****	0.3553***
	(0.0000)	(0.2510)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.12: $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

[16]We have 80 firms at most.

Table 3.15: Regression results of $CSAD_{m,t}$ on sized-based asymmetric renewable energy market returns

$\mathbf{CSAD_{m,t}}$	**Const.**	$\mathbf{D_{up}R_{m,t}}$	$\mathbf{D_{down}R_{m,t}}$	$\mathbf{D_{up}R^2_{m,t}}$	$\mathbf{D_{down}R^2_{m,t}}$	$\mathbf{CSAD_{m,t-1}}$
Panel A: Largest	0.0078***	0.2859***	-2.3000***	**-3.1269*****	**-2.6324*****	0.4105***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel B: Medium	0.0061***	0.3716***	-0.3866***	**-4.9820*****	**-4.1675*****	0.4647***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel C: Smallest	0.0068***	0.4555***	-0.4403***	**-5.2152*****	**-4.3073*****	0.3529***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.13: $CSAD_{m,t} = \gamma_0 + \gamma_1 D_{m,up}R_{m,t} + \gamma_2 D_{m,down}R_{m,t} + \gamma_3 D_{m,up}R^2_{m,t} + \gamma_4 D_{m,down}R^2_{m,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

3.2.6.2 CSSD as the measure of dispersion

Gleason et al. (2004) proposed that the *CSAD* and the *CSSD* as measures of the return dispersion can be swapped. Therefore, we replaced the dependent variable ($CSAD_{m,t}$) in Eq. 3.12, 3.13, 3.19, and 3.22 by the $CSSD_{m,t}$ and re-checked the herding results for robustness. The new equations are written as:

$$CSSD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSSD_{m,t-1} + \epsilon_t, \tag{3.23}$$

$$\begin{aligned} CSSD_{m,t} = \gamma_0 + \gamma_1 D_{m,up}R_{m,t} + \gamma_2 D_{m,down}R_{m,t} + \gamma_3 D_{m,up}R^2_{m,t} \\ + \gamma_4 D_{m,down}R^2_{m,t} + \gamma_5 CSSD_{m,t-1} + \epsilon_t \end{aligned} \tag{3.24}$$

$$\begin{aligned} CSSD_{m,t} = \gamma_0(z_t) + \gamma_1(z_t)R_{m,t} + \gamma_2(z_t)\left|R_{m,t}\right| + \gamma_3(z_t)R^2_{m,t} \\ + \gamma_4(z_t)CSSD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1,\dots,T. \end{aligned} \tag{3.25}$$

$$\begin{aligned} CSSD_{m,t} = \gamma_0(z_t) + \gamma_1(z_t)R_{m,t} + \gamma_2(z_t)\left|R_{m,t}\right| + \gamma_3(z_t)R^2_{m,t} + \gamma_4(z_t)R^2_{C300,t} \\ + \gamma_5(z_t)CSSD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1,\dots,T. \end{aligned} \tag{3.26}$$

Results in Table 3.16 and 3.17 provide exactly same information as before that herding significantly exists in the Chinese renewable energy market and is more pronounced during up than down markets even when we used *CSSD* as an alternative measure. Figure 3.3 and 3.4 plot the time-varying coefficient $\gamma_3(z_t)$ and $\gamma_4(z_t)$ in Eq. 3.25 and 3.26, respectively. Similar conclusion can be drawn that the within-industry herding has been time-varying and was more pronounced in the first and the last period. Weak herd or anti-herd behaviour appeared more frequently in other periods, where the stock market has taken part as a trading signals transmitter. Overall, our results remain robust when using the *CSSD* as a measure of the market return dispersion.

Table 3.16: Regression results of $CSSD_{m,t}$ on unconditional renewable energy market returns

$\mathbf{CSSD_{m,t}}$	**Const.**	$\mathbf{R_{m,t}}$	$\mathbf{\lvert R_{m,t}\rvert}$	$\mathbf{R^2_{m,t}}$	$\mathbf{CSSD_{m,t-1}}$
Full sample	0.0090***		0.2990***	**-3.1393***	0.5289***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
	0.0085***	-0.0522***	0.3360***	**-3.8858***	0.5402***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.23: $CSSD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSSD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 3.17: Regression results of $CSSD_{m,t}$ on asymmetric renewable energy market returns

$\mathbf{CSSD_{m,t}}$	**Const.**	$\mathbf{D_{up}R_{m,t}}$	$\mathbf{D_{down}R_{m,t}}$	$\mathbf{D_{up}R^2_{m,t}}$	$\mathbf{D_{down}R^2_{m,t}}$	$\mathbf{CSSD_{m,t-1}}$
Full sample	0.0085***	0.3023***	-0.3813***	**-4.3102***	**-3.7453***	0.5400***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes:
1. Eq. 3.24: $CSSD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSSD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 05/01/2015 to 29/04/2022;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Figure 3.3: Time-varying herding coefficient using Eq. 3.25

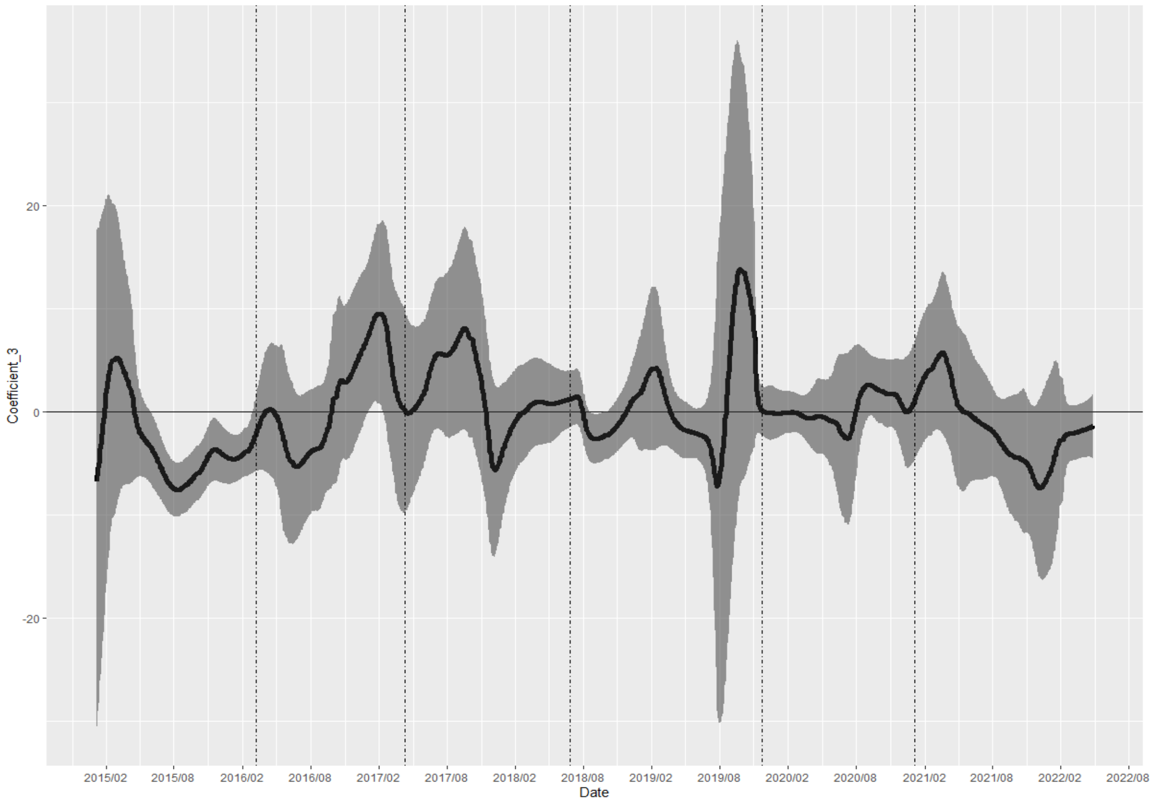
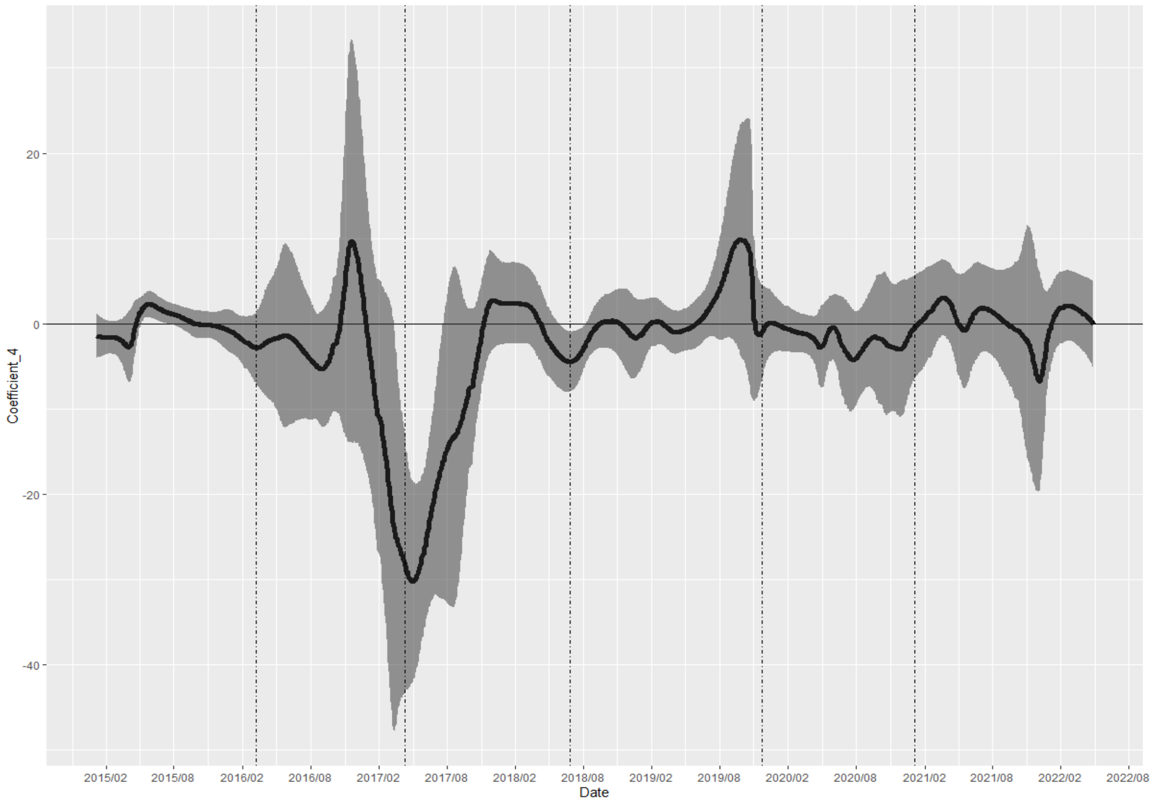


Figure 3.4: Time-varying herding coefficient using Eq. 3.26



3.2.7 Conclusion

We explore the existence of herd behaviour in Chinese renewable energy market using various techniques. The growth of renewable energy generation capacity and adoption has been tremendous over the years, where China's effort is prominent. The support from the Chinese government significantly promoted the rapid growth and development of Chinese renewable energy companies. However, there has been a paucity of research on the financial market dynamics of this emerging market from a behavioural perspective, especially with a focus on China. Our paper fills this gap.

We used modifications of the original static models proposed by Chang et al. (2000) and Chiang and Zheng (2010), which account for multicollinearity and autocorrelation problems, as well as a time-varying coefficient autoregressive model, for robustness, to detect the potential herding behaviour among renewable energy investors. By employing daily data from 5 January 2015, through 29 April

2022, covering both major peaks and troughs and bullish and bearish times, we documented significant time-varying herding pattern by sub-sample analysis and time-varying modelling, which stands on the contrary to earlier literature that pointed no local herding (herding within industry) in the U.S. [Trück and Yu (2016)] or North America, Europe, and Asia markets [Chang et al. (2020)] or in the Chinese market [Shen (2018)]. The behaviour is more profound during up than down markets and among smaller firms. When there was an absence of local herding, we showed that large price volatility in the general equity market affects the trading behaviour.

The findings support the idea that the Chinese stock market is immature and so inefficient [Geretto and Pauluzzo (2012)]. Herd trading has serious consequences and implications for investors and market regulators. Herding exacerbated the market inefficiency by pushing or dragging the stock prices away from the true fundamentals of companies, which induces higher volatility and leads to investors fears. While the number and size of Chinese renewable energy companies are growing, we should pay particular attention to preventing the vicious growth of stock prices, mitigating the risk of financial bubbles, and increasing market transparency.

APPENDIX H

Structural breaks

Table H.0.1: Bai and Perron (2003) test of multiple structural breaks in Eq. 3.12 for full sample

Sample: (01/01/2015 - 29/04/2022)				
Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1*	21.7665	108.8325	108.8325	22.40
2*	23.6232	118.1162	144.0285	18.37
3*	21.1570	105.7849	146.6325	16.16
4*	18.2022	91.0109	143.0628	14.25
5*	16.4864	82.4319	152.0984	12.14
UDMax statistic*: 118.1162, UDMax critical value**: 22.49				
WDMax statistic*: 152.0984, WDMax critical value**: 24.50				
Sequential F-statistic determined breaks:				5
Significant F-statistic largest breaks:				5
UDmax determined breaks:				2
WDmax determined breaks:				5
Estimated break dates:				
1: 09/03/2016				
2: 07/03/2016, 23/12/2019				
3: 07/03/2016, 15/08/2018, 23/12/2019				
4: 07/03/2016, 26/09/2018, 22/11/2019, 05/01/2021				
5: 07/03/2016, 10/04/2017, 26/06/2018, 22/11/2019, 05/01/2021				
Break test options:				
Bartlett kernel				
Prewhitening with AR(1)				
Newey-West automatic bandwidth and Lag lengths				
Different error distributions across breaks are allowed.				
Trimming = 0.15, Max. breaks = 5,				
*: Sig. level 0.01, **: Bai-Perron (2003) critical values				

BIBLIOGRAPHY

Adrangi, B. and Chatrath, A. (2008).
Do commodity traders herd?
Financial Review, 43(3):461–476.

Adrangi, B., Chatrath, A., Dhanda, K. K., and Raffiee, K. (2001).
Chaos in oil prices? evidence from futures markets.
Energy Economics, 23(4):405–425.

Aharon, D. Y. (2021).
Uncertainty, fear and herding behavior: Evidence from size-ranked portfolios.
Journal of Behavioral Finance, 22(3):320–337.

Aharon, D. Y., Umar, Z., and Vo, X. V. (2021).
Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies.
Financial Innovation, 7(1):1–25.

Ahmad, W. and Rais, S. (2018).
Time-varying spillover and the portfolio diversification implications of clean energy equity with commodities and financial assets.
Emerging Markets Finance and Trade, 54(8):1837–1855.

Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., and Sensoy, A. (2021).
Is gold a hedge or a safe-haven asset in the covid–19 crisis?
Economic Modelling, 102:105588.

Akram, Q. F. (2009).
Commodity prices, interest rates and the dollar.
Energy Economics, 31(6):838–851.

Akyildirim, E., Corbet, S., and Lucey, B. (2021).

China, coal, calamities and cryptos.
SSRN, page 3851253.

Al-Yousef, N. (2018).
Fundamentals and oil price behaviour: New evidence from co-integration tests with structural breaks and granger causality tests.
Australian Economic Papers, 57(1):1–18.

Alhaj-Yaseen, Y. S. and Rao, X. (2019).
Does asymmetric information drive herding? an empirical analysis.
Journal of Behavioral Finance, 20(4):451–470.

Amirat, A. and Alwafi, W. (2020).
Does herding behavior exist in cryptocurrency market?
Cogent Economics & Finance, 8(1):1735680.

Antonakakis, N., Chatziantoniou, I., and Gabauer, D. (2020).
Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions.
Journal of Risk and Financial Management, 13(4):84.

Aytaç, B., Coqueret, G., and Mandou, C. (2018).
Herding behavior among wine investors.
Economic Modelling, 68:318–328.

Bai, J. and Perron, P. (2003).
Computation and analysis of multiple structural change models.
Journal of Applied Econometrics, 18(1):1–22.

Baker, S. R., Bloom, N., and Davis, S. J. (2016).
Measuring Economic Policy Uncertainty*.
The Quarterly Journal of Economics, 131(4):1593–1636.

Balcilar, M., Bekiros, S., and Gupta, R. (2017).
The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method.
Empirical Economics, 53(3):879–889.

Balcilar, M., Demirer, R., and Hammoudeh, S. (2014).

What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors.
The North American Journal of Economics and Finance, 29:418–440.

Basher, S. A., Haug, A. A., and Sadorsky, P. (2012).
Oil prices, exchange rates and emerging stock markets.
Energy Economics, 34(1):227–240.

Baur, D. G. and Lucey, B. M. (2010).
Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold.
Financial Review, 45(2):217–229.

Baur, D. G. and McDermott, T. K. (2010).
Is gold a safe haven? International evidence.
Journal of Banking & Finance, 34(8):1886–1898.

Bekiros, S., Gupta, R., and Paccagnini, A. (2015).
Oil price forecastability and economic uncertainty.
Economics Letters, 132:125–128.

BenMabrouk, H. and Litimi, H. (2018).
Cross herding between american industries and the oil market.
The North American Journal of Economics and Finance, 45:196–205.

Bernales, A., Verousis, T., and Voukelatos, N. (2020).
Do investors follow the herd in option markets?
Journal of Banking & Finance, 119:104899.

Bikhchandani, S. and Sharma, S. (2000).
Herd behavior in financial markets.
IMF Staff papers, 47(3):279–310.

Bikhchandani, S. and Sharma, S. (2001).
Herd behavior in financial markets.
IMF Staff Papers, 47(3).

Bonaparte, Y. (2019).
Geopolitical oil price risk index.
J.P. Morgan Center for Commodities.
Working papers.

Bouri, E., Das, M., Gupta, R., and Roubaud, D. (2018).
Spillovers between bitcoin and other assets during bear and bull markets.
Applied Economics, 50(55):5935–5949.

Bouri, E., Gupta, R., and Roubaud, D. (2019).
Herding behaviour in cryptocurrencies.
Finance Research Letters, 29:216–221.

Bouri, E., Jalkh, N., Molnár, P., and Roubaud, D. (2017a).
Bitcoin for energy commodities before and after the December 2013 crash: Diversifier, hedge or safe haven?
Applied Economics, 49(50):5063–5073.

Bouri, E., Molnar, P., Azzi, G., Roubaud, D., and Hagfors, L. I. (2017b).
On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier?
Finance Research Letters, 20:192–198.

Casas, I. and Fernandez-Casal, R. (2019).
tvreg: Time-varying coefficient linear regression for single and multi-equations in r.
Available at SSRN 3363526.

Chang, C.-L., McAleer, M., and Wang, Y.-A. (2020).
Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19*.
Renewable and Sustainable Energy Reviews, 134:110349.

Chang, E. C., Cheng, J. W., and Khorana, A. (2000).
An examination of herd behavior in equity markets: An international perspective.
Journal of Banking & Finance, 24(10):1651–1679.

Chen, X. B., Gao, J., Li, D., and Silvapulle, P. (2018).
Nonparametric estimation and forecasting for time-varying coefficient realized volatility models.
Journal of Business & Economic Statistics, 36(1):88–100.

Chiang, T. C. and Zheng, D. (2010).
An empirical analysis of herd behavior in global stock markets.
Journal of Banking & Finance, 34(8):1911–1921.

Chiou, J.-S. and Lee, Y.-H. (2009).
Jump dynamics and volatility: Oil and the stock markets.
Energy, 34(6):788–796.

Chiu, D. (2017).
The east is green: China's global leadership in renewable energy.
New Perspectives in Foreign Policy, 13:3–12.

Choi, K. and Hammoudeh, S. (2010).
Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment.
Energy Policy, 38(8):4388–4399.

Christie, W. G. and Huang, R. D. (1995).
Following the pied piper: Do individual returns herd around the market?
Financial Analysts Journal, 51(4):31–37.

Clements, A., Hurn, S., and Shi, S. (2017).
An empirical investigation of herding in the u.s. stock market.
Economic Modelling, 67:184–192.

Corbet, S., Katsiampa, P., and Lau, C. K. M. (2020).
Measuring quantile dependence and testing directional predictability between bitcoin, altcoins and traditional financial assets.
International Review of Financial Analysis, 71:101571.

Corbet, S., Lucey, B., and Yarovaya, L. (2021).
Bitcoin-energy markets interrelationships - New evidence.
Resources Policy, 70:101916.

Corbet, S. and Yarovaya, L. (2020).
The environmental effects of cryptocurrencies.
Cryptocurrency and Blockchain Technology, 1:149.

Demirer, R., Lee, H.-T., and Lien, D. (2015).
Does the stock market drive herd behavior in commodity futures markets?
International Review of Financial Analysis, 39:32–44.

Diebold, F. X. and Yılmaz, K. (2012).

Better to give than to receive: Predictive directional measurement of volatility spillovers.
International Journal of Forecasting, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014).
On the network topology of variance decompositions: Measuring the connectedness of financial firms.
Journal of Econometrics, 182(1):119–134.

Diks, C. and Panchenko, V. (2006).
A new statistic and practical guidelines for nonparametric granger causality testing.
Journal of Economic Dynamics and Control, 30(9):1647–1669.

Duffee, G. R. (2001).
Asymmetric cross-sectional dispersion in stock returns: evidence and implications.
Working Paper Series 2000-18, Federal Reserve Bank of San Francisco.

Dutta, A. (2017).
Modeling and forecasting oil price risk: the role of implied volatility index.
Journal of Economic Studies, 44(6):1003–1016.

Economou, F., Hassapis, C., and Philippas, N. (2018).
Investors' fear and herding in the stock market.
Applied Economics, 50(34-35):3654–3663.

Engle, R. (2002).
Dynamic conditional correlation.
Journal of Business & Economic Statistics, 20(3):339–350.

Evrim Mandaci, P. and Cagli, E. C. (2022).
Herding intensity and volatility in cryptocurrency markets during the covid-19.
Finance Research Letters, 46:102382.

Fama, E. F. (1965).
The behavior of stock-market prices.
The Journal of Business, 38(1):34–105.

Fama, E. F. (1970).
Efficient capital markets: A review of theory and empirical work.
The Journal of Finance, 25(2):383–417.

Frankel, J. A. (2008).
The effect of monetary policy on real commodity prices.
University of Chicago Press.

Gallersdörfer, U., Klaaßen, L., and Stoll, C. (2020).
Energy consumption of cryptocurrencies beyond bitcoin.
Joule, 4(9):1843–1846.

Geretto, E. and Pauluzzo, R. (2012).
Stock exchange markets in china: Structure and main problems.
Transition Studies Review, 19(1):89–106.

Gleason, K. C., Mathur, I., and Peterson, M. A. (2004).
Analysis of intraday herding behavior among the sector etfs.
Journal of Empirical Finance, 11(5):681–694.

Granger, C. W. J. (1969).
Investigating causal relations by econometric models and cross-spectral methods.
Econometrica, 37(3):424–438.

Guo, J. (2019).
Oil price forecast using deep learning and arima.
2019 International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI), pages 241–247.

Guo, L., Shi, F., and Tu, J. (2016).
Textual analysis and machine leaning: Crack unstructured data in finance and accounting.
The Journal of Finance and Data Science, 2(3):153–170.

Hamilton, J. D. (1983).
Oil and the macroeconomy since World War II.
Journal of Political Economy, 91(2):228–248.

Hamilton, J. D. (1985).
Historical causes of postwar oil shocks and recessions.

The Energy Journal, 6(1):97–116.

Hamilton, J. D. (1996).
This is what happened to the oil price-macroeconomy relationship.
Journal of Monetary Economics, 38(2):215–220.

Hamilton, J. D. (2003).
What is an oil shock?
Journal of Econometrics, 113(2):363–398.

Hamilton, J. D. (2009).
Understanding Crude Oil Prices.
The Energy Journal, 0(2):179–206.

Hannah Ritchie, M. R. and Rosado, P. (2020).
Energy.
Our World in Data.
https://ourworldindata.org/energy.

He, M., Zhang, Y., Wen, D., and Wang, Y. (2021).
Forecasting crude oil prices: A scaled PCA approach.
Energy Economics, 97:105189.

He, Z., Zhou, F., Xia, X., Wen, F., and Huang, Y. (2019).
Interaction between oil price and investor sentiment: Nonlinear causality, time-varying influence, and asymmetric effect.
Emerging Markets Finance and Trade, 55(12):2756–2773.

Henry, E. (2008).
Are investors influenced by how earnings press releases are written?
The Journal of Business Communication, 45(4):363–407.

Hodrick, R. and Prescott, E. (1997).
Postwar u.s. business cycles: An empirical investigation.
Journal of Money, Credit and Banking, 29(1):1–16.

Jalan, A., Matkovskyy, R., and Yarovaya, L. (2021).
"Shiny" crypto assets: A systemic look at gold-backed cryptocurrencies during the covid-19 pandemic.
International Review of Financial Analysis, 78:101958.

Ji, Q., Bouri, E., Gupta, R., and Roubaud, D. (2018).
Network causality structures among bitcoin and other financial assets: A directed acyclic graph approach.
The Quarterly Review of Economics and Finance, 70:203–213.

Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019a).
Dynamic connectedness and integration in cryptocurrency markets.
International Review of Financial Analysis, 63:257–272.

Ji, Q., Bouri, E., Roubaud, D., and Kristoufek, L. (2019b).
Information interdependence among energy, cryptocurrency and major commodity markets.
Energy Economics, 81:1042–1055.

Jiang, S., Li, Y., Lu, Q., Wang, S., and Wei, Y. (2022).
Volatility communicator or receiver? Investigating volatility spillover mechanisms among bitcoin and other financial markets.
Research in International Business and Finance, 59:101543.

Kallinterakis, V. and Wang, Y. (2019).
Do investors herd in cryptocurrencies – and why?
Research in International Business and Finance, 50:240–245.

Kilian, L. (2009).
Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market.
American Economic Review, 99(3):1053–69.

Kilian, L. (2019).
Measuring global real economic activity: Do recent critiques hold up to scrutiny?
Economics Letters, 178:106–110.

Kilian, L. and Hicks, B. (2013).
Did unexpectedly strong economic growth cause the oil price shock of 2003–2008?
Journal of Forecasting, 32(5):385–394.

Kizys, R., Tzouvanas, P., and Donadelli, M. (2021).
From covid-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions.
International Review of Financial Analysis, 74:101663.

Kuang, W. (2021).
Are clean energy assets a safe haven for international equity markets?
Journal of Cleaner Production, 302:127006.

Kumar, A. (2020).
Empirical investigation of herding in cryptocurrency market under different market regimes.
Review of Behavioral Finance, 13(3):297–308.

Kumar, A., Badhani, K., Bouri, E., and Saeed, T. (2021).
Herding behavior in the commodity markets of the asia-pacific region.
Finance Research Letters, 41:101813.

Le, L.-T., Yarovaya, L., and Nasir, M. A. (2021a).
Did covid-19 change spillover patterns between fintech and other asset classes?
Research in International Business and Finance, 58:101441.

Le, T.-L., Abakah, E. J. A., and Tiwari, A. K. (2021b).
Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution.
Technological Forecasting and Social Change, 162:120382.

Li, J., Xu, Z., Xu, H., Tang, L., and Yu, L. (2017).
Forecasting oil price trends with sentiment of online news articles.
Asia-Pacific Journal of Operational Research, 34(2):1740019.

Li, S., Li, J., Lu, X., and Sun, Y. (2022).
Exploring the dynamic nonlinear relationship between crude oil price and implied volatility indices: A new perspective from mmv-mfdfa.
Physica A: Statistical Mechanics and its Applications, 603:127684.

Li, X. (2020).
When financial literacy meets textual analysis: A conceptual review.
Journal of Behavioral and Experimental Finance, 28:100402.

Li, X., Shang, W., and Wang, S. (2019).
Text-based crude oil price forecasting: A deep learning approach.
International Journal of Forecasting, 35(4):1548–1560.

Lippi, F. and Nobili, A. (2012).
Oil and the macroeconomy: A quantitative structural analysis.
Journal of the European Economic Association, 10(5):1059–1083.

Litimi, H., BenSaïda, A., and Bouraoui, O. (2016).
Herding and excessive risk in the american stock market: A sectoral analysis.
Research in International Business and Finance, 38:6–21.

Loughran, T. and McDonald, B. (2016).
Textual analysis in accounting and finance: A survey.
Journal of Accounting Research, 54(4):1187–1230.

Loughran, T., McDonald, B., and Pragidis, I. (2019).
Assimilation of oil news into prices.
International Review of Financial Analysis, 63:105–118.

Maghyereh, A. and Abdoh, H. (2020).
Tail dependence between bitcoin and financial assets: Evidence from a quantile cross-spectral approach.
International Review of Financial Analysis, 71:101545.

McQueen, G., Pinegar, M., and Thorley, S. (1996).
Delayed reaction to good news and the cross-autocorrelation of portfolio returns.
The Journal of Finance, 51(3):889–919.

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., and Franklin, E. C. (2018).
Bitcoin emissions alone could push global warming above 2 °c.
Nature Climate Change, 8(11):931–933.

Moshiri, S. and Foroutan, F. (2006).
Forecasting nonlinear crude oil futures prices.
The Energy Journal, 27(4):81–95.

Naeem, M. A. and Karim, S. (2021).
Tail dependence between bitcoin and green financial assets.
Economics Letters, 208:110068.

Narayan, P. K., Narayan, S., and Zheng, X. (2010).
Gold and oil futures markets: Are markets efficient?

Applied Energy, 87(10):3299–3303.

Newey, W. K. and West, K. D. (1994).
Automatic lag selection in covariance matrix estimation.
The Review of Economic Studies, 61(4):631–653.

Okorie, D. I. (2021).
A network analysis of electricity demand and the cryptocurrency markets.
International Journal of Finance & Economics, 26(2):3093–3108.

Okorie, D. I. and Lin, B. (2020).
Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy.
Energy Economics, 87:104703.

Pan, J. (2022).
Choices and actions to climate mitigation in China.
In *Climate Change Economics*, pages 345–359. Springer.

Peng, X. (2020).
Do precious metals act as hedges or safe havens for China's financial markets?
Finance Research Letters, 37:101353.

Pham, L. (2019).
Do all clean energy stocks respond homogeneously to oil price?
Energy Economics, 81:355–379.

Pham, L., Huynh, T. L. D., and Hanif, W. (2021).
Cryptocurrency, green and fossil fuel investments.
SSRN, page 3925844.

Phan, D. H. B., Narayan, P. K., and Gong, Q. (2021).
Terrorist attacks and oil prices: Hypothesis and empirical evidence.
International Review of Financial Analysis, 74:101669.

Platt, M., Sedlmeir, J., Platt, D., Xu, J., Tasca, P., Vadgama, N., and Ibañez, J. I. (2021).
The energy footprint of blockchain consensus mechanisms beyond proof-of-work.
In *2021 IEEE 21st International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, pages 1135–1144.

Poyser, O. (2018).
Herding behavior in cryptocurrency markets.
arXiv preprint arXiv:1806.11348.

Qadan, M. and Nama, H. (2018).
Investor sentiment and the price of oil.
Energy Economics, 69:42–58.

Ratner, M. and Chiu, C.-C. J. (2013).
Hedging stock sector risk with credit default swaps.
International Review of Financial Analysis, 30:18–25.

Ready, R. C. (2018).
Oil consumption, economic growth, and oil futures: The impact of long-run oil supply uncertainty on asset prices.
Journal of Monetary Economics, 94:1–26.

Reboredo, J. C. and Uddin, G. S. (2016).
Do financial stress and policy uncertainty have an impact on the energy and metals markets? A quantile regression approach.
International Review of Economics & Finance, 43:284–298.

Rehman, M. U. and Kang, S. H. (2021).
A time–frequency comovement and causality relationship between bitcoin hashrate and energy commodity markets.
Global Finance Journal, 49:100576.

Rezec, M. and Scholtens, B. (2017).
Financing energy transformation: The role of renewable energy equity indices.
International Journal of Green Energy, 14(4):368–378.

Richards, M. A. J. (1999).
Idiosyncratic risk: an empirical analysis, with implications for the risk of relative-value trading strategies.
International Monetary Fund.

Sadorsky, P. (2000).
The empirical relationship between energy futures prices and exchange rates.
Energy Economics, 22(2):253–266.

Saeed, T., Bouri, E., and Alsulami, H. (2021).
Extreme return connectedness and its determinants between clean/green and dirty energy investments.
Energy Economics, 96:105017.

Samuelson, P. A. (1965).
Proof that properly anticipated prices fluctuate randomly.
Industrial Management Review, 6(2):41.

Sari, R., Soytas, U., and Hacihasanoglu, E. (2011).
Do global risk perceptions influence world oil prices?
Energy Economics, 33(3):515–524.

Schinckus, C. (2021).
Proof-of-work based blockchain technology and anthropocene: An undermined situation?
Renewable and Sustainable Energy Reviews, 152:111682.

Shahbaz, M., Trabelsi, N., Tiwari, A. K., Abakah, E. J. A., and Jiao, Z. (2021).
Relationship between green investments, energy markets, and stock markets in the aftermath of the global financial crisis.
Energy Economics, 104:105655.

Shaikh, I. (2019).
The relation between implied volatility index and crude oil prices.
Engineering Economics, 30(5):556–566.

Shen, C. (2018).
Testing for herding behaviour among energy sectors in Chinese stock exchange.
Journal of Physics: Conference Series, 1053:012106.

Song, Y., Chen, B., Hou, N., and Yang, Y. (2022).
Terrorist attacks and oil prices: A time-varying causal relationship analysis.
Energy, 246:123340.

Stavroyiannis, S. and Babalos, V. (2019).
Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model.
Journal of Behavioral and Experimental Finance, 22:57–63.

Symitsi, E. and Chalvatzis, K. J. (2018).
Return, volatility and shock spillovers of bitcoin with energy and technology companies.
Economics Letters, 170:127–130.

Tan, L., Chiang, T. C., Mason, J. R., and Nelling, E. (2008).
Herding behavior in chinese stock markets: An examination of A and B shares.
Pacific-Basin Finance Journal, 16(1):61–77.

Trück, S. and Yu, Y.-J. (2016).
Investor herding and dispersing in the renewable energy sector.
Macquarie University Working paper, 16:2.

Ukpong, I., Tan, H., and Yarovaya, L. (2021).
Determinants of industry herding in the US stock market.
Finance Research Letters, 43:101953.

Umar, Z., Trabelsi, N., and Alqahtani, F. (2021).
Connectedness between cryptocurrency and technology sectors: International evidence.
International Review of Economics & Finance, 71:910–922.

Urquhart, A. and Zhang, H. (2019).
Is bitcoin a hedge or safe haven for currencies? An intraday analysis.
International Review of Financial Analysis, 63:49–57.

Uzonwanne, G. (2021).
Volatility and return spillovers between stock markets and cryptocurrencies.
The Quarterly Review of Economics and Finance, 82:30–36.

Vidal-Tomás, D., Ibáñez, A. M., and Farinós, J. E. (2019).
Herding in the cryptocurrency market: CSSD and CSAD approaches.
Finance Research Letters, 30:181–186.

Wang, G.-J., yu Ma, X., and yu Wu, H. (2020).
Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?
Research in International Business and Finance, 54:101225.

Wang, P., Zhang, H., Yang, C., and Guo, Y. (2021).
Time and frequency dynamics of connectedness and hedging performance in global stock markets: Bitcoin versus conventional hedges.
Research in International Business and Finance, 58:101479.

Wang, P., Zhang, W., Li, X., and Shen, D. (2019).
Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective.
Finance Research Letters, 31:1–18.

Wu, B., Wang, L., Lv, S.-X., and Zeng, Y.-R. (2021).
Effective crude oil price forecasting using new text-based and big-data-driven model.
Measurement, 168:108468.

Yao, J., Ma, C., and He, W. P. (2014).
Investor herding behaviour of Chinese stock market.
International Review of Economics & Finance, 29:12–29.

Yi, S., Xu, Z., and Wang, G.-J. (2018).
Volatility connectedness in the cryptocurrency market: Is bitcoin a dominant cryptocurrency?
International Review of Financial Analysis, 60:98–114.

Yin, L. and Feng, J. (2019).
Can investors attention on oil markets predict stock returns?
The North American Journal of Economics and Finance, 48:786–800.

Yousaf, I., Suleman, M. T., and Demirer, R. (2022).
Green investments: A luxury good or a financial necessity?
Energy Economics, 105:105745.

Youssef, M. (2020).
What drives herding behavior in the cryptocurrency market?
Journal of Behavioral Finance, pages 1–10.

Youssef, M. (2022a).
Do oil prices and financial indicators drive the herding behavior in commodity markets?
Journal of Behavioral Finance, 23(1):58–72.

Youssef, M. (2022b).
What drives herding behavior in the cryptocurrency market?
Journal of Behavioral Finance, 23(2):230–239.

Zeng, T., Yang, M., and Shen, Y. (2020).
Fancy bitcoin and conventional financial assets: Measuring market integration based on connectedness networks.
Economic Modelling, 90:209–220.

Zhang, J.-L., Zhang, Y.-J., and Zhang, L. (2015).
A novel hybrid method for crude oil price forecasting.
Energy Economics, 49:649–659.

Zhang, Y.-J. and Wei, Y.-M. (2010).
The crude oil market and the gold market: Evidence for cointegration, causality and price discovery.
Resources Policy, 35(3):168–177.

Zhao, L.-T., Zeng, G.-R., Wang, W.-J., and Zhang, Z.-G. (2019).
Forecasting oil price using web-based sentiment analysis.
Energies, 12(22):4291.

Zheng, D., Li, H., and Chiang, T. C. (2017).
Herding within industries: Evidence from Asian stock markets.
International Review of Economics & Finance, 51:487–509.

Zheng, D., Li, H., and Zhu, X. (2015).
Herding behavior in institutional investors: Evidence from China's stock market.
Journal of Multinational Financial Management, 32-33:59–76.