

## Article

# COVID-19 Effects on Arbitrage Trading in the Energy Market

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**Abstract:** This paper investigates the effects of coronavirus disease 2019 (COVID-19) on the performance of arbitrage trading in the energy market using daily data covering the period between 1 January 2015 and 5 December 2021. The investigation was achieved by utilizing a parametric pairs-trading model, where pairs of energy-related securities, including futures, stocks and ETFs traded in the United States, are formed. The empirical results suggest that the out-of-sample performances of pair trading declined sharply in the face of COVID-19. Dividing the whole data sample into two sub-samples, we found that the strategy performed well before COVID-19 but yielded poor results in the pandemic era. The analysis presented in this paper could serve as a benchmark for arbitrage-based trading models in the energy market during the pandemic.

**Keywords:** COVID-19; pairs trading; U.S. energy market

## 1. Introduction

Started in December 2019, the coronavirus pandemic 2019 (COVID-19) has created not only a global health crisis but also significant turmoil in financial markets around the world. One noteworthy event was the crash of oil prices on 20 April 2020. For the first time in history, the front-month May 2020 West Texas Intermediate Crude Oil contract settled at negative \$37.63 a barrel on the New York Mercantile Exchange. The oil price has gone up after the crash, but not yet recovered to the pre-pandemic level. As of 15 December 2021, the United States Oil Fund, a representative indicator of the oil price, closed at \$51.62. In comparison, the USO ranged between \$76 and \$105 during 2019. On the other hand, the COVID-19 has killed 826,364 people in the US as of 15 December 2021, with corresponding COVID-19 active cases of 10,138,661 (The COVID-19 related data is collected from Our World in Data: <https://ourworldindata.org/coronavirus-data> (accessed on 30 December 2021)). While there is no clear evidence on when the COVID-19 would end, it is crucial for financial market participants to reexamine their trading and valuation models and assess the impacts of COVID-19 quantitatively.

This paper investigates the effects of COVID-19 on energy market from one specific perspective—the performances of the pairs trading portfolios. Pairs trading is a statistical arbitrage trading strategy based on assets with similar characteristics but dissimilar valuation dynamics. First developed at Morgan Stanley during the 1980s, pairs trading aims at finding relative mispricing between securities and profiting from the convergence. The energy market provides an ideal group of candidates for pairs trading purpose. Energy-related securities, such as energy stocks, futures, Exchange-Traded Funds (ETFs), are ‘similar’ in the sense that their valuations are closely related to common fundamentals in the energy market. For example, ref. [1] reports that energy futures with different maturities are highly correlated. However, relative mispricings are possible due to different features and segments of the securities. Since COVID-19 has brought significant turbulence to the energy market, and energy-related securities are ideal for pairs trading, we are interested



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in studying the impact of COVID-19 on the energy market by studying the performances of pairs trading portfolios.

Using daily data from 1 January 2015 to 5 December 2021, we construct arbitrage portfolios using five energy futures, five largest and five smallest energy stocks, and five energy-related ETFs, for a total of 190 possible pairs. A parametric approach, which is known as pairs trading, is adopted to form the portfolios. It assumes that a linear combination of a pair of securities is stationary, and the deviation from the long-run (theoretical) equilibrium is temporary. The deviation is called the spread, which is the relative mispricing that the pairs trading strategy tries to capture. Profit can be generated if the spread converges to zero fast enough. To implement the model, we split the data of interest into two sets: the in-sample set, from which we calibrate the model parameters, and the out-of-sample set, on which we test the model performance. For each pair, we compute its realized returns, standard deviations, Sharpe ratios and standard deviations of the Sharpe ratios, for both the in-sample and out-of-sample sets. For comparative purpose, we further divide the whole data sample into two sub-sample periods, using 23 January 2021 (the date that the first case of COVID-19 in US was confirmed) as the break point, and conduct the same analysis for each sub-sample. The detail of the data split and data sub-sampling is summarized in Table 1. By doing so, we can compare the performances before and after the pandemics began, and how the spread of COVID-19 shapes the landscapes of arbitrage-based trading models.

**Table 1.** Data split and sub-samples.

Data Periods	In-Sample Set	Out-of-Sample Set
Full period	1 January 2015–22 January 2020	23 January 2020–5 December 2021
Sub-sample 1	1 January 2018–31 December 2018	1 January 2019–22 January 2021
Sub-sample 2	23 January 2020–22 January 2021	23 January 2021–5 December 2021

An emerging literature is devoted to understand the impact of COVID-19 on global economy and financial markets. See, for example, refs. [2–8] study the adverse impacts of COVID-19 on stock markets from various perspectives. In terms of the energy market, recent scholarly works have provided practical insights for interested market participants, and this paper joins in this line of efforts. Among them, ref. [9] investigates the nexus between pandemic, political risk, equity and energy markets; ref. [10] analyses the natural gas and electricity markets in Spain while ref. [11] focuses on the energy market in Italy. ref. [12] discusses the challenges posed by COVID-19 to the energy sector. ref. [13] studies the impact of COVID-19 on energy market volatility. refs. [3,4,14] examines the effects of the pandemic in an equilibrium framework where asset pricing implications are drawn. ref. [15] derives the optimal investment decision for electricity producers during a pandemic. The trading model in this paper follows from refs. [16–19].

This paper fills a gap in the literature as the first attempt to study the impact of COVID-19 on the energy market from the perspectives of arbitrage trading. What's more, our analysis spans a wide range of asset classes that are relevant for energy market participants. Previous literature on pairs trading in the energy market focuses on a single asset class. For example, ref. [20] studies the energy futures market and ref. [21] surveys energy stocks. Based on our knowledge, we are the first to combine energy futures, selected stocks and ETFs in a pairs trading setting. The results in this paper are of immediate usefulness to practitioners. On one hand, our results could serve as a benchmark for other trading strategies based on statistical arbitrage theory. Indeed, pairs trading is the cornerstone of various modern statistical arbitrage approaches. It is based on the mean-reverting property of the spread, or relative price difference between two securities. The idea can be easily extended to cases with multiple securities. Such approach is usually called basket trading in the financial industry but it builds on the basic case where a pair of two securities are formed and studied, exactly the task that we achieve in the present paper. On the other

hand, the main conclusion in this paper is preliminary: it implies that the conventional strategy, which once worked, breaks down during the COVID-19 pandemic and more advanced trading models are called for.

The rest of the paper is organized as follows. Section 2 introduces the portfolio construction process and assumptions. Section 3 gives an overview of the data and descriptive statistics. Section 4 reports the in-sample and out-of-sample results for the whole sample and each of the sub-samples. Section 5 concludes.

## 2. Portfolio Construction and Trading Strategy

Pairs trading is a popular investment approach used widely in the financial industry. This approach assumes that the market may deviate from their equilibrium values because of temporary shocks but eventually converge to them in the long run. Pairs trading typically consists of a long position in one of the two securities and a short position in the other one when a large deviation between the prices is observed and clears the exposure when the deviation disappears. Parametric pairs trading can be implemented with two steps. In the first step, we specify the parametric assumptions on the dynamics of the two securities prices and the spread between them. A specific trading strategy is designed in the second step. A trading strategy is a method of quantifying the threshold for buying and selling the assets based on the estimation of the spread. We discuss the model and the estimation approach in Section 2.1. The trading strategy with an example is illustrated in Section 2.2.

### 2.1. The Model

We follow the parametric approach to pairs trading adopted by refs. [16–18,22–26]. Let the price of stocks  $A$  and  $B$  at time  $t$  be  $P_{A,t}$  and  $P_{B,t}$ , respectively. We first apply the linear regression method to estimate the hedge ratio, i.e., we estimate  $\beta$  in the following linear model:

$$\ln(P_{A,t}) - \beta \ln(P_{B,t}) = X_t.$$

We let  $\hat{X}_t$  denote the estimated residual and call it the spread between stocks  $A$  and  $B$ . Following ref. [27], We assume  $\hat{X}_t$  follow an Ornstein–Uhlenbeck process, such that

$$d\hat{X}_t = \theta(\mu - \hat{X}_t)dt + \sigma dW_t$$

Or in discrete-time form,

$$\hat{X}_{t_i} - \hat{X}_{t_{i-1}} = \theta(\mu - \hat{X}_{t_{i-1}})(t_i - t_{i-1}) + \sigma\sqrt{t_i - t_{i-1}}\epsilon_i, \epsilon_i \stackrel{iid}{\sim} N(0, 1)$$

where  $i = 1, 2, \dots, n$  denotes the order of the data points. The parameters  $(\mu, \theta, \sigma)$  in the above model can be estimated by maximum likelihood method. The likelihood function can be approximated by Euler-Maruyama scheme, see e.g., refs. [28,29]. More specifically, the log likelihood function can be written as

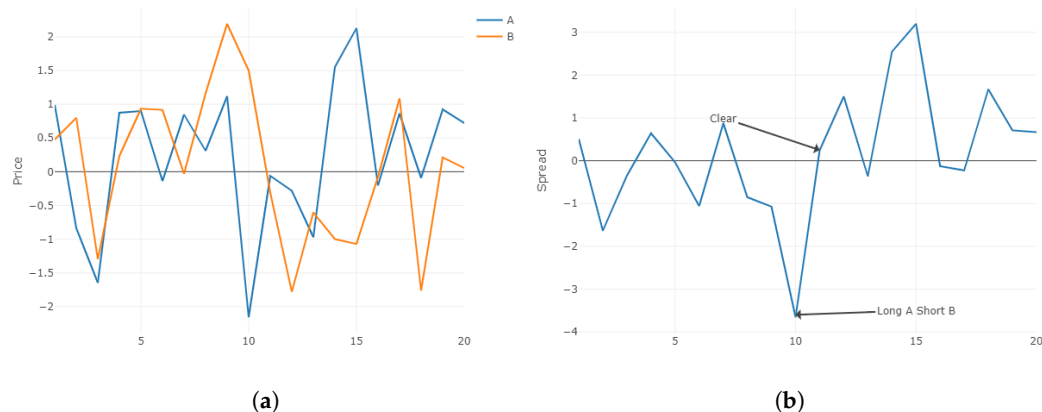
$$L(\hat{X} | \mu, \theta, \sigma) = -\frac{n}{2} - \frac{1}{2} \sum_{i=1}^n \ln\left(1 - e^{-2\theta(t_i - t_{i-1})}\right) - \frac{\theta}{\sigma^2} \sum_{i=1}^n \frac{\hat{X}_{t_i} - \mu - (\hat{X}_{t_{i-1}} - \mu)e^{-\theta(t_i - t_{i-1})}}{1 - e^{-2\theta(t_i - t_{i-1})}}$$

We get the estimates for parameters,  $\{\theta, \mu, \sigma\}$ , by maximizing the above log likelihood function over the data in the training set.

### 2.2. The Trading Strategy

We assume the parameters are constant during the data period under study, and apply the classical optimal trading rule. That is, we take positions at one standard deviation (i.e., when the spread is one standard deviation away from the mean, i.e.,  $\hat{X}_t \notin [\mu - \sigma, \mu + \sigma]$ ) and clear positions when the spread reverts back to the mean. When the spread is positive, we long the stock  $B$  and short the stock  $A$ ; otherwise we long the stock  $A$  and short the stock  $B$ . The relative position depends on the hedging ratio  $\beta$ . For example, if we long one unit of stock  $B$ , we short  $\beta$  units of stock  $A$ . This strategy is illustrated in Figure 1.

For two stocks A and B, the time series plot of the prices is given in Figure 1a, and the spread between A and B is given in Figure 1b. When, for example, the price of stock A is much lower than the price of stock B, the spread is far below its long-run mean as shown in Figure 1b. In this case, we construct a portfolio by taking a long position of stock A and a short position of stock B. When the market goes back to its mean, we clear the exposure. By doing so, we are able to profit from the spread convergence. In relative terms, price of Stock A (long position) rises and price of Stock B (short position) declines. The size of the profit is then determined by the differences between the entry and exit points. See ref. [19] for detailed discussion of this trading strategy.



**Figure 1.** Illustration of the pairs trading of stocks A and B. (a) Prices of stocks A and B. (b) Spreads between stocks A and B.

### 3. Data and Descriptive Statistics

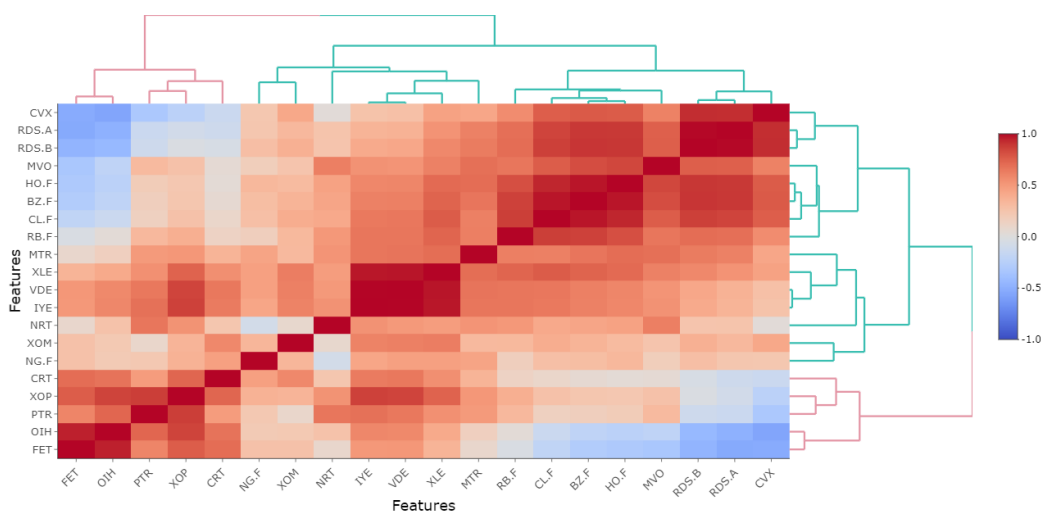
We choose five energy futures: BZ, CL, HO, NG and RB; five largest energy equities: XOM, CVX, RDS-B, RDS-A, and PTR; five smallest energy equities: MTR, CRT, NRT, MVO, and FET; and five energy related ETF: XLE, VDE, XOP, IYE, and OIH. Since there are 20 energy-related securities under study, and two securities are needed to form a trading pair, the total number of possible pairs is  $C_2^{20} = 190$ . We compute the return of all possible 190 pairs under the trading strategy and the entry-exit rule described in Section 2 given the actual daily prices between 1 January 2015 and 5 December 2021. To compare the performances and to determine the overall effects of COVID-19 on pairs trading, we split the whole data period into two sub-samples, using 23 January 2020 as the dividing point. For each sub-samples, we further separate the data set into the in-sample (training) set and the out-of-sample (test) set. Specifically, for the full period, we treat the data between 1 January 2015 and 22 January 2020 as the in-sample set, and the data between 23 January 2020 and 5 December 2021 as the out-of-sample set. The rationale behind such separation is that we would like to see whether a constant set of model parameters calibrated before the pandemic performs similarly during the pandemic. For sub-sample 1, we treat the data between 1 January 2018 and 1 January 2019 as the in-sample data, and the data between 1 January 2019 and 22 January 2020 as the out-of-sample data; for sub-sample 2, we treat the data between 23 January 2020 and 22 January 2021 as the in-sample data, and the data between 23 January 2021 and 5 December 2021 as the out-of-sample data. Time series of selected futures, equities and ETFs are plotted in Figure 2.



**Figure 2.** Time series plot of BZ, NG, XOM, CVX, MTR, CRT, XLE and VDE.

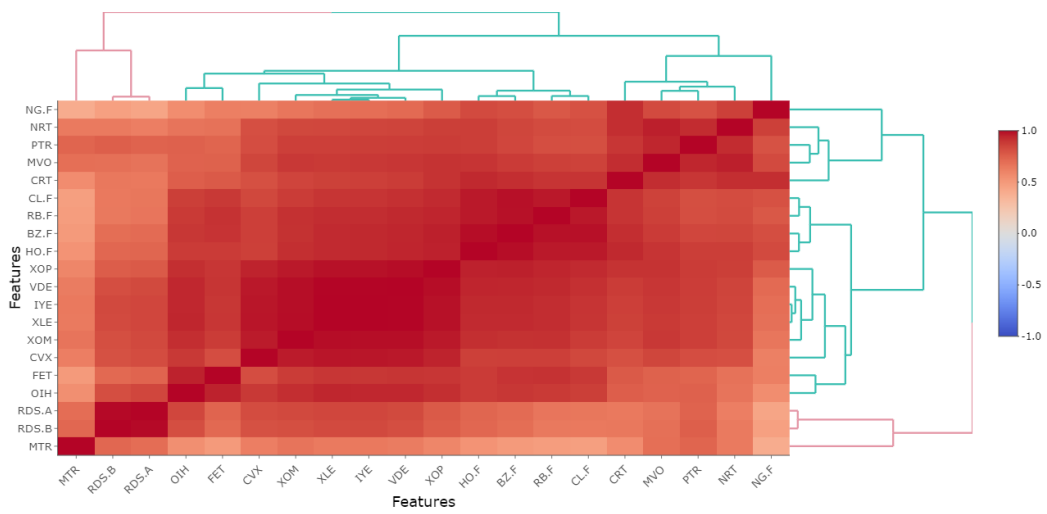
Pairs trading is implemented by finding two stocks whose prices move together historically to make sure that the resulting spread will be in the direction of mean reversion. Such two stocks are considered ‘similar’ in the trading sense. In practice, the correlation coefficient is used to measure the ‘similarity’ between two stocks. In this regard, we construct heat maps to visualize the general degree of ‘similarities’ between asset returns in an asset pool.

In Figures 3–5, using heat maps, we plot the correlation matrix among the twenty energy-related securities for different date and sample periods. Figure 3 suggests that the correlation structure changes after COVID-19 began, as panel (b) is generally darker than panel (a), implying a higher level of co-movement between assets in the energy sector during the pandemic. In contrast, Figure 4a is similar to Figure 4b. This again motivates us to study the COVID-19’s effect on pairs trading performance, since the change in correlation structure may result in the breaking down of previously established patterns in arbitrage-based trading.



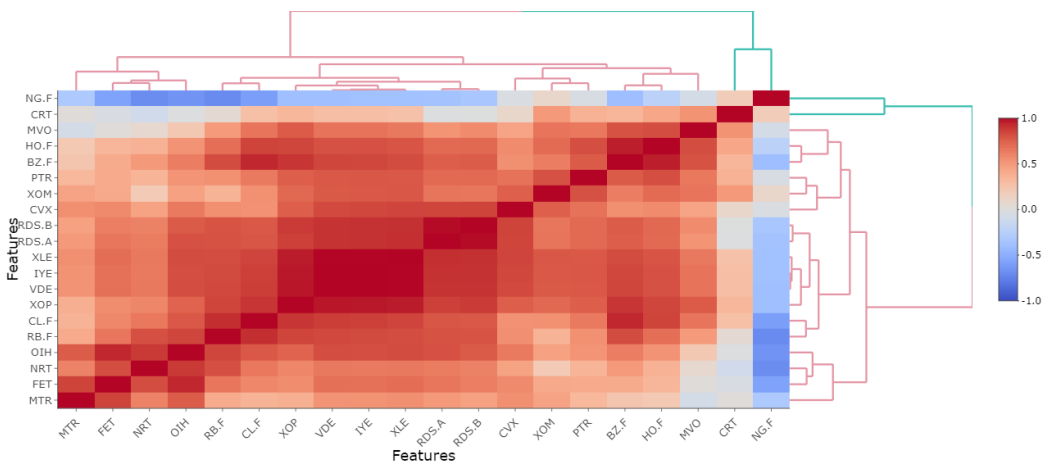
(a)

**Figure 3.** Cont.

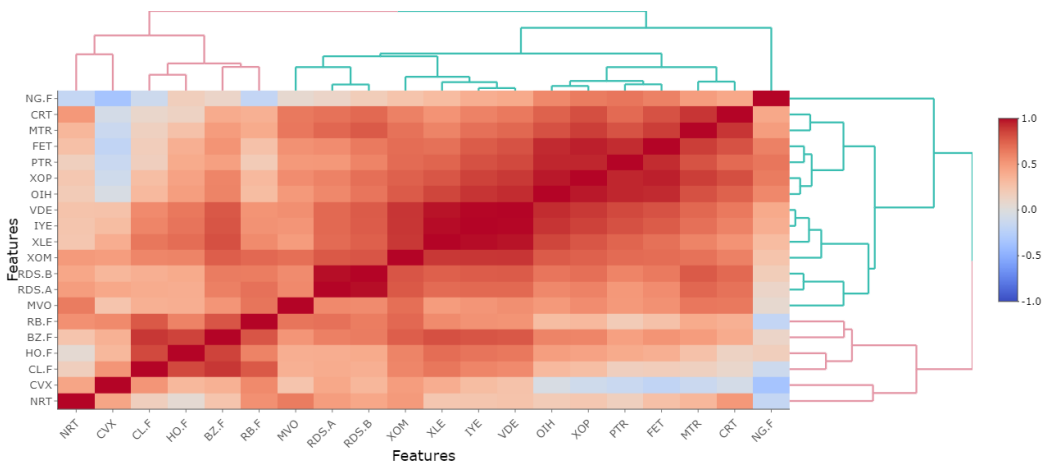


(b)

**Figure 3.** Correlation matrix of energy-related securities for (a) in-sample set and (b) out-of-sample set of the full data sample.

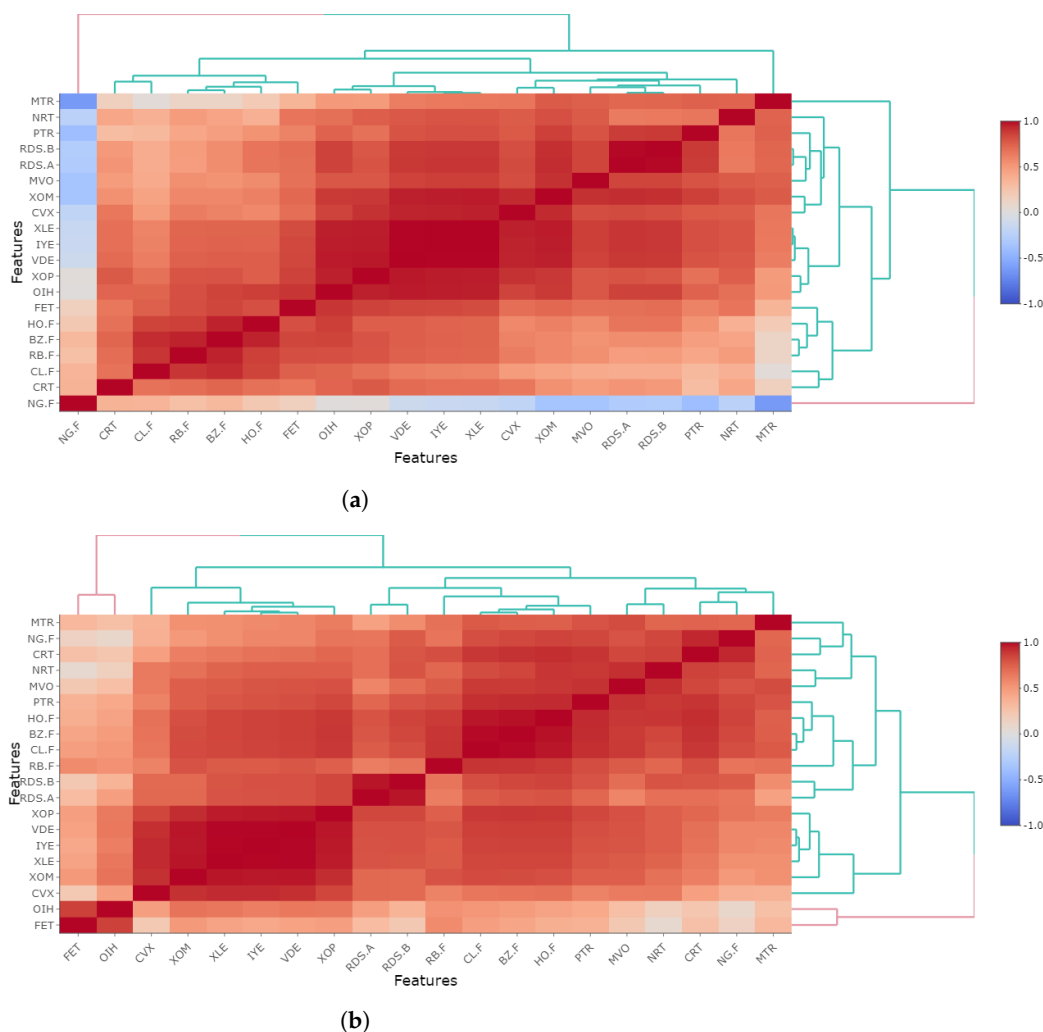


(a)



(b)

**Figure 4.** Correlation matrix of energy-related securities for (a) in-sample set and (b) out-of-sample set of the first sup-sample period.



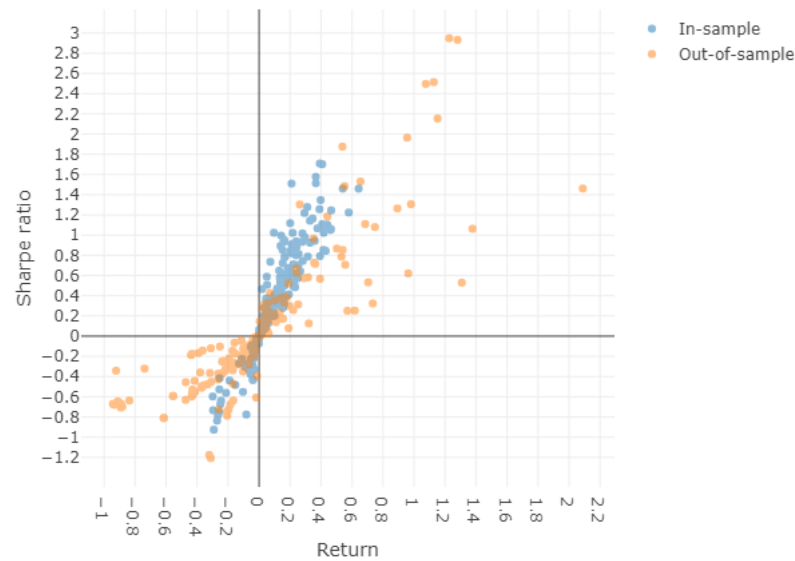
**Figure 5.** Correlation matrix of energy-related securities for (a) in-sample set and (b) out-of-sample set of sup-period 2.

#### 4. Results

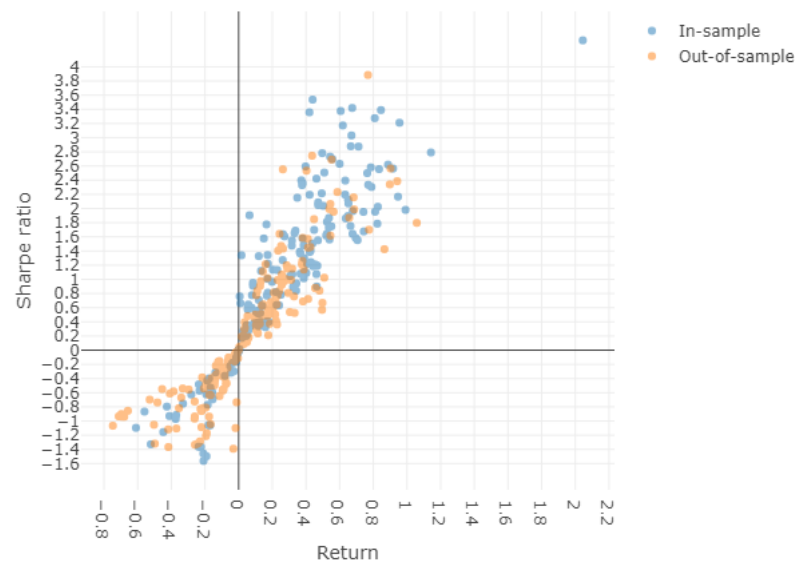
The results of the pairs trading on all 190 pairs are summarized in Figures 6–8 for different sample periods, and the main statistics are reported in Table 2.

To give the readers an intuitive comparison of the out-of-sample and in-sample performances among various periods, we plot the Sharpe ratios against the average return of all the 190 pairs. In Figures 6 and 8, the out-of-sample performances are clearly worse than the in-sample performances, however, in Figure 7, the out-of-sample performances are consistent with those of the in-sample period.

Examining the results, three observations are drawn. First, by comparing the means and standard deviations of out-of-sample returns in Table 2, it is obvious that out-of-sample performance of the first sub-sample data (with mean of return being 0.0692, and mean of the Sharpe ratio being 0.2869) is much better than those of the full sample period and the second sub-sample period with mean of return being 0.0108, and mean of the Sharpe ratio being 0.0763 for the full sample and with mean of return being 0.02, and mean of the Sharpe ratio being 0.1133 for the second sub-sample). Because in the first sub-sample period, the out-of-sample data is before the pandemic, and in other cases, the out-of-sample data is after the pandemic, the above comparison implies that the COVID-19 pandemic has exerted a strong negative impact on the performance of pairs trading in the energy-related financial market.



**Figure 6.** Plot of Sharpe ratios against returns of 190 pairs based on the whole sample period.



**Figure 7.** Plot of Sharpe ratios against returns of 190 pairs based on the first sub-sample period.

Second, the in-sample performance of the second sub-sample was outstanding; however, the corresponding out-of-sample performance was poor. This is because the pandemic shock has had a huge impact on the stock price volatility, and brought statistical arbitrage opportunity to some energy related futures or equities. However, such opportunities only exist in the in-sample data, and cannot be carried to the out-of-sample period. Also, the impact of COVID-19 event is not consistent among the twenty securities in our pool. The standard deviation of the return of the pairs trading among the 190 pairs is 3.6687, and the standard deviation of the corresponding Sharpe ratios is 3.1260.

Third, the performance of the second sub-sample is slightly better than that of the whole sample, in terms of both the mean of the return and the mean of the Sharpe ratios (as shown in the fourth and second row in Table 2, 0.200 vs. 0.0108 for the return; and 0.1133 vs. 0.0763 for the Sharpe ratios). This means that the pairs identified using the data before the pandemic as training data no longer work, and the pairs based on the data after the pandemic perform better. Similar to our earlier finding, this result shows that the COVID-19 pandemic brought a structural change to the energy market and impacted the performance of pairs trading.



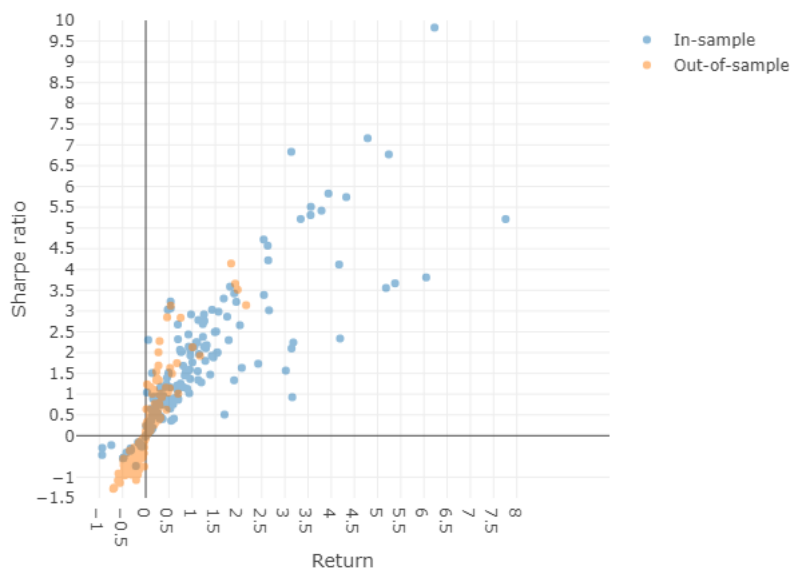


Figure 8. Plot of Sharpe ratios against returns of 190 pairs based on the second sub-sample period.

Table 2. Performance measures.

Data Period		Mean of Return	StdDev of Return	Mean of SR	StdDev of SR
Full sample	in-sample	0.1103	0.1775	0.3775	0.5577
	out-of-sample	0.0108	0.4597	0.0763	0.6769
Sub-sample 1	in-sample	0.2706	0.3670	1.0440	1.2117
	out-of-sample	0.0692	0.3337	0.2869	0.9981
Sub-sample 2	in-sample	1.6419	3.6687	2.0939	3.1260
	out-of-sample	0.0200	0.4123	0.1133	0.9473

Also, we implement the Wilcoxon–Mann–Whitney test to compare the level differences of out-of-sample performance during different sampling periods. We are interested in knowing whether such differences across data samples are statistically significant. For this purpose, we compare the distributions of either the returns or the Sharpe ratios for the full sample (or the sub-sample 2) to those for the sub-sample 1. The steps of the Wilcoxon–Mann–Whitney test are outlined below:

1. Let the distribution of the strategy returns for the full sample be  $F(x)$ , and the corresponding distribution for the sub-sample 1 be  $G(x)$ . In the Wilcoxon–Mann–Whitney test, the null hypothesis,  $H_0$ , is:

$$H_0 : F(x) = G(x - \theta), \theta = 0;$$

and the alternative hypothesis,  $H_1$ , is

$$H_1 : F(x) = G(x - \theta), \theta < 0.$$

That is, we want to test whether the distribution of the returns for the sub-sample 1 is a location shift to the right of the corresponding distribution of the returns for the full sample.

2. The  $p$ -value of the test is computed.
3. A similar test is conducted to compare the distributions of the Sharpe ratios.

- The same procedure is repeated to compare the distributions of returns and Sharpe Ratios between sub-sample 2 and sub-sample 1.

The *p*-values of the above tests are reported in Table 3. From this table, we conclude that the performance of pairs trading based on the sub-sample 1 is better than the full sample or the sub-sample 2. The results from the Wilcoxon–Mann–Whitney test imply that the out-of-sample performance of pairs trading has declined on a statistically significant sense during the COVID-19 pandemic.

**Table 3.** *p*-values for the Wilcoxon–Mann–Whitney Test.

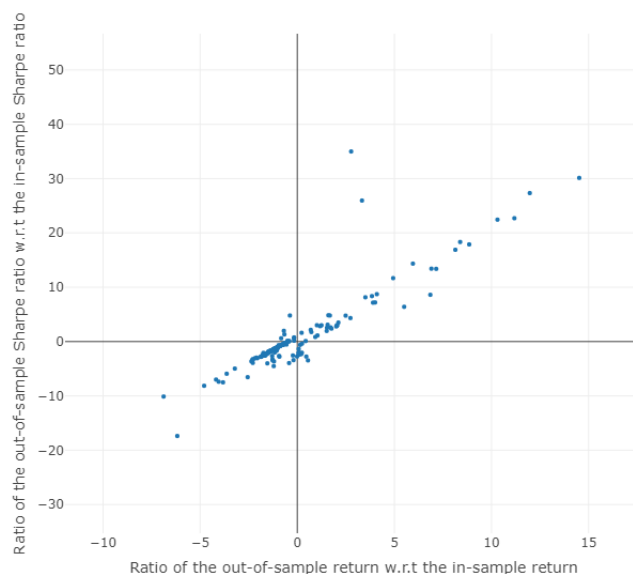
Data Period	Returns	Sharpe Ratios
Full sample	0.0035 ***	0.0130 **
Sub-sample 2	0.0014 ***	0.0036 ***

\*\*\* and \*\* denote significance level of 1% and 5% respectively.

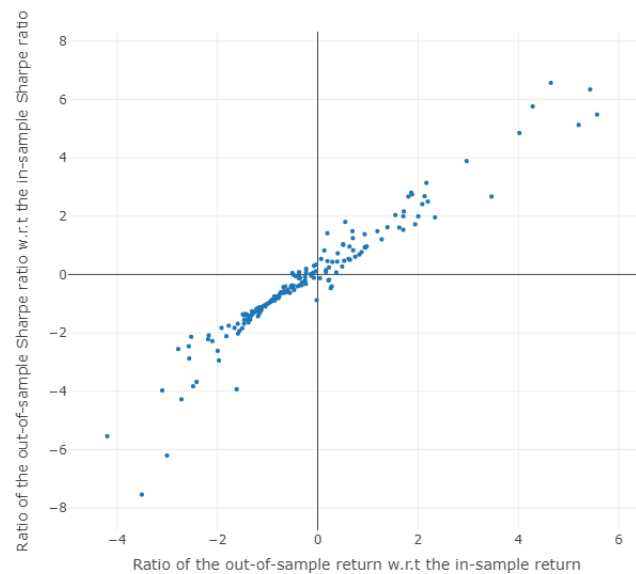
Finally, we report the ratio of the in-sample performance with respect to the out-of-sample performance for the three data periods in Figures 9–11. The ratio in these figures is defined as:

$$ratio_i = \frac{Z_{2,i} - Z_{1,i}}{\|Z_{1,i}\|}$$

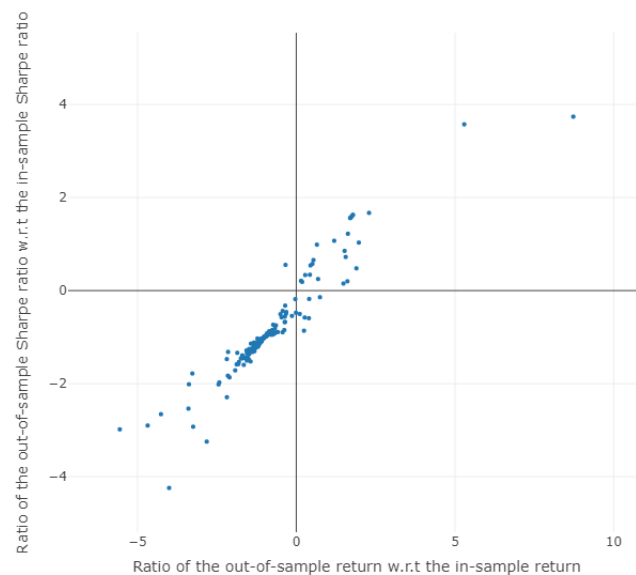
where  $Z_{1,i}$  is the return or Sharpe ratio of the in-sample set for the *i*-th pair, and  $Z_{2,i}$  is the corresponding value of the out-of-sample set for the *i*-th pair. It is clear that in Figures 9 and 10, most of the points are above the 45 degree line, while in Figure 11, most of the points are below the 45 degree line. This pattern implies that the pandemic increased the return volatility of energy-related securities, and made pairs trading more risky when the training data included the time period after the pandemic started.



**Figure 9.** The ratio of the Sharpe ratio between in-sample and out-of-sample data vs. The ratio of the return between in-sample and out-of-sample data, in the whole sample period.



**Figure 10.** The ratio of the Sharpe ratio between in-sample and out-of-sample data vs. The ratio of the return between in-sample and out-of-sample data, in the first sub-sample period.



**Figure 11.** The ratio of the Sharpe ratio between in-sample and out-of-sample data vs. The ratio of the return between in-sample and out-of-sample data, in the second sub-sample period.

## 5. Conclusions

In this paper, we have investigated one aspect of the COVID-19 effects on the energy market. By constructing pairs trading portfolios from a representative group of energy-related securities and examining their performances, we can draw a few important implications.

First, we find that the performance of the strategy degenerated sharply in the face of COVID-19, as shown by the much lower out-of-sample average Sharpe ratios, lower average realized returns and higher variation of Sharpe ratios. The huge gap between the in-sample and out-of-sample performance measures suggests that simply recycling parameters does not generate sound results in the pandemic era. Second, the same strategy works much better if only the pre-pandemic data (sub-sample period 1) is studied. Performance measures improve: higher average Sharpe Ratios and lower variation of Sharpe ratios. It indicates that the arbitrage trading strategy works before the COVID-19 emerged, and the pandemic completely reshapes the strategy. Third, using data after the pandemic started

(sub-period 2) only slightly improves the performance. Out-of-sample results are still poor after controlling sub-samples, implying that the effect of COVID-19 is adverse or even destructive. Besides, two other implications are especially important for practitioners. First, increasing the asset span, as we do in the present paper, does not necessarily improve the results. Second, a heat map might serve as a good graphical indicator and an intuitive visual tool in the preparatory analysis for arbitrage-based trading strategies. Detailed usage and a more deterministic link between heat maps and strategy performance may warrant further examination for the interested parties.

The findings in this paper point out the importance of model innovations or modifications during the pandemic. Future research could be taken in multiple directions. For example, we can allow for time-varying parameters in the baseline model, or relax the model with more general set-ups. ref. [30] proposes a pairs trading algorithm based on general state spaces. They find that both the Sharpe ratios and realized returns are improved by applying their framework to the equity market. Further investigations can be performed by following this line of research by viewing COVID-19 as a change in the model's state space. We leave this for future investigation.

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## Abbreviations

The following abbreviations are used in this manuscript:

BZ	Brent crude oil
CL	Crude oil
HO	Heating oil
NG	Natural gas
RB	RBOB gasoline
XOM	Exxon Mobil Corporation
CVX	Chevron Corporation
RDS-A	Royal Dutch Shell
RDS-B	Shell Transport and Trading Company
PTR	PetroChina Company Limited
MTR	Mesa Royalty Trust
CRT	Cross Timbers Royalty Trust
NRT	North European Oil Royalty Trust
MVO	MV Oil Trust
FET	Forum Energy Technologies, Inc
XLE	Energy Select Sector SPDR Fund

VDE	Vanguard Energy Index Fund ETF Shares
XOP	SPDR Series Trust—SPDR S&P Oil & Gas Exploration & Production ETF
IYE	iShares U.S. Energy ETF
OIH	VanEck Vectors Oil Services ETF
WTI	West Texas Intermediate Crude Oil

## References

- Alexander, C. Correlation and cointegration in energy markets. In *Managing Energy Price Risk*; Kaminski, V., Ed.; Risk Publications: London, UK, 1999.
- Alfaro, L.; Chari, A.; Greenland, A.; Schott, P. *Aggregate and Firm-Level Stock Returns during Pandemics, in Real Time*; NBER Working Paper, No. 26950; National Bureau of Economic Research: Cambridge, MA, USA, 2020.
- Baldwin, R.; Di Mauro, B.W. *Economics in the Time of COVID-19*; VoxEU; CEPR Press: London, UK, 2020.
- Yilmazkuday, H. Coronavirus Disease 2019 and the Global Economy. *Transport Policy*, Forthcoming. Available online: <https://ssrn.com/abstract=3554381> (accessed on 1 January 2022).
- Ahundjanov, B.B.; Akhundjanov, S.B.; Okhunjanov, B.B. Information Search and Financial Markets under COVID-19. *Entropy* **2020**, *22*, 791. [[CrossRef](#)]
- Cao, K.H.; Li, Q.; Liu, Y.; Woo, C.-K. COVID-19 Adverse Effects on a Stock Market Index. *Appl. Econ. Lett.* **2020**, *14*, 1157–1161. [[CrossRef](#)]
- Cox, J.; Greenwald, D.L.; Ludvigson, S.C. *What Explains the COVID-19 Stock Market*; Discussion Paper; National Bureau of Economic Research: Cambridge, MA, USA, 2020.
- Yilmazkuday, H. COVID-19 effects on the S&P 500 index. *Appl. Econ. Lett.* **2021**. Available online: <http://dx.doi.org/10.2139/ssrn.3555433> (accessed on 1 January 2022).
- Sharif, A.; Aloui, C.; Yarovaya, L. COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence from the Wavelet-based Approach. *Int. Rev. Financ. Anal.* **2020**, *70*, 101496. [[CrossRef](#)]
- Abadie, L.M. Energy Market Prices in Times of COVID-19: The Case of Electricity and Natural Gas in Spain. *Energies* **2021**, *14*, 1632. [[CrossRef](#)]
- Ghiani, E.; Galici, M.; Mureddu, M.; Pilo, F. Impact on Electricity Consumption and Market Pricing of Energy and Ancillary Services during Pandemic of COVID-19 in Italy. *Energies* **2020**, *13*, 3357. [[CrossRef](#)]
- Navon, A.; Machlev, R.; Carmon, D.; Onile, A.E.; Belikov, J.; Levron, Y. Effects of the COVID-19 Pandemic on Energy Systems and Electric Power Grids—A Review of the Challenges Ahead. *Energies* **2021**, *14*, 1056. [[CrossRef](#)]
- Shaikh, I. Impact of COVID-19 pandemic on the energy markets. *Econ. Chang. Restruct* **2021**. Available online: <https://link.springer.com/article/10.1007/s10644-021-09320-0> (accessed on 1 January 2022).
- Detemple, J. Asset Prices and Pandemics: The Effects of Lockdowns. *Q. J. Financ.* **2022**, *12*, 1. [[CrossRef](#)]
- Detemple, J.; Kitapbayev, Y. Optimal Power Investment and Pandemics: A Micro-Economic Analysis. *Energies* **2021**, *14*, 814. [[CrossRef](#)]
- Bai, Y.; Wu, L. Analytic value function for optimal regime-switching pairs trading rules. *Quant. Financ.* **2018**, *18*, 637–654. [[CrossRef](#)]
- Elliott, R.J.; Van Der Hoek, J.; Malcolm, W.P. Pairs trading. *Quant. Financ.* **2005**, *5*, 271–276. [[CrossRef](#)]
- Elliott, R.J.; Bradrania, R. Estimating a regime switching pairs-trading model. *Quant. Financ.* **2018**, *18*, 877–883. [[CrossRef](#)]
- Zeng, Z.; Lee, C.G. Pairs trading: Optimal thresholds and profitability. *Quant. Financ.* **2014**, *14*, 1881–1893. [[CrossRef](#)]
- Kanamura, T.; Rachev, S.; Fabozzi, F. *The Application of Pairs Trading to Energy Futures Markets*; Working Paper; Yale School of Management: New Haven, CT, USA, 2008.
- Salas Najera, C. Pair Trading and VAR Analysis Applied to Energy Stocks. 2019. Available online: <https://ssrn.com/abstract=3458559> (accessed on 1 January 2022).
- Clegg, M.; Krauss, C. Pairs trading with partial cointegration. *Quant. Financ.* **2018**, *18*, 121–138. [[CrossRef](#)]
- Cummins, M.; Bucca, A. Quantitative spread trading on crude oil and refined products markets. *Quant. Financ.* **2012**, *12*, 1857–1875. [[CrossRef](#)]
- Stübinger, J.; Endres, S. Pairs trading with a mean-reverting jump-diffusion model on high-frequency data. *Quant. Financ.* **2018**, *18*, 10. [[CrossRef](#)]
- Tourin, A.; Yan, R. Dynamic pairs trading using the stochastic control approach. *J. Econ. Dyn. Control* **2014**, *37*, 1972–1981. [[CrossRef](#)]
- Vidyamurthy, G. *Pairs Trading: Quantitative Methods and Analysis*; Wiley: Hoboken, NJ, USA, 2004.
- Dempster, M.A.H.; Medova, E.; Tang, K. Long term spread option valuation and hedging. *J. Bank. Financ.* **2008**, *32*, 2530–2540. [[CrossRef](#)]
- Kloeden, P.E.; Platen, E. Numerical solutions of stochastic differential equations. *Appl. Math.* **1992**, *23*. [[CrossRef](#)]
- Talay, D.; Tubaro, L. Expansion of the global error for numerical schemes solving stochastic differential equations. *Stoch. Anal. Appl.* **1990**, *8*, 483–509. [[CrossRef](#)]
- Zhang, G. Pairs trading with general state space models. *Quant. Financ.* **2021**, *21*, 1567–1587. [[CrossRef](#)]