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Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19*☆

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ABSTRACT

Environmental change created worldwide interest in investing in renewable energy. Less reliance on fossil fuels would have a substantial influence on investors for alternative energy, especially renewable energy. The literature has concentrated on empirical studies of herding behaviour in finance, but not in renewable energy. This paper fills the gap by investigating herding in renewable energy, using daily closing prices in renewable and fossil fuel energy stock returns in the USA, Europe, and Asia, for March 24, 2000–May 29, 2020, which covers the Global Financial Crisis (GFC) (2007–2009), the coronavirus crises of SARS (2003). And the ongoing COVID-19 (2019–2020) pandemic. The paper shows that: (1) for low extreme oil returns, investors are more likely to display herding in the stock market; (2) for SARS and COVID-19, herding is more likely during extremely high oil returns after the GFC; and (3) herding is more likely during periods of extremely low oil returns during the coronavirus crises. These results suggest that after the GFC, investors are more sensitive to asset losses, so they will be more likely to display herding in the stock market. However, during SARS and COVID-19, investors panic so they may unwisely sell their assets. There are strong cross-sector herding spillover effects from US fossil fuel energy to renewable energy, especially before the GFC, while the US fossil fuel energy market has a significant influence on the Europe and Asia renewable energy returns during COVID-19. During SARS, which was not a pandemic, US fossil fuels only had an impact on US renewable energy returns.

1. Introduction

Global warming and climate change created worldwide interest in investing in renewable energy sources. Consequently, less reliance and use of traditional (or fossil fuel) energy would have a substantial influence on investors for alternative energy sources and influence the renewable energy market.

Investor herding behaviour is based on investor psychology to follow the performance of others. On the basis of private information or public knowledge about the behaviour of others, investors mimic the behaviour and actions of other investors.

The extant literature has concentrated on empirical studies of herding behaviour in financial stock markets to explain the volatility of stock returns ([1] Christie and Huang, 1995). However, there has been a lack of research of herding behaviour in renewable energy markets.

[2] Muth (1961) proposed rational expectations and assumed that investors are rational and do not make systematic mistakes [3]. Fama (1970) proposed the efficient market hypothesis, and assumed that prices will fully reflect all the available information in financial markets when they are working efficiently. Both economists and practitioners are interested in the herding effect on stock prices as investors in financial markets are known to be influenced by others in their decision making

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(for example, see Ref. [4] Bikhchandani and Sharma, 2001).

However, herding behaviour can lead to significant mispricing, and might create additional risks in financial markets. The most well-known example is the subprime mortgage crisis in the USA, starting in the beginning of 2007, which subsequently led to the Global Financial crisis (GFC) in 2007–2009. Before the GFC started, herding behaviour was observed in the US stock market ([5] Avery and Zemsky, 1998 [4]; Bikhchandani and Sharma, 2001).

The 2019 World Energy Outlook report (https://www.iea.org/reports/world-energy-outlook-2019 [accessed 29 February 2020]) has noted that new power capacity will grow nearly 8500 GW, of which two-thirds will likely be renewable energy in 2020. This rapid growth rate reflects strong policy support that clean energy technology will play an important role in reaching sustainable energy goals, and thereby also reduce the risk of investing in renewable energy stocks.

In late December 2019, the novel SARS-CoV-2 virus that causes the COVID-19 disease originated in Wuhan, China. Although the data change dramatically on a daily basis, at the time of writing (July 20, 2020), COVID-19 is known to have led to more than 14.5 million infected cases worldwide, and more than 600,000 deaths, with the number of infections and deaths in the USA alone accounting for almost 4 million cases and more than 143,000 deaths, respectively (see Coronavirus Cases – Worldwide, Worldometer, https://www.worldometers.info/coronavirus/).

COVID-19 has also spread to more than 213 countries and territories around the world, and 2 international conveyances, specifically cruise liners) in just over four months. The [6,7] World Health Organization (WHO) belatedly declared a global public health emergency on January 30, 2020. At the end of January 2020, Italy, Australia and the USA were the first countries to impose travel bans on foreign nationals entering their countries if they had visited China in the previous two weeks. Such travel bans were inexplicably and inexcusably criticized by the WHO, which has since then changed its stance dramatically.

Most countries seem to have taken COVID-19 seriously. Amid the anticipation of a prolonged coronavirus pandemic, this has also caused fear to investors in financial markets of a global credit crunch. Such concern was exacerbated by increased volatility in the US dollar which, in turn, contributed to broad-based selling of stocks and creating a severe and vicious circle.

However, oil price movements could lead to a substantial impact on both the fossil fuel and renewable energy sectors. The average performance of the fossil fuel energy sectors will influence the average performance of the renewable energy sectors. This type of cross-sector effect from the fossil fuel energy to the renewable energy markets has not previously been examined in the extant literature.

This paper intends to fill this gap, and will examine the herding behaviour of the energy sectors in the USA, Europe, and Asia stock markets, and also test the cross-section herding behaviour from the fossil fuel to the renewable energy markets. The paper will also examine the risk spillover effects during three types of global crises, namely the GFC, SARS, and the COVID-19 pandemic. Moreover, the paper will compare herding behaviour during the extreme positive and negative oil price returns before, during and after the GFC, SARS, and COVID-19 crises.

The remainder of the paper is as follows. Section 2 presents a literature review of herding behaviour in financial markets. Section 3 discusses the model specification and alternative tests of herding behaviour in different sectors. Section 4 presents the data in the financial, fossil fuel energy, and renewable energy markets. The alternative empirical tests of herding behaviour are presented and discussed in Section 5. Section 6 gives some concluding remarks.

2. Literature review

2.1. Herding behaviour in financial markets

The foundations of empirical research offered several definitions of herding behaviour [4]. Bikhchandani and Sharma (2001) defined rational herding behaviour as an obvious intent to copy the behaviour of other investors, which can destabilize markets and increase volatility. Moreover, "spurious herding" refers to a group of investors who, when facing similar decision problems and information sets, will make similar decisions and lead to an efficient outcome.

Most empirical studies with a focus on rational herding show that investors who follow others may yield important information and obtain maximum profits ([8] Bikhchandani et al., 1992 [9]; Devenow and Welch, 1996).

[4] Bikhchandani and Sharma (2001) provide three reasons that causes investor herding, including informational cascades, reputation-based herding, and compensation-based herding. Informational cascades refer to several investors observing the outcome of the previous decision-maker and, considering it useful, will do likewise in their own decisions. The theory does not necessarily apply to financial markets as prices will directly reflect the previous investor's decision. Moreover, the investor can observe the appropriate information through public information ([10] Banerjee, 1992 [8]; Bikhchandani et al., 1992 [11]; Welch, 1992 [5]; Avery and Zemsky 1998).

[12] Scharfstein and Stein (1990) and [13] Graham (1999) presented reputation-based herding and argued that, if the uncertainty about the ability of managers who want to protect their own reputation or, if public information is not consistent with the manager's private information, they are likely to follow the decisions of other managers.

[14] Roll (1992) developed compensation-based herding and argued that, if a manager's compensation depends on how they perform, this will likely distort the manager's incentives and lead to an inefficient portfolio, which also leads to herding behaviour.

[15] Lakonishok et al. (1992) defined herding as the average tendency of a group of money managers to buy (sell) stocks, relative to what could be expected if money managers traded independently. The authors use their model to measure herding behaviour at the individual level through the correlations in trading patterns for a particular group of traders. And their observed tendency to buy and sell the same set of stocks.

However, due to a lack of information at the investor level for practical reasons, research moved in a different direction to capture market-wide herding behaviour by examining the existence of a non-linear relationship between asset returns dispersions and market returns.

Based on the market-wide approach [1], Christie and Huang (1995) suggested the Cross-Section Standard Deviation (CSSD) model and argued that, when there is herding behaviour in the market, dispersions from the mean returns are expected to be lower. They also found that, for extreme market movements (1% and 5% upturns and downturns for market returns), investors would be more likely to imitate the actions of other investors in the market. However, the disadvantage of CSSD is that it can easily be affected by outliers empirically, so it is difficult to find any evidence of herding behaviour in normal conditions ([16] Tan et al., 2008).

[17] Chang et al. (2000) improved the measurement of dispersion and suggested the Cross-Section Absolute Deviation (CSAD) model. Many studies have followed the CSAD model to capture evidence of market-wide herding behaviour [18]. Litimi et al. (2016) tested 12 sectors in the NASDAQ stock exchange from 1985 to 2013, and found that only two sectors, namely Public Utilities and Transportation, exhibited herding behaviour.

However, the authors conclude that periods of turmoil would trigger herding in the consumer non-durables, energy, health care, public utilities, technology, and transportation sectors. Subsequent studies have confirmed the findings in Ref. [18] Litimi et al. (2016), and also found herding behaviour was frequently present during the GFC and periods of bubbles ([19] BenSaïda, 2017 [20]; BenMabrouk and Litimi, 2018)).

Herding evidence in the Chinese stock market is mixed, as some studies have found no herding while others have suggested herding behaviour [21]. Demirer and Kutan (2006) used the CSSD model and tested 18 sectors in the Shanghai and Shenzhen Stock Exchanges from 1999 to 2002, but no evidence of herding behaviour was found during the rising and falling market conditions in all sectors.

[16] Tan et al. (2008) used the CSAD model to examine Chinese A-shares and B-shares in the Shanghai and Shenzhen Stock Exchange from 1994 to 2003. Their empirical results concluded that there was significant herding behaviour during rising and falling market conditions, and stronger asymmetric herding in Shanghai A-shares in rising markets.

Contrary to the results in Ref. [16] Tan et al. (2008) [22], Chiang et al. (2010) found herding behaviour occurred in both the Shanghai A-shares and Shenzhen A-shares, while Shanghai B-shares and Shenzhen B-shares displayed herding behaviour only when the markets were declining. A similar result was also found in Ref. [23] Yao et al. (2014), who concluded there was strong herding behaviour in the B-share markets.

Investors were more likely to display herding behaviour when the market was declining than when the market was rising in the Shanghai and Shenzhen Stock Exchange markets from 1999 to 2008. However, this is not consistent with the results presented in Ref. [21] Demirer and Kutan (2006), who were unable to find any evidence of herding behaviour in the Chinese stock exchange markets.

In European markets [24], Caparrelli et al. (2004) found herding behaviour in the Italian stock exchange markets from 1998 to 2001, and stronger herding during periods of extremely high returns [25,26]. Economou et al. (2011, 2016) examined herding behaviour in four south European stock exchange markets, namely Greece, Italy, Portugal and Spain, from 1998 to 2008.

They concluded that there was herding behviour in the Greece and Italy stock exchange markets, while there was no evidence of herding for the Spain market. The authors also confirmed the finding of significant asymmetries between rising and falling share markets, but herding behaviour was stronger in falling markets, and was even more prominent during the GFC.

[27] Mobarek et al. (2014) confirmed that the PIIGS (Portugal, Italy, Ireland, Greece, Spain) markets were more intensely affected by both the Eurozone crisis and the GFC, and the Nordic markets were more strongly affected by the Eurozone crisis than the GFC. Several empirical studies have argued that financial crises are the result of widespread herding behaviour among market participants [28]. Chiang and Zheng (2010) found that herding behaviour was more apparent during crisis periods in the Latin American and Asian stock exchange markets.

[29] Bowe and Domuta (2004) examined the Jakarta Stock Exchange (JSX) in Indonesia for the period of the 1997 Asian financial crisis, and concluded that foreign herding increased herding during the crisis period [30,31]. Galariotis et al. (2016 a, b) found significant evidence of herding behaviour for high liquidity stocks during the 2007–2009 GFC for G5 countries (namely, France, Germany, Japan, UK, and USA) stock exchange markets. Similar findings were confirmed by Ref. [32] Bekiros et al. (2017).

Some empirical findings have concluded that the US stock market plays a significant role in financial transactions across global stock markets [27]. Chiang and Zheng (2010) tested 18 countries, and divided the sample into three groups, namely advanced stock markets, Latin American markets, and Asian markets, for 1989–2009 and found that most investors exhibited herding behaviour with the US market, in addition to their domestic markets.

Consistent evidence presented by Ref. [33] Galariotis et al. (2015) concluded that the UK market showed herding behaviour around the US market during the Asian crisis and the Dotcom bubble crisis. On the contrary, the UK market had no evidence to affect US market herding behaviour for any time periods [34]. Zheng et al. (2017) focused primarily on Asian markets, and concluded that only Japan and Korea investors followed the US stock market more closely than did investors in other Asian markets.

The crude oil market is used frequently as an important factor in terms of the volatility of stocks in energy sectors. Much of the empirical analysis has concentrated on market fluctuations in crude oil prices and associated financial markets ([35] Oberndorfer, 2009 [36]; Ramos and Veiga, 2011 [37]; Zamani, 2016 [38]; Chang et al., 2019). Earlier research by Refs. [39] Chang et al. (2013) found asymmetric effects of negative and positive shocks of equal magnitude on the conditional variances between crude oil returns and stock index returns.

Recent research by Ref. [40] Chang et al. (2018) focused on the European energy stock markets, and led to mixed results for predicting the trends in Brent crude oil and European energy stocks. Research by Ref. [41] Caporin et al. (2019) used intra-day data of energy futures stocks, and concluded that the results for the returns relationships and volatility spillovers are highly variable, according to the trading range, as well as considerations of daily and day-night effects, temporal aggregation, and different data frequencies.

Recent research by Ref. [42] Chang et al. (2020) uses a financial market-based approach to investigate whether positive stock returns cause changes in CO2 emissions based on the Granger causality test, which will enable a clear directional statement regarding the predictability between stock returns and CO2 emissions. The empirical data included annual CO2 emissions from fuel combustion of three fossil energy sources, namely coal, oil and gas, based on 18 countries with sophisticated financial markets listed in the Morgan Stanley Capital International (MSCI) World Index for 1971–2017. It was shown that all the statistically significant causality findings are uni-directional from stock market returns to CO2 emissions from coal, oil and gas, but not the reverse.

For the purpose of conducting tests of herding behaviour, many studies have examined if the stock market also shows herding behaviour around the crude oil market ([43,44] Balcilar et al., 2014, 2017 [45]; Ulussever and Demirer, 2017) [21]. BenMabrouk and Litimi (2018) examined all domestic US firms listed on NYSE, AMEX and NASDAQ, from 2000 to 2017, and concluded that US industries display significant herding behaviour for both upturn/downturn extreme oil market returns, although herding behaviour is more prevalent during extreme downturns in oil prices. However, the authors found the energy sector showed herding behaviour during upturns in extreme oil returns.

Few studies have focused only on the energy sector [46]. Shen (2010) examined 10 Chinese energy stock sectors, which included New Energy, Wind Energy, Scarce Resources, Nuclear Power, Stored Energy, Biomass Energy, Fuel Cell, Coal Chemical, Water and Power, and Petroleum sections. The author showed herding behaviour in the energy sectors, except for the New Energy and Nuclear Power sectors.

[47] Trueck and Yu (2018) focused on renewable energy, and conducted a simple test of herding behaviour for the US renewable energy sector from 2000 to 2015. They concluded there was no evidence of herding behaviour in the US renewable energy sector, which contradicts the empirical findings of several previous research studies.

Several studies have concluded that the fossil fuel energy sector has been strongly connected to oil prices, but there has been little support for renewable energy sector as being dependent on the oil market ([48] Shah et al., 2018). Some studies have argued that oil price movements play an active role in determining the profitability of clean energy investment projects.

[49] Reboredo (2015) concluded that oil price behaviour provides market-based incentives to develop the green economy, but the incentives are asymmetric, which indicate that oil prices are high. The development of the green economy can be fostered through the fossil fuel market without the need to implement specific energy policies. On the contrary, when oil prices are low, the market provides inadequate incentives, such that the development of the green economy needs to be supported by green energy policies.

Some research has examined the relationship between renewable and non-renewable energy consumption, and concluded the appropriateness of substitutability between the two energy sources ([50] Apergis and Payne, 2012)) [51]. Marques et al. (2010) emphasized that both the intersection of fossil fuel energy sources (that is, oil, coal, and natural gas) and consequent CO2 emissions restrain renewable deployment.

The following section introduces two standard measures of returns dispersion and alternative models to test herding behaviour across different sectors.

3. Methodology

When investors are fully rational, CAPM assumes a linear relationship between the required rate of return of securities. Such market risk of securities might not be the appropriate solution to attain market equilibrium.

However, CAPM, as proposed by financial economists such as [52, 53] Treynor (1961, 1962) [54], Sharpe (1964) [55], Lintner (1965) and [56] Mossin (1966), has failed numerous empirical tests as investors in the market often display herding behaviour such that individual stock returns deviate significantly from market returns.

In this section, we introduce the two most common measures of returns dispersion, namely the cross-section Standard Deviation (CSSD) and the cross-section Absolute Deviation (CSAD), and present the empirical model to be used in testing for herding behaviour.

3.1. CSSD and CSAD measures

Christie and Huang (1995) suggest CSSD as a proxy for herding, which is expressed as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}$$

where $R_{i,t}$ is the observed return of stock i at time t; $R_{m,t}$ is the average return of the equally weighted portfolio at time t; and N is the number of stocks in the market portfolio.

However, CSSD imposes restrictions, for example, it does not take into consideration the asymmetric property in the returns distribution, and is affected by the existence of outliers [17]. Chang et al. (2000) extend the CSSD measure and propose he CSAD measure as a proxy for herding inspired by the capital asset pricing model (CAPM), which is given as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$$

where $R_{i,t}$ is the observed return of stock i at time t; $R_{m,t}$ is the average return of the equally weighted portfolio at time t; and N is the number of stocks in the market portfolio.

3.2. Empirical model and tests of herding

3.2.1. Model I: herding in the energy sector

When markets exhibit herding behaviour, the path of stock returns should converge towards the average market trend, instead of deviating from market returns. As a result, the relationship between CSAD and the average market returns should be nonlinear, which is captured by $R_{m,t}^2$. As there exists a negative relationship between dispersion and market returns, the coefficient γ_3 in equation (1) should take a negative value when there exists herding behaviour (for further details, see Ref. [17] Chang et al. (2000)).

As given in equation (1):

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{1}$$

$R_{m,t}$ is the daily average returns of the markets at time t, so that a negative value of γ_3 indicates that stocks exhibit herding at the industry level.

The null hypothesis of herding behaviour is: $H_0 : \gamma_3 \leq 0$. Following [57] Bouri et al. (2019), the null hypothesis of non-herding can also be represented as: $H_0 : \gamma_3 \geq 0$. However, many studies have had difficulty in capturing herding evidence based on the CSSD measure ([1] Christie and Huang,1995 [17]; Chang et al., 2000), or found inconsistent evidence.

3.2.2. Model II: energy sector herding around the oil market

Model II adds the squared market returns of the crude oil spot prices to test if crude oil contributes some impact on investor behaviour in the market. This is given in equation (2) as:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \gamma_4 R_{oil,t}^2 + \varepsilon_t \tag{2}$$

where $R_{oil,t}^2$ is the squared returns of the crude oil spot price. For equation (2), a negative value of γ_3 indicates local herding behaviour, and a negative value of γ_4 means that the local market displays herding around the crude oil market.

3.2.3. ***Model III: energy sector*** *herding* ***during oil market extreme movements***

We follow [1] Christie and Huang (1995) to define extreme market movements (that is, upturns and downturns), which are based on observing 1% and 5% of sample observations appearing in the extremities of the distribution to detect extreme movements. Model 3 adds the extreme crude oil price movements to equation (2), as given in equation (3):

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \gamma_4 R_{oil,t}^2 + \gamma_5 D_t^{up,oil} R_{m,t}^2 + \gamma_6 D_t^{down,oil} R_{m,t}^2 + \varepsilon_t \tag{3}$$

where the dummy variables represent the extreme returns in crude oil prices, consistent with previous studies.

The extreme movements in returns are defined as the returns of oil prices lying within the 5% lower and upper tails of the returns distribution: $D_t^{up,oil} = 1$ if the returns of the crude oil market lie in the extreme upper tail of the returns distribution; $D_t^{down,oil} = 1$ if the returns of the crude oil market lies in the extreme lower tail of the returns distribution. Hence, if herding is enhanced during extreme oil market movements, then the coefficients γ_5 and γ_6 should be negative.

3.2.4. Model IV: cross-sector herding spillovers and risk spillovers from the fossil fuel to the renewable energy market

As described above, some empirical studies have found that the US stock market frequently plays a significant role in financial transactions across global stock markets (for example, see Ref. [28] Chiang and Zheng, 2010). Following this line of thinking, the Europe and the Asia renewable markets are frequently influenced by investor behaviour in the US fossil fuel energy market (including the US, Brazil, and Canada markets). In order to capture this cross-sector herding spillover and risk spillover from the fossil fuel to the renewable energy market, we add fossil fuel energy to equation (3), as given in equation (4):

$$CSAD_{i,t} = \alpha + \gamma_1 R_{m,i,t} + \gamma_2\left|R_{m,i,t}\right| + \gamma_3 R_{m,i,t}^2 + \gamma_4 R_{oil,t}^2 + \gamma_5 D_t^{up,oil} R_{m,t}^2 + \gamma_6 D_t^{down,oil} R_{m,t}^2 + \gamma_7 R_{m,j,t}^2 + \gamma_8 CSAD_{j,t} + \varepsilon_t \tag{4}$$

where $i =$ one of the US, Europe, or Asia renewable energy markets, $j =$ either the US or Asia fossil fuel energy market; and $CSAD_{i,t}$ is the measure for returns dispersion in area-sector i.

The difference compared with equation (3) is that $R_{m\_j,t}^2$ and $CSAD_{j,t}$ are included in the specification to capture the dispersions and squared market returns for the area-sector j. A negative and statistically significant estimated γ_3 would indicate market-wide herding behaviour. Moreover, a negative and statistically significant estimated γ_7 in equation (4) would suggest area-sector i market herding behaviour around the area-sector j market. A positive and statistically significant estimated γ_8 would imply that the area-sector j market has a dominant influence on the area-sector i market.

4. Data

The paper uses daily closing stock prices of energy sectors in the USA, Asia, and Euro regions, and covers the period March 24, 2000–May 29, 2020. The data set covers 104 renewable energy companies and 112 Fossil Fuel Energy companies. Of the 104 renewable energy companies, there are 53 in the USA, 3 in Canada, 1 in Chile, and 2 in Brazil; there are 24 in Europe, namely 1 in Austria, 1 in Belgium, 3 in France, 1 in Finland, 6 in Germany, 1 in Ireland, 1 in Norway, 1 in Portugal, 2 in Spain, 2 in Sweden, 3 in Switzerland, and 2 in the UK; of 21 in Asia, there are 3 in Hong Kong, 14 in Japan, 2 in South Korea, and 2 in Taiwan. Of the total of 112 Fossil Fuel Energy companies, there are 98 in the USA, and 9 in Canada; 5 in Asia include 1 in China, 2 in Hong Kong, and 2 in Indonesia.

Of the 216 individual stocks, there are 104 renewable energy companies which have invested in renewable energy and related alternative energy techniques, and 112 companies which have invested in fossil fuel energy sources, such as natural gas and coal, and oil exploration and production. In order to test the effect of extreme oil returns on local herding, WTI crude oil price returns are also included in the data set. All the data are obtained from DataStream.

Three types of crises are included in the testing of market herding behaviour. The first is the GFC from July 2, 2007–December 31, 2009. Second, the SARS epidemic was first identified in Foshan, Guangdong, China in November 2002, but was not identified until much later. This paper uses February 10, 2003 for the global SARS commencement when the [6] World Health Organization (WHO) Beijing office received an email message describing a "strange contagious disease" that has "already left more than 100 people dead" in Guangdong Province in the space of one week, and describes "a 'panic' attitude, where people are emptying pharmaceutical stocks of any medicine they think may protect them.

We set the global SARS epidemic as ending on July 5, 2013 when the WHO announced that the last local transmission area was removed from the list. In total, more than 8000 people from 29 different countries and territories were infected, and 774 died worldwide ([6] WHO, 2003).

For a variety of reasons, to date there is no general agreement as to the exact timing of the COVID-19 crisis, as most countries worldwide began to take the novel coronavirus seriously only after the WHO declared a global public health emergency on January 30, 2020. This date is used as the commencement of the coronavirus crisis ([7] WHO, 2020). It is worth noting that [58] Liang, Liang and Ou et al. (2020) make it clear that numerous hospitals in China had been collecting data on critical illness of hospitalized patients who had been infected with a new type of coronavirus, specifically pneumonia, subsequently diagnosed as COVID-19, since November 21, 2019.

The novelty of the paper is to investigate and compare herding behaviour for different types of crises, namely: (1) GFC from July 2, 2007–December 31, 2009; (2) SARS from February 10, 2003–July 5, 2003; and (3) the ongoing COVID-19 from January 30, 2020 to May 29, 2020. The daily data are current.

In this paper, the Cross-Section Absolute Deviation (CSAD) measure is used as a proxy for herding, inspired by the capital asset pricing model. The rate of asset returns is obtained by taking the first difference of the natural logarithm of daily price data for two consecutive days, and multiplying by 100 (that is, the log-difference in prices). Figs. 1 and 2 show the trends in the stock returns and CSAD for each fossil fuel and renewable energy stock for the full sample period, namely March 24, 2000 to May 29, 2020.

The descriptive statistics of the variables are given in Table 1. The column for the standard deviation (Std.Dev) shows that the WTI spot returns have the highest value at 2.760, followed by the Asia fossil fuel energy stock market returns at 2.703, and the US fossil fuel energy sector returns at 2.468. Not surprisingly, the Euro renewable energy stock market gives the lowest standard deviation value at 1.068.

Similar to most financial data series, all energy returns have either positive or negative skewness, which shows the distribution is not symmetric. The Euro and Asia renewable energy stock returns have negative skewness, which indicates greater extreme losses than extreme gains, while the US and Asia fossil fuel energy stock returns and WTI oil returns have positive skewness, with greater extreme gains than extreme losses.

Furthermore, all kurtosis statistics are significantly higher than 3, implying that there is a higher probability of extreme market movements in the direction of losses than of profits. The Jarque-Bera Lagrange multiplier test statistics confirm the existence of non-normal distributions in all cases, as all test statistics are significant at the 1% level for all returns series.

5. Empirical results

The purpose of this section is to examine if herding behaviour is present in the renewable energy sectors in the US, Europe, and Asia stock markets, and to investigate if there are risk spillover effects between the fossil fuel and renewable energy sectors. This is a novel aspect of the paper in comparison with previous studies. Another novelty of the paper is to compare the impacts of the GFC and ongoing COVID-19 crises. The following sections report the empirical results.

5.1. Herding effects in energy sectors

The herding tests for Model I are presented in Table 2, where the estimated γ_3 are positive and statistically significant in all renewable and fossil fuel energy markets, which suggest non-herding behaviour in energy markets. Not surprising, these empirical results are consistent with previous studies for testing the overall energy stock market (see, for example [18], Litimi et al. (2016) [20], BenMabrouk and Litimi (2018), and [47] Trueck and Yu (2018)).

5.2. Energy sector herding around WTI oil prices

The results of Model II are presented in Table 3. As equation (2), the purpose is to test if the crude oil market influences herding behaviour in the energy markets. The estimated γ_3 indicate local herding, while the estimated γ_4 suggests that the local market is herding around the crude oil market. The estimated γ_4 is positive and significant in the energy markets, which shows non-herding behaviour in energy markets with regard to WTI oil price movements.

5.3. Energy sector herding during extreme oil market movements

The results of Model III are presented in Table 4. As equation (3), the estimated γ_5 and γ_6 show the extreme upper movements in oil price returns and extreme lower movements in oil price returns, defined as the returns of oil prices lying within the 5% lower and upper tails of the returns distribution. As shown in Table 4, the estimated γ_6 are negative and significant only for the Euro renewable energy market.

The empirical findings indicate non-herding behaviour in energy markets with regard to extreme movements in WTI oil prices. Herding is more likely to be prevalent in the Euro renewable markets during extreme downturns in oil returns. The empirical results are similar to those in a recent study by Ref. [20] BenMabrouk and Litimi (2018), who found herding behaviour in energy markets during extreme downward movements in oil prices.

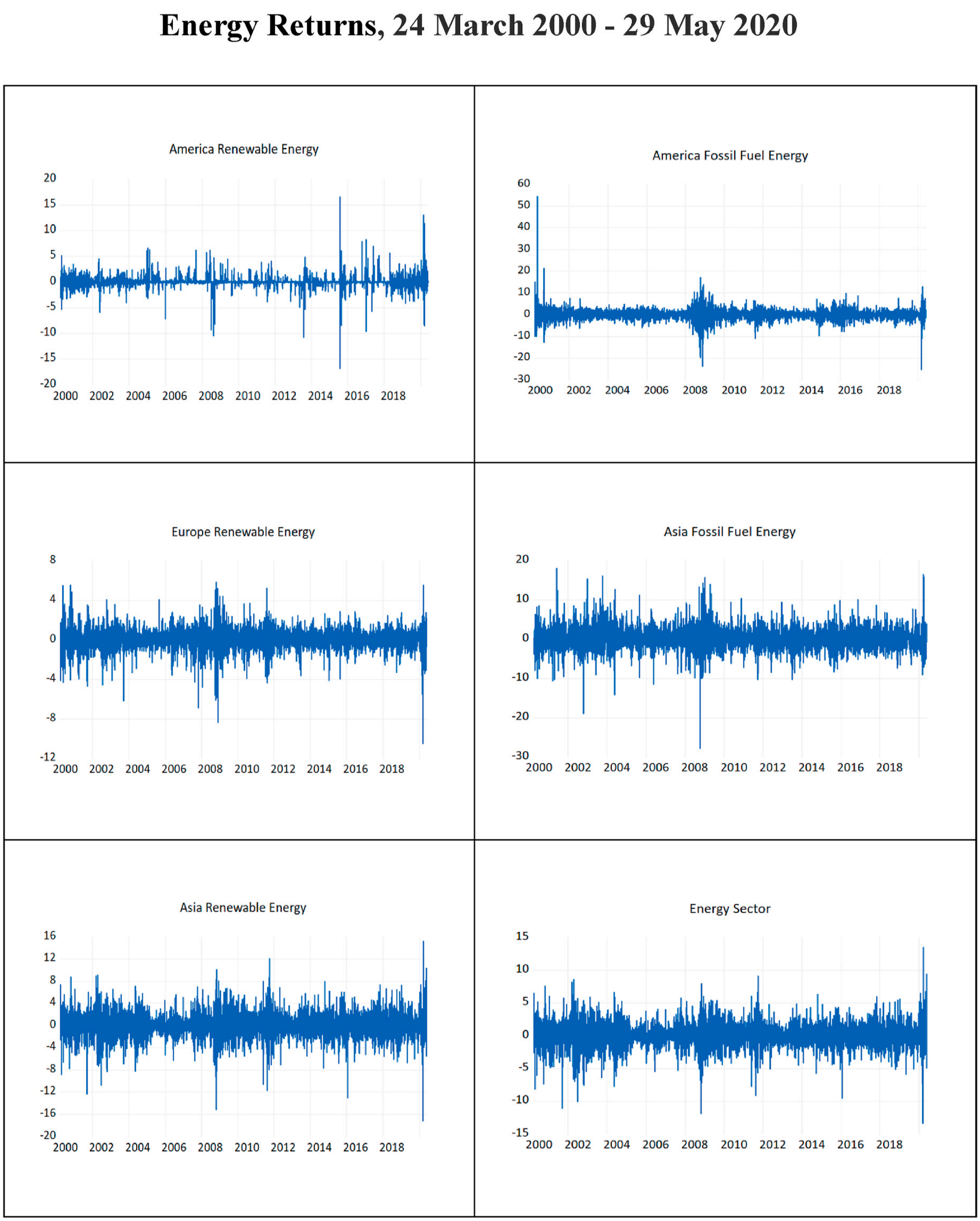

Fig. 1. Energy returns, March 24, 2000–May 29, 2020.

5.4. *Cross-sector herding and risk spillovers from fossil fuel to renewable energy markets*

The results of Model IV are presented in Tables 5 and 6. Table 5 shows the cross-sector herding and risk spillovers from the US fossil fuel energy market to the US renewable energy market, Europe renewable energy market, and Asia renewable energy market, respectively. The estimated γ_7 are negative and statistically significant in Table 5, which indicates a cross-sector herding effect from the US fossil fuel energy market to the US and Europe renewable energy markets. The estimated γ_8 are positive and statistically significant in Table 6, which indicates theUS fossil fuel energy market has risk spillovers to the Europe and Asia renewable energy markets.

Table 6 shows the cross-sector herding and risk spillovers from the Asia fossil fuel market to the US renewable energy market, Europe renewable energy market, and Asia renewable energy markets, respectively. The insignificant estimated γ_7 in Table 6 indicate there are no cross-sector herding effects from the Asia fossil fuel energy market to the

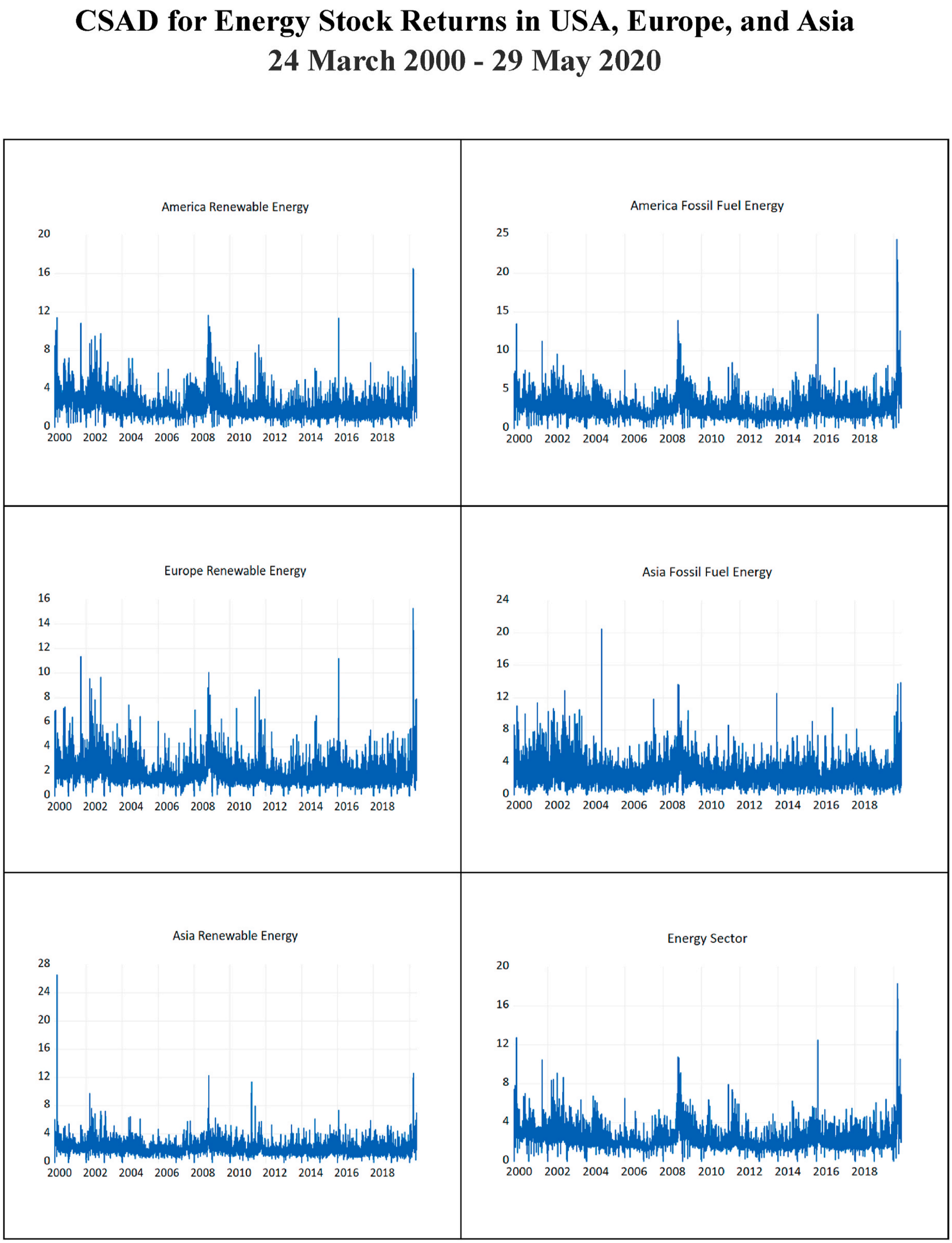

Fig. 2. CSAD for energy stock returns in USA, Europe, and Asia.

renewable energy markets. The estimated γ_8 are positive and statistically significant in Table 6, which indicates that the Asia fossil fuel energy market has risk spillovers for all renewable energy markets.

The empirical results in Tables 5 and 6 are extended using one-period lagged WTI oil to test cross-section herding and risk spillovers from US fossil fuel energy to the renewable energy market in Appendix 1: Table 5, and one-period lagged WTI oil, cross-section herding and risk spillovers from Asia fossil fuel energy to the renewable energy market in Appendix 2: Table 6. The empirical findings using one-period lagged values are broadly consistent with those in Tables 5 and 6

As an extension of Appendix 1: Table 5 for GFC, SARS and COVID-19 from US fossil fuel energy to the renewable energy market in Appendix 3, and an extension of Appendix 2: Table 6 for GFC, SARS and COVID-19 from US fossil fuel energy to the renewable energy market in Appendix

Table 1
Descriptive statistics for stock and oil returns.

Sector/Region		No. Firms	Mean	StdDev	Max	Min	Skewness	Kurtosis	J-B
Renewable Energy Stock Returns	**USA**	59	0.030	1.590	26.257	−26.693	0.057	59.699	705249.3
	Euro	24	0.017	1.068	5.810	−10.489	−0.600	9.304	9029.710
	Asia	21	0.022	2.218	15.157	−17.138	−0.162	7.391	4253.527
Fossil Fuel Energy Stock Returns	**USA**	107	−0.007	2.468	54.401	−25.286	1.526	57.060	643159.2
	Asia	5	0.059	2.703	17.989	−27.927	0.118	9.076	8109.820
WTI Oil Price Returns	**Global**	1	0.018	2.760	42.583	−28.138	0.713	33.216	200666.8

Note: The sample covers the period March 24, 2000–May 29, 2020. All Jarque-Bera (J-B) statistics are significant at 1%.

Table 2
Estimates of herding behaviour.

Sector/Region		α	γ_1	γ_2	γ_3	adj. R^2	F-stat.
Renewable Energy	**USA**	1.390*** (0.025)	−0.005 (0.011)	0.483*** (0.035)	0.032*** (0.008)	0.460	696.70
	Euro	1.171*** (0.019)	0.003 (0.009)	0.504*** (0.026)	0.028*** (0.006)	0.593	1150.59
	Asia	1.413*** (0.021)	0.032*** (0.009)	0.403*** (0.028)	0.020*** (0.006)	0.398	582.73
Fossil Fuel Energy	**USA**	1.884*** (0.031)	−0.021 (0.014)	0.417*** (0.044)	0.047*** (0.010)	0.381	453.34
	Asia	1.965*** (0.033)	0.034*** (0.013)	0.454*** (0.033)	0.028*** (0.006)	0.226	368.63

Notes.
1. The table reports estimates for the benchmark model I: $CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ denotes the cross-section absolute deviation of stock returns with respect to the market portfolio return $R_{m,t}$ for each market *i*. The sample covers the period March 24, 2000–May 29, 2020.
2. All F-statistics are significant at 1%. White's heteroskedasticity-robust standard errors are in parentheses, *, **, and *** denote significance at 10%, 5% and 1%, respectively.

4, the empirical findings are also broadly consistent with those found above.

5.5. Herding effects during the three crises

Table 7 presents the results of Model III, and Tables 8 and 9 present the results for Model IV during the GFC from July 2, 2007–December 31, 2009, the ongoing COVID-19 from January 30, 2020 to date, and SARS from 10 February - July 5, 2003, respectively. Moreover, Table 8 presents the results of cross-sector spillovers from the US fossil fuel energy market to other renewable energy markets, and its counterpart of risk spillovers. Table 9 presents the results of cross-sector spillovers from the Asia fossil fuel energy market to other renewable energy markets, and its counterpart of risk spillovers.

Table 7 reports the estimated γ_5 and γ_6 in equation (3) for extreme upturns and extreme downturns, respectively. The estimated γ_5 are negative and significant in all energy markets after the GFC, but this is not the case during the COVID-19 and SARS crises, as the estimated γ_5 are not significant for all energy markets. The US fossil fuel energy market has significantly positive estimated γ_5 during COVID-19. These empirical results indicate that after the GFC, herding in energy markets is more prevalent during periods of extremely high oil returns.

The estimated γ_6 are more likely to be negative and significant during periods of crisis. During the GFC, the estimated γ_6 is significantly negative only in the European renewable energy market, while after the GFC, the estimated γ_6 are significantly negative in both the Asia renewable energy and US fossil fuel energy markets. Similarly, during the SARS epidemic, the estimated γ_6 are significantly negative for the renewable energy market in the Europe.

These empirical results imply that, after the GFC, investors are more sensitive to asset losses, so they will be more likely to exhibit herding behaviour with other investors in the stock market. For the two coronavirus crises, investors do not display panic behaviour with regard to extreme oil prices, which is somewhat surprising given expectations.

Table 8 reports the estimated γ_7 and γ_8 in equation (4). The negative estimated γ_7 show cross-sector herding effects from the US fossil fuel energy market to the renewable energy market and also risk spillovers, while the positive estimated γ_8 show risk spillover effects from the US fossil fuel energy market to the renewable energy market.

The estimated γ_7 are negative and significant before the GFC, and during the COVID-19 crises, but this does not occur during the GFC. The empirical results imply that before the GFC, investor herding behaviour might have caused the bubble in the US market, and accelerated the cross-sector herding effects from theUS fossil fuel energy to the renewable energy markets. These results confirm the results of Bekiros et al. (2017), who stated that herding might cause dynamic phenomena such

Table 3
Estimates of herding behaviour with crude oil price returns.

Sector/Region		α	γ_1	γ_2	γ_3	γ_4	adj. R^2	F-stat.
Renewable Energy	**USA**	1.370*** (0.024)	−0.004 (0.011)	0.496*** (0.033)	0.029*** (0.007)	0.002** (0.001)	0.464	513.37
	Euro	1.160*** (0.019)	0.004 (0.009)	0.511*** (0.027)	0.026*** (0.006)	0.001* (0.001)	0.595	853.80
	Asia	1.404*** (0.020)	0.032*** (0.009)	0.409*** (0.027)	0.018*** (0.006)	0.001** (0.001)	0.400	432.82
Fossil Fuel Energy	**USA**	1.811*** (0.035)	−0.019 (0.013)	0.466*** (0.043)	0.034*** (0.010)	0.007*** (0.002)	0.424	383.70
	Asia	1.960*** (0.033)	0.034*** (0.013)	0.457*** (0.034)	0.027*** (0.006)	0.001 (0.001)	0.226	277.00

Notes.
1. The table reports estimates for Model II: $CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{oil,t} + \varepsilon_t$, where $R_{oil,t}$ denotes crude oil spot returns.
2. All F-statistics are significant at 1%. White's heteroskedasticity-robust standard errors are in parentheses, *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table 4
Estimates of herding behaviour with extreme oil returns.

Sector/Regions		α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj. R^2	F-stat.
Renewable Energy	**USA**	1.375*** (0.024)	−0.006 (0.011)	0.482*** (0.030)	0.033*** (0.007)	0.002** (0.001)	0.010* (0.006)	−0.014 (0.010)	0.467	422.48
	Euro	1.178*** (0.017)	0.001 (0.008)	0.467*** (0.022)	0.040*** (0.005)	0.002** (0.001)	0.002 (0.005)	−0.029*** (0.006)	0.604	677.56
	Asia	1.406*** (0.020)	0.031*** (0.009)	0.402*** (0.027)	0.020*** (0.006)	0.001** (0.001)	0.006 (0.005)	−0.008 (0.007)	0.401	338.05
Fossil Fuel Energy	**USA**	1.803*** (0.031)	−0.020* (0.012)	0.480*** (0.035)	0.030*** (0.008)	0.007*** (0.002)	0.025 (0.008)	−0.003 (0.012)	0.427	310.99
	Asia	1.956*** (0.034)	0.034*** (0.013)	0.466*** (0.037)	0.024*** (0.008)	0.001 (0.001)	0.002 (0.010)	0.006 (0.007)	0.226	189.93

Notes.
1. The table reports estimate for Model III: $CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{oil,t} + \gamma_5 D_t^{up,oil} R^2_{m,t} + \gamma_6 D_t^{down,oil} R^2_{m,t} + \varepsilon_t$, where $R_{oil,t}$ denotes crude oil spot returns. The dummy variable represents the extreme return of crude oil, $D_t^{up,oil} = 1$ if the returns of the crude oil market lie in the extreme upper tail of the returns distribution, and $D_t^{down,oil} = 1$ if the returns of the crude oil market lie in the extreme lower tail of the returns distribution.
2. All F-statistics are significant at 1%. White's heteroskedasticity-robust standard errors are in parentheses, *, **, and *** denote significance at 10%, 5% and 1%, respectively.

as bubbles and crashes.

Similarly, the estimated negative γ_7 are also found during the COVID-19 and SARS crises. However, during the ongoing COVID-19, the US fossil fuel energy market has a greater impact on all the renewable energy markets while, during the SARS epidemic, the US fossil fuel energy market only has an impact on the US renewable energy sector. Given the empirical findings, investors in the renewable energy markets display panic behaviour in the fossil fuel energy market, so they may unwisely follow the fluctuations in the fossil fuel energy market, thereby creating a vicious cycle.

The estimated γ_8 are all positive during all the crisis periods. With significant estimates in most of the periods before and after the three crises, the empirical results suggest strong risk spillovers from the US fossil fuel market to the other renewable markets. During SARS, only the USfossil fuel market has been found to affect the US renewable market, but not the Europe and Asia markets.

Table 9 presents the cross-sector effects from the Asia fossil fuel markets to renewable energy markets, as well as risk spillovers from the Asia fossil fuel markets to the renewable markets. None of the estimated γ_7 is statistically significant and negative in any market during any crisis. During SARS, the estimated γ_7 is statistically significant and negative for the Asia renewable energy market, which shows that the Asia fossil fuel market causes herding to the Asia renewable energy market.

However, the estimated γ_8 is significantly positive before, during and after the GFC. Again, not surprisingly, none of the estimated γ_8 is significant and positive during the COVID-19 and SARS crises. This indicates that during the two coronavirus crises, the Asia fossil fuel energy markets have displayed little power to dominate risk in any renewable energy markets.

In view of the above empirical findings, it is possible that excess volatility in crude oil price induces herding behaviour in the fossil fuel energy market, and by extension, there seems to be a cross-section herding effect from US fossil fuels to renewables. If this is the case, given the empirical results, we can conclude that US fossil fuels dominated the cross-section herding in the renewables energy market. Although the crude oil price variations might be regarded as an overall factor in the world economy, the fossil fuel companies in the USA seem to dominate the herding effect in the local renewables energy market.

6. Concluding remarks

There has been a lack of research focus on herding behaviour in the renewable energy market. For this reason, this paper attempts to fill the gap in the literature in two respects, using the most recent available data:

(1) to examine if herding behaviour is present in the renewable energy sectors in the US, Europe, and Asia stock markets; and
(2) to test for dynamic risk spillovers between the fossil fuel and renewable energy sectors.

Table 5
Cross-section herding behaviour and risk spillovers from US fossil fuel energy market.

Renewable Regions	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
USA	0.841*** (0.043)	0.004 (0.016)	0.502*** (0.018)	0.016*** (0.001)	−0.001 (0.001)	−0.005 (0.008)	0.006 (0.009)	−0.002* (0.001)	0.302*** (0.024)	0.683	258.01
Euro	0.681*** (0.026)	0.005 (0.011)	0.418*** (0.049)	−0.001 (0.017)	0.001 (0.001)	0.004* (0.002)	0.006 (0.004)	−0.004*** (0.001)	0.197*** (0.012)	0.418	201.42
Asia	1.232*** (0.038)	0.030*** (0.009)	0.399*** (0.026)	0.023*** (0.005)	0.002 (0.001)	−0.002 (0.006)	−0.022** (0.010)	0.005*** (0.001)	0.072*** (0.019)	0.583	378.82

Notes.
1. The table reports estimates for the model IV:$CSAD_{i,t} = \alpha + \gamma_1 R_{m\_i,t} + \gamma_2 |R_{m\_i,t}| + \gamma_3 R^2_{m\_i,t} + \gamma_4 R^2_{oil,t} + \gamma_5 D_t^{up,oil} R^2_{m,t} + \gamma_6 D_t^{down,oil} R^2_{m,t} + \gamma_7 R^2_{m\_j,t} + \gamma_8 CSAD_{j,t} + \varepsilon_t$, where $i =$ *renewable energy sector in U.S., Europe and Asia*, $j =$ *traditional energy sector in U.S. and Asia*. The cross-sector herding effects are present if γ_7 is negative, and risk spillover effects are present if γ_8 is positive.
2. All F-statistics are significant at 1%. White's heteroskedasticity-robust standard errors are in parentheses, *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table 6
Cross-section herding behaviour and risk spillover from Asia fossil fuel energy market.

Renewable Regions	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
USA	1.220***	0.001	0.572***	0.013***	0.001	0.003	0.009	0.003***	0.069***	0.633	323.95
	(0.022)	(0.014)	(0.017)	(0.001)	(0.001)	(0.009)	(0.010)	(0.001)	(0.009)		
Euro	0.883***	0.003	0.451***	−0.002	0.001**	0.008***	0.007	0.001	0.064***	0.372	163.83
	(0.022)	(0.011)	(0.044)	(0.015)	(0.001)	(0.002)	(0.004)	(0.001)	(0.006)		
Asia	1.274***	0.028***	0.420***	0.020***	0.001*	0.003	−0.014*	0.001	0.045***	0.514	410.19
	(0.027)	(0.008)	(0.024)	(0.005)	(0.001)	(0.006)	(0.008)	(0.001)	(0.009)		

Notes: See Table 5.

For the empirical analysis, the daily data are for the period March 24, 2000–May 29, 2020. The renewable and fossil fuel energy stock returns in the US, Europe, and Asia are used to examine herding behaviour.

Two important research findings, in which the paper differs from previous studies in the literature, are as follows. First, earlier studies have focused primarily on the broad category sectors that have included a large component of the energy sectors. In this paper, both renewable and fossil fuel energy are separated for analysis in the US, Europe, and Asia markets. Significant evidence of herding behaviour was found during negative extreme oil market days in all energy sectors, except for

Table 7
Herding behaviour with extreme oil returns for GFC, SARS and COVID-19.

Sub-sample	Sector/ Region		α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj. R^2	F-*stat.*
Before GFC 2000/3/24–2007/6/29	**Renewable Energy**	**USA**	1.565***	0.016	0.466***	0.037***	0.006***	0.003	0.002	0.527	230.02
			(0.035)	(0.014)	(0.036)	(0.006)	(0.002)	(0.009)	(0.019)		
		Euro	1.240***	0.008	0.508***	0.036***	0.004	0.007	0.006	0.690	477.90
			(0.028)	(0.010)	(0.032)	(0.007)	(0.002)	(0.006)	(0.017)		
		Asia	1.484***	0.053***	0.424***	0.015	−0.001	0.009	0.027***	0.402	155.46
			(0.033)	(0.015)	(0.048)	(0.010)	(0.001)	(0.010)	(0.009)		
	Fossil Fuel Energy	**USA**	1.742***	0.003	0.543***	0.029***	0.009***	−0.001	−0.004	0.549	449.01
			(0.033)	(0.012)	(0.033)	(0.005)	(0.002)	(0.006)	(0.010)		
		Asia	2.009***	0.045**	0.585***	0.017	0.003	0.018	0.001	0.247	113.37
			(0.062)	(0.021)	(0.063)	(0.011)	(0.002)	(0.011)	(0.019)		
GFC 2007/7/2–2009/12/31	**Renewable Energy**	**USA**	1.798***	−0.007	0.335***	0.045*	0.015***	0.024	−0.025	0.326	27.70
			(0.093)	(0.029)	(0.117)	(0.027)	(0.003)	(0.064)	(0.023)		
		Euro	1.609***	0.020	0.264***	0.050***	0.009***	0.032	−0.029**	0.394	55.13
			(0.059)	(0.021)	(0.065)	(0.014)	(0.003)	(0.055)	(0.011)		
		Asia	1.794***	0.033	0.337***	0.011	0.005***	0.023	−0.012	0.289	32.96
			(0.062)	(0.023)	(0.082)	(0.022)	(0.002)	(0.028)	(0.015)		
	Fossil Fuel Energy	**USA**	2.053***	−0.041	0.474***	0.009	0.020***	0.076	0.003	0.313	25.78
			(0.097)	(0.033)	(0.121)	(0.026)	(0.005)	(0.095)	(0.024)		
		Asia	2.696***	0.030	0.274*	0.039	0.002	0.065	0.015	0.179	23.47
			(0.131)	(0.040)	(0.158)	(0.036)	(0.003)	(0.047)	(0.027)		
After GFC 2010/1/1–2020/1/29	**Renewable Energy**	**USA**	1.142***	−0.016	0.406***	0.055***	0.008***	−0.032***	−0.038	0.495	225.02
			(0.025)	(0.013)	(0.040)	(0.010)	(0.002)	(0.009)	(0.025)		
		Euro	1.044***	−0.001	0.394***	0.062***	0.005***	−0.036***	−0.037	0.611	381.79
			(0.019)	(0.011)	(0.027)	(0.006)	(0.002)	(0.009)	(0.027)		
		Asia	1.281***	0.010	0.334***	0.042***	0.005***	−0.024***	−0.035**	0.383	174.20
			(0.026)	(0.011)	(0.036)	(0.010)	(0.002)	(0.008)	(0.016)		
	Fossil Fuel Energy	**USA**	1.683***	−0.001	0.268***	0.071***	0.040***	−0.051***	−0.068**	0.402	124.30
			(0.038)	(0.015)	(0.065)	(0.019)	(0.003)	(0.012)	(0.030)		
		Asia	1.829***	0.025	0.313***	0.035***	0.001	−0.038***	−0.007	0.144	60.43
			(0.041)	(0.016)	(0.052)	(0.012)	(0.002)	(0.013)	(0.025)		
COVID-19 2020/1/30–2020/5/29	**Renewable Energy**	**USA**	2.672***	−0.044	−0.068	0.065**	0.001	−3.253	0.005	0.546	11.96
			(0.375)	(0.082)	(0.242)	(0.026)	(0.002)	(6.532)	(0.019)		
		Euro	2.068***	0.004	−0.004	0.063***	0.001	−0.925	−0.015	0.656	28.83
			(0.243)	(0.064)	(0.187)	(0.019)	(0.001)	(5.337)	(0.012)		
		Asia	1.977***	0.006	0.063	0.045***	−0.001	3.804	0.007	0.735	61.43
			(0.231)	(0.044)	(0.148)	(0.014)	(0.001)	(4.120)	(0.009)		
	USA	**USA**	3.853***	−0.136	0.342	0.035	0.007**	−25.286*	−0.008	0.503	13.14
			(0.726)	(0.119)	(0.043)	(0.041)	(0.003)	(14.408)	(0.025)		
		Asia	1.559***	0.050	0.818***	−0.007	−0.001	7.401	0.015	0.622	107.33
			(0.273)	(0.053)	(0.198)	(0.018)	(0.001)	(4.649)	(0.008)		
SARS 2003/2/10–2003/7/5	**Renewable Energy**	**USA**	1.729***	−0.077	0.293*	0.099**	−0.001	0.017	−0.043	0.631	22.37
			(0.103)	(0.059)	(0.154)	(0.037)	(0.003)	(0.061)	(0.036)		
		Euro	1.399***	−0.028	0.504***	0.038	0.003	−0.017	−0.046*	0.621	26.29
			(0.125)	(0.040)	(0.151)	(0.032)	(0.003)	(0.052)	(0.024)		
		Asia	1.691***	0.017	0.430***	−0.001	−0.001	0.005	−0.013	0.443	22.39
			(0.136)	(0.031)	(0.142)	(0.026)	(0.003)	(0.051)	(0.021)		
	Fossil Fuel Energy	**USA**	1.535***	−0.110***	0.572***	0.054*	0.006	−0.061	−0.024	0.732	99.40
			(0.119)	(0.037)	(0.149)	(0.030)	(0.005)	(0.049)	(0.027)		
		Asia	2.366***	0.069	0.418	0.054	−0.005	−0.145	−0.020	0.158	5.53
			(0.409)	(0.089)	(0.439)	(0.090)	(0.008)	(0.099)	(0.049)		

Notes: See Table 4. GFC denotes the Global Financial Crisis.

Table 8
Cross-Section Herding from US Fossil Fuel Energy Market to Renewable Energy Market for GFC and COVID-19. Notes: See Table 5. GFC denotes the Global Financial Crisis.

Sub-sample	Renewable Energy	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
Before GFC 2000/3/24–2007/6/29	**USA**	1.007*** (0.050)	−0.008 (0.016)	0.500*** (0.030)	0.024*** (0.006)	0.001 (0.001)	0.002 (0.005)	0.017* (0.009)	−0.002*** (0.001)	0.233*** (0.026)	0.695	206.62
	Euro	0.867*** (0.037)	0.018 (0.013)	0.398*** (0.037)	0.042*** (0.011)	0.001 (0.001)	−0.001 (0.003)	0.002 (0.007)	−0.003*** (0.001)	0.159*** (0.016)	0.435	131.40
	Asia	1.425*** (0.056)	0.044*** (0.011)	0.415*** (0.043)	0.016* (0.009)	−0.01 (0.001)	0.012 (0.011)	0.030*** (0.009)	0.008*** (0.001)	0.010 (0.024)	0.665	249.54
GFC 2007/7/2–2009/12/31	**USA**	0.955*** (0.127)	−0.081* (0.045)	0.633*** (0.104)	0.006 (0.010)	0.009*** (0.002)	0.053 (0.048)	0.001 (0.008)	0.007** (0.003)	0.361 (0.069)	0.703	80.93
	Euro	0.874*** (0.079)	−0.005 (0.023)	0.355*** (0.088)	0.008 (0.025)	0.001 (0.001)	0.044 (0.035)	−0.004 (0.004)	−0.001 (0.002)	0.193*** (0.034)	0.503	46.41
	Asia	1.491*** (0.120)	0.038* (0.020)	0.298** (0.112)	0.023 (0.025)	0.004** (0.002)	0.009 (0.038)	−0.030 (0.026)	−0.001 (0.002)	0.132** (0.045)	0.438	55.80
After GFC 2010/1/1–2020/1/29	**USA**	0.837*** (0.045)	0.008 (0.018)	0.563*** (0.025)	0.016*** (0.002)	−0.002 (0.002)	0.014** (0.006)	0.009 (0.023)	0.012** (0.005)	0.179*** (0.031)	0.792	261.46
	Euro	0.747*** (0.027)	−0.020* (0.010)	0.280*** (0.041)	0.003 (0.021)	−0.001 (0.001)	0.005* (0.003)	0.019 (0.013)	−0.002 (0.002)	0.129*** (0.015)	0.253	64.32
	Asia	1.049*** (0.049)	0.012 (0.009)	0.403*** (0.033)	0.033*** (0.007)	0.003 (0.002)	−0.030*** (0.009)	−0.038** (0.017)	−0.005* (0.003)	0.117*** (0.028)	0.563	250.33
COVID-19 2020/1/30–2020/5/29	**USA**	1.171*** (0.436)	0.019 (0.101)	−0.081 (0.174)	0.035 (0.011)	−0.001 (0.001)	0.958*** (4.550)	0.008 (0.005)	−0.008* (0.005)	0.364** (0.147)	0.690	98.81
	Euro	0.697*** (0.186)	0.062* (0.051)	0.215** (0.099)	−0.004 (0.010)	0.001 (0.001)	−4.053 (3.692)	0.012** (0.005)	−0.006*** (0.002)	0.225*** (0.052)	0.509	15.20
	Asia	1.160*** (0.239)	−0.011 (0.038)	0.287*** (0.121)	0.025*** (0.008)	−0.001** (0.001)	1.321 (3.135)	0.011** (0.005)	−0.010*** (0.002)	0.165** (0.078)	0.853	1356.30
SARS 2003/2/10–2003/7/5	**USA**	0.699*** (0.197)	−0.103*** (0.038)	0.653*** (0.149)	−0.021 (0.041)	−0.001 (0.002)	0.034** (0.017)	0.001 (0.009)	−0.072*** (0.015)	0.523*** (0.111)	0.712	29.55
	Euro	1.129*** (0.271)	0.024 (0.042)	0.397* (0.222)	−0.003 (0.068)	0.001 (0.003)	−0.029 (0.041)	−0.001 (0.018)	0.003 (0.024)	0.136 (0.126)	0.254	5.70
	Asia	1.471*** (0.209)	0.031 (0.032)	0.439*** (0.136)	0.002 (0.024)	−0.002 (0.003)	0.014 (0.057)	−0.012 (0.021)	−0.028 (0.021)	0.137 (0.111)	0.523	22.03

Table 9
Cross-section herding and risk spillover from Asia fossil fuel energy to renewable energy market for GFC and COVID-19.

Sub-sample	Renewable Energy	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
Before GFC 2000/3/24–2007/6/29	**USA**	1.328*** (0.029)	−0.015 (0.015)	0.626*** (0.031)	0.012** (0.005)	0.003*** (0.001)	0.006* (0.003)	0.019** (0.007)	−0.001 (0.001)	0.045*** (0.010)	0.607	225.68
	Euro	1.044*** (0.029)	0.012 (0.013)	0.415*** (0.039)	0.047*** (0.012)	0.002* (0.001)	0.004 (0.004)	0.003 (0.007)	−0.001 (0.001)	0.055*** (0.009)	0.397	120.22
	Asia	1.417*** (0.047)	0.046*** (0.012)	0.417*** (0.043)	0.016* (0.009)	−0.001 (0.001)	0.013 (0.010)	0.031*** (0.009)	−0.001 (0.001)	0.030** (0.011)	0.444	188.18
GFC 2007/7/2–2009/12/31	**USA**	1.400*** (0.092)	−0.120** (0.046)	0.817*** (0.114)	−0.008 (0.010)	0.016*** (0.004)	0.113 (0.084)	0.010 (0.017)	0.002 (0.001)	0.130*** (0.031)	0.570	137.13
	Euro	1.100*** (0.073)	−0.016 (0.024)	0.378*** (0.087)	0.006 (0.025)	0.003** (0.001)	0.053* (0.040)	−0.005 (0.006)	0.001 (0.001)	0.060*** (0.018)	0.458	40.15
	Asia	1.519*** (0.100)	0.037* (0.020)	0.308** (0.102)	0.020 (0.025)	0.005** (0.002)	0.005 (0.027)	−0.029 (0.024)	0.002 (0.001)	0.087*** (0.023)	0.447	126.05
After GFC 2010/1/1–2020/1/29	**USA**	1.110*** (0.026)	0.006 (0.017)	0.580*** (0.023)	0.016*** (0.002)	0.006*** (0.002)	0.011** (0.005)	0.017 (0.022)	0.005** (0.002)	0.009 (0.013)	0.776	281.59
	Euro	0.894*** (0.020)	−0.020* (0.010)	0.305*** (0.041)	−0.003 (0.021)	0.002** (0.001)	0.006* (0.003)	0.015 (0.013)	0.001 (0.001)	0.026*** (0.007)	0.223	56.23
	Asia	1.173*** (0.035)	0.012 (0.009)	0.406*** (0.032)	0.033*** (0.007)	0.004* (0.002)	−0.030*** (0.009)	−0.046** (0.017)	−0.001 (0.002)	0.029** (0.013)	0.561	247.11
COVID-19 2020/1/30–2020/5/29	**USA**	2.089*** (0.279)	0.059 (0.082)	0.072 (0.140)	0.027*** (0.009)	0.001 (0.007)	−6.245 (5.664)	−0.004 (0.011)	0.008 (0.007)	0.045 (0.080)	0.660	111.21
	Euro	1.247*** (0.176)	0.090* (0.050)	0.281** (0.110)	−0.008 (0.011)	0.002 (0.001)	−7.880* (4.336)	0.006 (0.010)	0.003 (0.006)	0.049 (0.053)	0.396	6.33
	Asia	1.676*** (0.181)	0.012 (0.044)	0.168 (0.130)	0.034*** (0.009)	−0.001 (0.001)	2.970 (5.254)	0.005 (0.009)	−0.001 (0.005)	0.072 (0.057)	0.818	168.91
SARS 2003/2/10–2003/7/5	**USA**	1.429*** (0.127)	−0.111** (0.050)	0.772*** (0.210)	−0.046 (0.056)	0.002 (0.003)	0.029 (0.031)	0.003 (0.016)	−0.001 (0.002)	0.020 (0.035)	0.581	15.20
	Euro	1.355*** (0.192)	0.008 (0.041)	0.420* (0.030)	−0.002 (0.068)	0.001 (0.003)	−0.024 (0.037)	0.001 (0.017)	0.004 (0.003)	−0.008 (0.025)	0.240	6.10
	Asia	1.577*** (0.149)	0.018 (0.030)	0.478*** (0.131)	−0.005 (0.022)	−0.001 (0.003)	0.004 (0.060)	−0.011 (0.021)	−0.006* (0.003)	0.041 (0.032)	0.528	27.51

Notes: See Table 5. GFC denotes the Global Financial Crisis.

the fossil fuel energy sector in the Asia market.

The empirical results suggest that investors are more likely to display herding behaviour during extreme low oil price returns, particularly in the fossil fuel energy sectors. This finding contradicts that of [20] Ben-Mabrouk and Litimi (2018), who found no empirical evidence of herding in energy markets during extreme downturns in crude oil market returns.

Interestingly, after the GFC, all markets for both renewable and fossil fuel energy sectors show that herding becomes more prevalent during the extreme upturn in oil price returns. After the GFC, investors are more sensitive to asset losses, so they will be more likely to display herding behaviour in the stock market. As distinct from the GFC, when investors are facing the uncertain upheaval in the coronavirus crises, they panic with regard to taking any risks, so they may unwisely sell all their assets, thereby creating a vicious cycle.

Second, this paper focuses on three renewable energy markets in the USA, Europe, and Asia, which previous studies do not seem to have undertaken. As the economic costs in developing renewable energy are still considerable, the renewable energy market seems to be vulnerable to any shocks in the fossil fuel energy market. Following this line of thought, we have examined the cross-section herding and risk spillovers from the fossil fuel energy market to the renewable energy stock market.

The empirical results show that the US fossil fuel energy market has strong cross-sector herding spillovers and risk spillovers to any renewable energy markets. This behaviour also occurs during the ongoing COVID-19 pandemic.

However, it is not surprising that, during the SARS epidemic, only the US fossil fuel market is found to dominate its own renewable market, but does not seem to affect the Europe and Asia markets.

What might be said about the renewable and fossil fuel energy markets in a dramatically changed world after the ongoing COVID-19 pandemic has receded is an issue of immense concern. International trade issues will likely become more tenuous and lead to a greater number of economic and financial trading blocks. The dynamic physical and financial relationships between renewable and fossil fuel energy sources, as well as optimal hedge ratios among the three traditional fossil fuel and numerous alternative renewable energy sources will necessarily change dramatically in both the short and long run.

The connection of renewable and fossil fuel energy sources with agricultural commodities, such as sugar cane (in Brazil and Thailand, among other countries) and corn (especially in the USA), for generating bio-ethanol as an alternative renewable energy source will also need to be considered in the bubbling mix. These issues are left for future research.

CRediT Statement

Chia-Lin Chang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, suprvision, Project administration, Funding acquisition. Michael McAleer: Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing - original draft, Writing - review & editing, Supervision, Funding acquisition. Yu-Ann Wang: Software, Investigation, Data curation, Writing - original draft, Writing - review & editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1: Table 5One-Period Lagged WTI Oil, Cross-Section Herding and Risk Spillovers (from US Fossil Fuel Energy to Renewable Energy Market)

Renewable Energy Market	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
USA	0.841***	0.004	0.502***	0.016***	−0.001	−0.005	0.006	−0.002*	0.302***	0.683	258.01
	(0.043)	(0.016)	(0.018)	(0.001)	(0.001)	(0.008)	(0.009)	(0.001)	(0.024)		
Euro	0.713***	0.003	0.434***	−0.002	−0.001	0.010***	0.016***	−0.003***	0.179***	0.415	189.08
	(0.029)	(0.011)	(0.047)	(0.016)	(0.001)	(0.002)	(0.003)	(0.001)	(0.012)		
Asia	1.113***	0.027***	0.441***	0.013***	−0.001	0.010**	0.022**	−0.002***	0.138***	0.527	415.48
	(0.053)	(0.008)	(0.023)	(0.004)	(0.001)	(0.004)	(0.010)	(0.001)	(0.029)		

1. The table reports estimates for the model $CSAD_{i,t} = \alpha + \gamma_1 R_{m.i,t} + \gamma_2 |R_{m.i,t}| + \gamma_3 R^2_{m.i,t} + \gamma_4 R^2_{oil,t-1} + \gamma_5 D_t^{up,oil} R^2_{m,t-1} + \gamma_6 D_t^{down,oil} R^2_{m,t-1} + \gamma_7 R^2_{m_j,t-1} + \gamma_8 CSAD_{j,t-1} + \varepsilon_t$, where $i =$ *renewable energy sector in U.S., Europe and Asia*, $j =$ *traditional energy sector in U.S. and Asia*. The cross-sector herding effects are present if γ_7 is negative, and risk spillover effects are present if γ_8 is positive.

2. All F-statistics are significant at 1%. White's heteroskedasticity-robust standard errors are in parentheses, *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Appendix 2: Table 6 One-Period Lagged WTI Oil, Cross-Section Herding and Risk Spillovers (from Asia Fossil Fuel Energy to Renewable Energy Market)

Renewable Regions	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	F-stat.
USA	1.235***	−0.008	0.578***	0.013***	0.001*	0.020***	0.015***	0.003***	0.059***	0.635	259.18
	(0.022)	(0.015)	(0.018)	(0.002)	(0.001)	(0.005)	(0.005)	(0.001)	(0.009)		
Euro	0.899***	0.003	0.451***	0.001	0.001	0.015***	0.016***	0.001	0.056***	0.377	179.18
	(0.023)	(0.011)	(0.047)	(0.016)	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)		
Asia	1.274***	0.028***	0.420***	0.020***	0.001*	0.003	−0.014*	0.001	0.045***	0.514	410.19
	(0.027)	(0.008)	(0.024)	(0.005)	(0.001)	(0.006)	(0.008)	(0.001)	(0.009)		

Note: See details in Appendix 1: Table 5.

Appendix 3 – Extension of Appendix 1: Table 5 for GFC, SARS and COVID-19 (from US Fossil Fuel Energy to Renewable Energy Market)

Sub-sample	Renewable Energy	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	*F*-stat.
Before GFC 2000/3/24–2007/6/29	**USA**	1.007***	−0.008	0.500***	0.024***	0.001	0.002	0.017*	−0.002***	0.233***	0.695	206.62
		(0.050)	(0.016)	(0.030)	(0.006)	(0.001)	(0.005)	(0.009)	(0.001)	(0.026)		
	Euro	0.891***	0.011	0.392***	0.045***	0.001	0.001	0.034**	−0.003***	0.146***	0.440	125.18
		(0.037)	(0.013)	(0.038)	(0.011)	(0.001)	(0.002)	(0.016)	(0.001)	(0.016)		
	Asia	1.198***	0.046***	0.396***	0.021**	0.002*	0.004	−0.009*	−0.002**	0.142***	0.458	182.69
		(0.102)	(0.011)	(0.045)	(0.009)	(0.001)	(0.008)	(0.005)	(0.001)	(0.053)		
GFC 2007/7/2–2009/12/31	**USA**	0.955***	−0.081*	0.633***	0.006	0.009***	0.053	0.001	0.007**	0.361	0.703	80.93
		(0.127)	(0.045)	(0.104)	(0.010)	(0.002)	(0.048)	(0.008)	(0.003)	(0.069)		
	Euro	0.979***	0.003	0.371***	0.010	0.003**	0.002	0.010***	−0.001	0.135***	0.478	48.04
		(0.090)	(0.024)	(0.093)	(0.025)	(0.001)	(0.022)	(0.002)	(0.001)	(0.035)		
	Asia	1.335***	0.033*	0.408***	−0.002	−0.003*	0.064**	0.055***	−0.002	0.195***	0.526	51.10
		(0.097)	(0.018)	(0.040)	(0.005)	(0.002)	(0.029)	(0.012)	(0.003)	(0.046)		
After GFC 2010/1/1–2020/1/29	**USA**	0.837***	0.008	0.563***	0.016***	−0.002	0.014**	0.009	0.012**	0.179***	0.792	261.46
		(0.045)	(0.018)	(0.025)	(0.002)	(0.002)	(0.006)	(0.023)	(0.005)	(0.031)		
	Euro	0.828***	−0.022**	0.292***	0.004	0.001	0.006**	0.029**	0.001	0.071***	0.241	60.49
		(0.027)	(0.010)	(0.039)	(0.019)	(0.001)	(0.003)	(0.011)	(0.002)	(0.015)		
	Asia	1.152***	0.009	0.414***	0.028***	0.002	−0.003	0.026	−0.001	0.049*	0.557	225.48
		(0.047)	(0.010)	(0.030)	(0.006)	(0.002)	(0.005)	(0.018)	(0.003)	(0.026)		
COVID-19 2020/1/30–2020/5/29	**USA**	1.171***	0.019	−0.081	0.035	−0.001	0.958***	0.008	−0.008*	0.364**	0.690	98.81
		(0.436)	(0.101)	(0.174)	(0.011)	(0.001)	(4.550)	(0.005)	(0.005)	(0.147)		
	Euro	0.464**	0.099***	0.207**	−0.004	−0.001	3.218	0.016***	−0.007***	0.330***	0.570	60.14
		(0.235)	(0.035)	(0.096)	(0.009)	(0.001)	(2.685)	(0.003)	(0.002)	(0.072)		
	Asia	1.436***	0.040	0.205	0.031***	−0.001	2.903	0.017***	−0.002	0.092	0.834	116.34
		(0.254)	(0.043)	(0.145)	(0.010)	(0.001)	(4.212)	(0.003)	(0.001)	(0.062)		
SARS 2003/2/10–2003/7/5	**USA**	0.699***	−0.103***	0.653***	−0.021	−0.001	0.034**	0.001	−0.072***	0.523***	0.712	29.55
		(0.197)	(0.038)	(0.149)	(0.041)	(0.002)	(0.017)	(0.009)	(0.015)	(0.111)		
	Euro	0.947***	0.013	0.318*	0.032	−0.006***	0.035	0.013	−0.057**	0.324***	0.315	8.74
		(0.246)	(0.039)	(0.185)	(0.053)	(0.002)	(0.028)	(0.014)	(0.027)	(0.114)		
	Asia	1.549***	0.025	0.454***	−0.002	0.001	−0.047**	−0.023	−0.025	0.094	0.526	23.25
		(0.223)	(0.031)	(0.126)	(0.022)	(0.003)	(0.022)	(0.024)	(0.029)	(0.107)		

Note: See details in Appendix 1: Table 5.

Appendix 4 – Extension of Appendix 2: Table 6 for GFC, SARS and COVID-19

Sub-sample	Renewable Energy	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	adj. R^2	*F*-stat.
Before GFC 2000/3/24–2007/6/29	**USA**	1.324***	−0.017	0.631***	0.010*	0.003***	0.013**	0.016***	−0.001	0.043***	0.607	217.78
		(0.029)	(0.015)	(0.030)	(0.005)	(0.001)	(0.005)	(0.005)	(0.001)	(0.010)		
	Euro	1.054***	0.009	0.424***	0.044***	0.002*	0.004	0.036	−0.001	0.043***	0.406	123.50
		(0.030)	(0.013)	(0.039)	(0.012)	(0.001)	(0.004)	(0.015)	(0.001)	(0.010)		
	Asia	1.417***	0.046***	0.417***	0.016*	−0.001	0.013	0.031***	−0.001	0.030**	0.444	188.18
		(0.047)	(0.012)	(0.043)	(0.009)	(0.001)	(0.010)	(0.009)	(0.001)	(0.011)		
GFC 2007/7/2–2009/12/31	**USA**	1.563***	−0.152***	0.847***	−0.012	0.008**	0.045	0.011**	0.003	0.103***	0.499	127.36
		(0.100)	(0.052)	(0.119)	(0.011)	(0.003)	(0.041)	(0.004)	(0.002)	(0.032)		
	Euro	1.112***	0.003	0.384***	0.013	0.005***	0.007	0.010***	0.001	0.047***	0.459	46.38
		(0.072)	(0.025)	(0.090)	(0.024)	(0.002)	(0.017)	(0.002)	(0.001)	(0.017)		
	Asia	1.519***	0.037*	0.308**	0.020	0.005**	0.005	−0.029	0.002	0.087***	0.447	126.05
		(0.100)	(0.020)	(0.102)	(0.025)	(0.002)	(0.027)	(0.024)	(0.001)	(0.023)		
After GFC 2010/1/1–2020/1/29	**USA**	1.125***	0.004	0.587***	0.015***	0.002	0.023*	0.023	0.001	0.018	0.773	297.21
		(0.025)	(0.017)	(0.024)	(0.002)	(0.002)	(0.011)	(0.018)	(0.002)	(0.011)		
	Euro	0.905***	−0.025**	0.298***	0.002	0.003***	0.006**	0.029**	0.001	0.017**	0.230	56.69
		(0.020)	(0.010)	(0.039)	(0.019)	(0.001)	(0.003)	(0.012)	(0.001)	(0.007)		
	Asia	1.173***	0.012	0.406***	0.033***	0.004*	−0.030***	−0.046**	−0.001	0.029**	0.561	247.11
		(0.035)	(0.009)	(0.032)	(0.007)	(0.002)	(0.009)	(0.017)	(0.002)	(0.013)		
COVID-19 2020/1/30–2020/5/29	**USA**	2.052***	0.039	0.072	0.029***	0.002*	−10.671*	−0.013	0.017***	−0.039	0.689	75.91
		(0.263)	(0.079)	(0.128)	(0.009)	(0.001)	(6.086)	(0.011)	(0.006)	(0.051)		
	Euro	1.314***	0.095**	0.248*	−0.002	0.001	−4.296	0.005	0.006	0.057	0.355	29.27
		(0.164)	(0.045)	(0.125)	(0.013)	(0.001)	(4.338)	(0.007)	(0.004)	(0.037)		
	Asia	1.676***	0.012	0.168	0.034***	−0.001	2.970	0.005	−0.001	0.072	0.818	168.91
		(0.181)	(0.044)	(0.130)	(0.009)	(0.001)	(5.254)	(0.009)	(0.005)	(0.057)		
SARS 2003/2/10–2003/7/5	**USA**	1.494***	−0.118**	0.798***	−0.053	0.001	0.018	0.012	0.002	−0.004	0.575	15.96
		(0.098)	(0.049)	(0.211)	(0.055)	(0.002)	(0.040)	(0.023)	(0.003)	(0.028)		
	Euro	1.350***	0.001	0.410*	0.001	−0.004*	0.028	0.015	0.001	0.013	0.242	7.12
		(0.183)	(0.040)	(0.224)	(0.067)	(0.002)	(0.035)	(0.017)	(0.004)	(0.033)		
	Asia	1.577***	0.018	0.478***	−0.005	−0.001	0.004	−0.011	−0.006*	0.041	0.528	27.51
		(0.149)	(0.030)	(0.131)	(0.022)	(0.003)	(0.060)	(0.021)	(0.003)	(0.032)		

Note: See details in Appendix 1: Table 5.
(from US Fossil Fuel Energy to Renewable Energy Market).

References

[1] Christie WG, Huang RD. Following the pied piper: do individual returns herd around the market? Financ Anal J 1995;51(4):31–7.
[2] Muth JF. Rational expectations and the theory of price movements. Econometrica 1961;29(3):315–35.
[3] Fama EF. Efficient capital markets: a review of theory and empirical work. J Finance 1970;25(2):383–417.
[4] Bikhchandani S, Sharma S. Herd behavior in financial markets. Inter-national Monetary Fund 2001;47(13):279–310.
[5] Avery C, Zemsky P. Multidimensional uncertainty and herd behavior in financial markets. Am Econ Rev 1998;88(4):724–48.
[6] Who. "Update 95 - SARS: chronology of a serial killer," world health organization [online] Available at. 2003. https://www.who.int/csr/don/2003_07_04/en/. [Accessed 30 March 2020].
[7] Who. "Coronavirus disease (COVID-19) outbreak," world health organization [online] Available at: https://www.who.int/westernpacific/emergencies/covid-19. [Accessed 30 March 2020].
[8] Bikhchandani S, Hirshleifer D, Welch I. A theory of fads, fashion, custom, and cultural change as informational cascades. J Polit Econ 1992;100(5):992–1026.
[9] Devenow A, Welch I. Rational herding in financial economics. Eur Econ Rev 1996;40(3):603–15.
[10] Banerjee AV. A simple model of herd behavior. Q J Econ 1992;107(3):797–817.
[11] Welch I. Sequential sales, learning, and cascades. J Finance 1992;47(2):695–732.
[12] Scharfstein DS, Stein JC. Herd behavior and investment. Am Econ Rev 1990;80(3):465–79.
[13] Graham JR. Herding among investment newsletters: theory and evidence. J Finance 1999;54(1):237–68.
[14] Roll R. A mean/variance analysis of tracking error. J Portfolio Manag 1992;18(4):13.
[15] Lakonishok J, Shleifer A, Vishny RW. The impact of institutional trading on stock prices. J Financ Econ 1992;32(1):23–43.
[16] Tan L, Chiang TC, Mason JR, Nelling E. Herding behavior in Chinese stock markets: an examination of A and B shares. Pac Basin Finance J 2008;16(1–2):61–77.
[17] Chang EC, Cheng JW, Khorana A. An examination of herd behavior in equity markets: an international perspective. J Bank Finance 2000;24(10):1651–79.
[18] Litimi H, BenSaïda A, Bouraoui O. Herding and excessive risk in the American stock market: a sectoral analysis. Res Int Bus Finance 2016;38:6–21.
[19] BenSaïda A. Herding effect on idiosyncratic volatility in U.S. Industries. Finance Res Lett 2017;23:121–32.
[20] BenMabrouk H, Litimi H. Cross herding between American industries and the oil market. N Am J Econ Finance 2018;45:196–205.
[21] Demirer R, Kutan AM. Does herding behavior exist in Chinese stock markets? J Int Financ Mark Inst Money 2006;16(2):123–42.
[22] Chiang TC, Li J, Tan L. Empirical investigation of herding behavior in Chinese stock markets: evidence from quantile regression analysis. Global Finance J 2010;21(1):111–24.
[23] Yao J, Ma C, He WP. Investor herding behaviour of Chinese stock market. Int Rev Econ Finance 2014;29:12–29.
[24] Caparrelli F, D`Arcangelis AM, Cassuto A. Herding in the Italian stock market: a case of behavioral finance. J Behav Finance 2004;5(4):222–30.
[25] Economou F, Kostakis A, Philippas N. Cross-country effects in herding behaviour: evidence from four south European markets. J Int Financ Mark Inst Money 2011;21(3):443–60.
[26] Economou F, Katsikas E, Vickers G. Testing for herding in the athens stock exchange during the crisis period. Finance Res Lett 2016;18:334–41.
[27] Mobarek A, Mollah S, Keasey K. A cross-country analysis of herd behavior in Europe. J Int Financ Mark Inst Money 2014;32:107–27.
[28] Chiang TC, Zheng D. An empirical analysis of herd behavior in global stock markets. J Bank Finance 2010;34(8):1911–21.
[29] Bowe M, Domuta D. Investor herding during financial crisis: a clinical study of the Jakarta stock exchange. Pac Basin Finance J 2004;12(4):387–418.
[30] Galariotis EC, Krokida S-I, Spyrou SI. Bond market investor herding: evidence from the European financial crisis. Int Rev Financ Anal 2016;48:367–75.
[31] Galariotis EC, Krokida S-I, Spyrou SI. Herd behavior and equity market liquidity: evidence from major markets. Int Rev Financ Anal 2016;48:140–9.
[32] Bekiros S, Jlassi M, Lucey B, Naoui K, Uddin GS. Herding behavior, market sentiment and volatility: will the bubble resume? N Am J Econ Finance 2017;42:107–31.
[33] Galariotis EC, Rong W, Spyrou SI. Herding on fundamental information: a comparative study. J Bank Finance 2015;50:589–98.
[34] Zheng D, Li H, Chiang TC. Herding within industries: evidence from asian stock markets. Int Rev Econ Finance 2017;51:487–509.
[35] Oberndorfer U. Energy prices, volatility, and the stock market: evidence from the Eurozone. Energy Pol 2009;37(12):5787–95.
[36] Ramos SB, Veiga H. Risk factors in oil and gas industry returns: international evidence. Energy Econ 2011;33(3):525–42.
[37] Zamani N. How the crude oil market affects the natural gas market? Demand and supply shocks. Int J Energy Econ Pol 2016;6(2):217–21.
[38] Chang C-L, McAleer M, Tian JR. Modeling and testing volatility spillovers in oil and financial markets for the USA, the UK, and China. Energies 2019;12(8):1–27.
[39] Chang C-L, McAleer M, Tansuchat R. Conditional correlations and volatility spillovers between crude oil and stock index returns. N Am J Econ Finance 2013;25(2):116–38.
[40] Chang C-L, Ilomaki J, Laurila H, McAleer M. Moving average market timing in European energy markets: production versus emissions. Energies 2018;11(12):1–24.
[41] Caporin MC-L, McAleer M. Are the S&P 500 index and crude oil, natural gas and ethanol futures related for intra-day data? Int Rev Econ Finance 2019;59:50–70.
[42] Chang C-L, Ilomaki J, Laurila H, McAleer M. Causality between CO2 emissions and stock markets. Energies 2020;13(11):1–14.
[43] Balcilar M, Demirer R, Hammoudeh S. What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors. N Am J Econ Finance 2014;29:418–40.
[44] Balcilar M, Demirer R, Ulussever T. Does speculation in the oil market drive investor herding in emerging stock markets? Energy Econ 2017;65:50–63.
[45] Ulussever T, Demirer R. Investor herds and oil prices evidence in the gulf cooperation Council (GCC) equity markets. Central Bank Review 2017;17(3):77–89.
[46] Shen C. Testing for herding behaviour among energy sectors in Chinese stock exchange. J Phys Conf 2018;1053:1–7.
[47] Trueck S, Yu Y. "Investor herding and dispersing in the renewable energy sector," working paper No. 16-02, centre for financial risk, faculty of business and economics. Macquarie University; 2018.
[48] Shah IH, Hiles C, Morley B. How do oil prices, macroeconomic factors and policies affect the market for renewable energy. Appl Energy 2018;215:87–97.
[49] Reboredo Juan C. Is there dependence and systemic risk between oil and renewable energy stock prices. Energy Econ 2015;48:32–45.
[50] Apergis N, Payne JE. Renewable and non-renewable energy consumption-growth nexus: evidence from a panel error correction model. Energy Econ 2012;34(3):733–8.
[51] Marques AC, Fuinhas JA, Pires Manso JR. Motivations driving renewable energy in European countries: a panel data approach. Energy Pol 2010;38(11):6877–85.
[52] Treynor J. Market value, time, and risk. 1961. p. 95–209. " Unpublished manuscript, dated 8/8/61, No.
[53] Treynor Jack L. Toward a theory of market value of risky assets. 1962. Unpublished manuscript. Subsequently, published as [Chapter 2] of Korajczyk.
[54] Sharpe WF. Capital asset prices: a theory of market equilibrium under conditions of risk. J Finance 1964;19(3):425–42.
[55] Lintner J. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Rev Econ Stat 1965;47:13–37.
[56] Mossin J. Equilibrium in a capital asset market. Econometrica 1966;34(4):768–83.
[57] Bouri E, Gupta R, Roubaud D. Herding behaviour in cryptocurrencies. Finance Res Lett 2019;29:216–21.
[58] Liang WH, Liang HR, L M, Ou, et al. Development and validation of a clinical risk score to predict the occurrence of critical illness in hospitalized patients with COVID-19. Journal of the American Medical Association (JAMA) Internal Medicine 2020;180(8):1081–9. https://doi.org/10.1001/jamainternmed.2020.2033. In this issue.