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MISPRICINGS IN GLOBAL ENERGY MARKETS

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Abstract

Financial market participants can benefit from understanding how shocks affect equity mispricings. Energy corporates have been exposed to multiple structural changes over the past decades. This paper applies the pairs trading algorithm of (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) (Journal of Futures Markets, 2018) to analyse mean reversion of cointegrated stocks in global energy equity markets. Using daily data covering the US, Europe and Asia we report positive risk adjusted returns that supersede their corresponding equity index counterparts. Pairs trading profitability is enhanced when filtering stocks with the measure of capital expenditure (CAPEX).

Keywords: Mispricings, Energy markets, Energy transition, Pairs trading

1. Introduction

Revenues in the oil and gas industry have been hit hard over the past two decades. The 2014-2016 crude oil price plunge and the pandemic driven turmoil in energy markets have caused a huge rise of stock price volatility in energy corporates. Energy equities are in consequence trading at less than half of the levels prior to the 2014 oil price shock. The sector has severely undercut business growth and investment in new capacity at a time in which green investing and the global commitment to achieve climate neutrality reaches its momentum.[1] In this paper we illustrate the process by which recent periods of instability in the energy sector led to stock pricing inefficiencies in long term related assets. Our paper relates to a significant part of Robert Webb´s work as it uses the cointegration approach to examine asset pricing inefficiencies. There are a number of important contributions of Robert in the area including (Low, Muthuswamy, and Webb 1999), (Frijns, Tourani-Rad, and Webb 2016). (Webb 1985) among others. Here we exploit temporary mispricings via the use of arbitrage-based pairs trading strategies across cointegrated assets that share a common underlying factor. We apply the framework introduced in (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) (FFPT thereafter) to which Robert Webb contributed extensively as an editor. Pairs trading is an arbitrage-based strategy that it is activated when the underlying spread value reaches a threshold or strike level. It is therefore equivalent to a derivative in that it represents a contingent claim.

Pairs trading relies on a well-known trading rule for cointegrated price series based on simultaneous long–short positions that are closed when prices revert to a long-run relationship. When an investor

[1] Indicatively, BP´s share prices fell by 44% over 2014-2015 period and by 55% in the first three quarters of 2020. Over the same period the US company Exxon Mobil Corp´s market value has fallen from more than $400 billion in 2014 to around $260 billion in October 2021 (source Bloomberg October 2021 available athttps://www.bloomberg.com/news/articles/2021-10-13/trillion-dollar-esg-boom-is-punishing-old-school-energy-stocks

opens a position, he shorts the overpriced asset and longs the underpriced one, until the mispricing is eliminated (see (Gatev, Goetzmann, and Rouwenhorst 2006)).

In this paper we use the framework introduced by (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) to identify how deviations from underlying fundamentals can be used to earn pairs trading profitability with a persistence linked trading trigger. We analyze for this purpose a sample of daily prices of European, US and Asian energy corporations covering the 2002-2021 period. Results from pairs trading strategies show that there is positive profitability in the three geographical areas that supersede profitability obtained by benchmark indexes. Reported risk adjusted returns of the proposed strategies capture the multiple price shocks seen in the energy market and are also higher than those estimated in the pairs trading literature. The novelty of the approach applied here is that it considers the capital expenditure (CAPEX) ratio as a key metric for reflecting the response of energy corporates to time changing (financial, regulatory, and economic) conditions. By measuring the evolution of new capacity investment, the CAPEX measure signals the degree of commitment with the energy transition. Our results demonstrate improved performance under the CAPEX restriction for the three geographical areas considered.

While crude oil has been an integral component for economic development it is currently at the center of the climate change debate due to the contribution of fossil fuel energy sources to global greenhouse emissions. (Atanasova and Schwartz 2019) have recently analyzed the extent to which capital markets reflect the possibility that fossil fuel reserves may become "stranded assets" in the transition to a low carbon economy. They underline that mispricing of stranded assets can bring potential systemic risk to an economy that is transforming to fulfil the objectives under the Paris Agreement (COP26). In this paper we shed light to this recent literature by analyzing price inefficiencies in global energy markets.

The rest of the paper is organized as follows. Section 2 presents the empirical cointegration framework. Cointegration results are presented in Section 3. Section 4 describes pairs trading profitability. Conclusions are presented in section 5.

2. The Empirical Model

In this section we summarize the account of the empirical framework in FFPT. Let´s assume that y_t and x_t are two $I(1)$ cointegrated stocks. If there are no limitations on borrowing no cost other than arbitrage transaction cost and no limitations in short sale, we can write the long-term relationship as

$$y_t = \gamma_0 + \gamma_1 x_t + z_t \qquad (1)$$

where z_t is the cointegrating error. The resulting dynamics between y_t and x_t are represented by the following VECM:

$$\Delta P = \begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} z_{t-1} + u_t \qquad (2)$$

where: α_1 and α_2 refer to the speed of mean reversion; u_t is a vector white noise with i.i.d shocks.

Note that the lags of ΔP are chosen in order to obtain white noise errors.

3. Price Discovery and Pairs Trading

We collect the daily closing prices for the January 2002- November 2021 period from the following energy index components: S&P 500 Energy traded in dollar, Europe Energy and minerals index, and Asia Energy and Minerals. Prices are all in dollars. Column 1 in Table **1** reports the number of corporates included in each of the indexes analyzed, while the column 2 in the same table reports the number of companies for which we have data available from 2002. The number of companies considered for each geographical area are therefore 40, 68 and 138 for the US, Europe, and Asia. The data source is Factset [2] from which we also collect quarterly data on capital expenditure (CAPEX) for the corresponding companies. By analyzing pairs trading from 2002 our analysis covers a number of regime changes in the crude oil price seen over the past two decades which include: a) the period prior to the GFC, characterized by the industrialization of the Asian countries and boom and bust cycles in commodity markets (see (Figuerola-Ferretti, Gilbert, and McCrorie 2015); b) the GFC episode and the corresponding crude oil price swing in July 2008 ((Figuerola-Ferretti, McCrorie, and Paraskevopoulos 2020)); c) the 2010-2012 European sovereign debt crisis (see (Lane 2012) for a full account of this episode); d) the 2014-2016 commodity price shock, and the signature of the Paris agreement in 2015; e) the 2020 pandemic driven energy shock and the 2021 post COVID recovery energy market´s turmoil. We are therefore able to analyze pairs trading profitability under different market states. We follow the method in (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) and perform a cointegration analysis to identify paired corporates traded (and whose headquarters are located) within three different geographical areas: US, Europe, and Asia. The underlying presumption is that cointegrated pairs are linked via the long-term relationship represented by the linear process specified in Equation 1). Long term commonalities are driven by related demand and supply fundamentals across paired assets. These arise because assets are restricted to trade in the same geographical area and to belong to the same (or highly related) sector. Once these filters have been imposed, we proceed to test for cointegration. Firms that are restricted to be in the same sector and geographical area will have common monetary policy exposures, similar patterns of R&D intensities as well as common regulation schemes.

Table 1: Number of Firms

Sector	Total	Total since 2002
US Energy	64	40
EU Energy	70	68
Asia Energy	144	138

Note: This table presents the number of firms included in the sample for the period between January 2002 and November 2021.

Two I(1) series will be cointegrated if there is a linear combination between them that is stationary or I(0). In order to identify the paired stocks that belong to the same geographical area we first apply the Augmented Dickey Fuller method to test for unit roots which are a necessary condition for cointegration. We fail to reject the unit root hypothesis all individual stocks traded in the samples of US, European and Asian companies (results can be provided upon request). In what follows we find cointegrated pairs of stocks with the restriction that they belong to the same geographical area as well as to the same sector (the energy sector in the case of US, and the energy and mineral sector for the case of Europe and Asia.) In order to calculate out of sample profitability the VECM model specified in Equation (2) is estimated for the cointegrated pairs using a rolling window approach. Estimation details for this framework are specified in (Johansen 1995) and (Juselius 2006). We follow the procedure in FFPT implying that we use a three-year window from t to t+3 (estimation period) to identify paired stocks and then estimate the cointegrated vector for each of the identified pairs. Estimated coefficients of the selected pairs are then used to perform the trading strategy for the next 6-month window covering the t+3 to t+3.5. This process is repeated trough the remaining sample period. Cointegration is also exploited to determine price leadership between paired assets. The

[2] The data codes corresponding to US, Europe, and Asia in Factset are SPN03, FS2100R3, and FS2100A2 respectively. SPN03 represents 63 US Energy companies and FS2100R3 includes 72 European Energy and Mineral companies. FS2100A2 covers 147 Energy and Refinery companies traded in Asia Pacific.

leader asset is thus used to replicate the follower. Following FFPT price discovery is determined as a function of the speed of mean reversion to temporary deviations from long term equilibrium as specified in Equation (2). Table 2 reports descriptive statistics for the number of cointegrated pairs. As it is expected from Table 1, the highest number of cointegrated pairs arises in the Asian area.

VECM estimates across the three geographical areas considered are reported in Table 3. Given the time rage exploited in this exercise (from January 2002 to November 2021) our moving window approach imply that we have 35 rolling samples. We therefore report average values of estimated parameters for the different percentile levels. We find that the coefficient α_1 is significantly negative for all percentiles in the three geographical areas suggesting that the price follower restores temporary mispricings in the cointegrating error by decreasing α_1 units in response to one unit increase in the error correction term. The corresponding α_2 parameter is positive in all percentiles for all geographical areas. However, it is not significant in 80% of the cases as VECM estimates are obtained in a context in which the follower is the dependent variable set to be explained by the leader, which acts as an independent variable.

Table 2: Descriptive Statistics for the Number of Cointegrated Pairs

Sector	Mean	Standard Deviation	Maximum	Minimum
US Energy	28	34	167	10
EU Energy	151	129	540	14
Asia Energy	373	266	1288	33

Note: This table presents descriptive statistics of the number of pairs. Pairs are identified over a 3-year period according to the Johansen cointegration test at the 5% significant level. The Johansen test is conducted on a rolling-window basis. The sample period is January 2002 to November 2021.

Table 3: VECM Coefficient Estimation Results

		Percentiles				
Sector	Parameter	5^{th}	25^{th}	Median	75^{th}	95^{th}
US Energy	α_1	-0.069	-0.101	-0.207	-0.494	-0.211
	α_2	0.009	0.022	0.042	0.060	0.077
EU Energy	α_1	-0.004	-0.015	-0.042	-0.407	-0.510
	α_2	0.000	0.001	0.004	0.011	0.036
Asia Energy	α_1	-0.001	-0.002	-0.0052	-0.015	-0.098
	α_2	0.000	0.000	0.001	0.002	0.005

Note: This table presents the values of a_1 and a_2 obtained using the Johansen cointegration methodology. The percentiles for α_2 is computed using the absolute values. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021. VECM, vector error correction model.

Table 4 reports average estimated γ_1 coefficients by percentiles and geographical areas. This coefficient measures the units of the leader asset that are required to replicate the follower and therefore represents the hedge ratio under pairs trading strategies. Reported average estimates are varied, and the differences across percentiles are larger if the number of energy corporates in each of the geographical areas considered is higher.

Table 4: Slope Coefficient Estimation Results for Cointegration Error

		Percentiles				
Sector	**Parameter**	5^{th}	25^{th}	**Median**	75^{th}	95^{th}
US Energy	γ_1	0.27	0.52	0.97	3.41	16.57
EU Energy	γ_1	0.07	0.53	3.61	8.69	16.29
Asia Energy	γ_1	0.06	0.38	1.25	5.91	33.49

Note: The summary statistics of the estimated values of γ_1 are reported. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021.

4. Profitability of Pairs Trading

The identification of price leadership and cointegration allows design of the pairs trading algorithm. The trading mechanism is described as follows: An arbitrager will open a long-short position when temporary mispricings measured by the cointegration spread reaches the persistence dependent trigger defined as $\rho = (1 + \alpha_1 - \gamma_1\alpha_2)$ units of the standard deviation of historical cointegration spreads. Note that ρ is the first order autoregressive coefficient of the cointegration error (see FFPT). The pair's trading position is closed the day after reversion occurs. If there is no convergence the position is closed at the end of the 6-month trading period. Given that the data starts in January 2002 the first trading date starts in the first business day of January 2005. We follow the framework of FFPT, which implies mean reverting pairs are identified to deliver stationary profits. Slow adjustment to the long-term equilibrium implies that mispricings can be exploited to earn pairs trading long-term profitability.

4.1 The baseline case

In what follows, pairs trading performance is analysed for the three geographical areas of interest: US, EU, and Asia. The underlying presumption is that high volatility in the energy markets complicates the stock valuation process leading to temporary mispricings. Applying the "persistence calibrated" standard deviation trigger introduced in FFTP, the risk and return characteristics are examined at the portfolio level.

Table 5: Persistency Linked Trading Trigger (ρ)

		Percentiles				
Sector	**Parameter**	5^{th}	25^{th}	**Median**	75^{th}	95^{th}
US Energy	ρ	0.69	0.77	0.84	0.91	0.98
EU Energy	ρ	0.67	0.91	0.97	0.98	0.99
Asia Energy	ρ	0.90	0.96	0.97	0.97	0.97

Note: This table presents the values of persistency-linked trading trigger $\rho = 1 + \alpha_1 - \alpha_1\gamma_2$, which is computed using vector error correction model estimates obtained from the Johansen cointegration methodology. As the trading strategy is conducted on a rolling-window basis, these reported values are an average value computed from a series of threshold numbers of each percentile. The sample period is January 2002 to November 2021.

Estimates reported in Table 5 show that there is error persistence delivering average value comparable to that reported by FFPT for the oil and energy sectors. A comparison of estimated coefficients across the different geographical areas shows that pairs within the Asian market exhibit the highest degree of persistence in the 5th percentile with a value of 0.90. The highest coefficient reported for the 75th and 95th percentiles are 0.98 and 0.99 respectively.

Because strategy profitability is induced from two positions, payoffs generated from pairs trading strategies are interpreted as excess returns from one dollar investment in simultaneous long-short positions.

Table 6: Pairs Trading Profitability

					Percentiles			
Sector	**Mean**	**Median**	**Stdev**	**Skewness**	**Kurtosis**	**Max**	**Min**	**Sharpe Ratio**
US Energy	0.0979 (2.01)**	0.0000	0.1638	0.62	11.37	0.13	-0.07	0.60
EU Energy	0.1191 (2.11)**	-0.0075	0.2156	4.07	51.27	0.32	-0.08	0.55
Asia Energy	0.0937 (2.23)**	0.0000	0.1141	1.00	12.61	0.11	-0.07	0.82

*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of excess returns for pairs trading strategies. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 7: Regional Benchmark Stock Index Performance

					Percentiles			
Sector	**Mean**	**Median**	**Stdev**	**Skewness**	**Kurtosis**	**Max**	**Min**	**Sharpe Ratio**
US S&P 500	0.0843 (1.72)	0.1372	0.1979	-0.74	19.75	0.11	-0.14	0.43
EU EuroStoxx 600	0.0394 (0.83)	0.1203	0.1923	-0.49	14.05	0.10	-0.12	0.20
Asia MSCI AC	0.0399 (0.88)	0.1772	0.1834	-0.7	12.56	0.09	-0.12	0.22

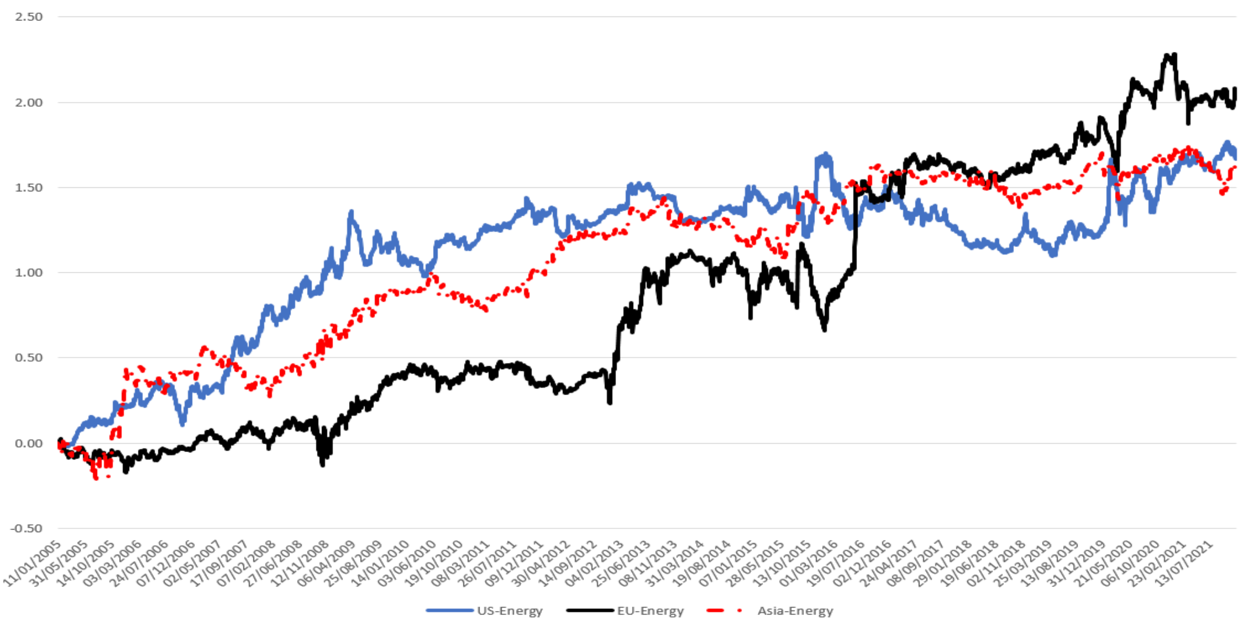
*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of regional stock indices performance. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 6 reports risk-return estimates for the three portfolios considered. For space saving purposes only equal weights are considered. As reported in the literature (see FFPT and references therein) value weighted portfolios lead to lower volatility of returns which implies by relying on equally weighed metrics we are choosing the least conservative weighting scheme. Reported estimates show that all pair's portfolios gain statistically significant positive excess returns. Annualized average return estimates are 9.8%, 11.9% and 9.37% for US, Europe, and Asia respectively. Results therefore show a clear positive performance, which is consistent across different geographical areas. Results in Table 6 may be compared with those reported in Table 7 which reports benchmark equity index performance for the three areas considered. We use the S&P500 as the US benchmark the EU Eurostoxx 600 for the European benchmark and the Asia MSCI index for the Asian benchmark. We can see that the three pair's portfolios outperform their benchmark index counterparts. Moreover, while the reported kurtosis in pairs trading portfolios is of comparable size to those reported by benchmark indexes, pairs trading profitability exhibits a positively skewed distribution while the three market indexes considered show a negative skew in the return distribution. The finding of positively skewed returns in the three pairs trading portfolios is consistent with the literature (see (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018), (Gatev, Goetzmann, and Rouwenhorst 2006) and (Jurek and Yang 2007)).

We next consider the volatility related metrics. Interestingly, we can see that the Asian portfolio exhibits the lowest volatility of returns suggesting that there are diversification benefits from building portfolios with a larger number of pairs. The level of kurtosis is however lowest for the US portfolio suggesting that the US cointegration based portfolios exhibit lower tail risk.

Measures of risk adjusted performance are reported in the last column of Table 6. These are Sharpe ratios constructed assuming zero risk-free interest rates. As it is the case in FFPT we exploit the fact that interest rates have been at historical minimum levels over our sample period. All reported Sharpe ratios are suggesting long-term risk adjusted profitability which beats market index benchmarks and is maximized in the Asian case.

Figure 1: Time Series Evolution of Pairs Trading Profitability in US, EU, and Asia



In what follows we analyze the time series evolution of pairs trading profitability. Figure 1 illustrates this evolution for US, Europe, and Asia respectively. We can see that there are four main turning points seen in the patterns of cumulative profitability which correspond to the following global events: the 2008 global financial crisis, the 2010-2012 European sovereign debt crisis, the 2014-2016 crude oil price collapse, and the 2020 pandemic crisis. These global events have been widely documented in the literature. (Figuerola-Ferretti, McCrorie, and Paraskevopoulos 2020), find bubble behavior in crude oil prices in high point of the GFC, and in the last quarter of 2014. While (Cervera and Figuerola-Ferretti 2021) corroborate those findings and suggest that there was also a bubble in Brent crude oil (but not in WTI) in 2011. Moreover, they also demonstrate that there was bubble behavior in energy corporate CDSs during the same documented periods, given special emphasis on the 2014-2015 crude oil price collapse which has been addressed in the literature (see (Kilian 2017) and (Antonakakis et al. 2018) among others). It is interesting to observe that the line representing profitability in the EU crosses the corresponding US and Asian line showing higher profitability for EU in the aftermath of 2016. This suggests that Europe was not as affected by the 2014-2016 episode as the US or Asia. Indeed, this period combined the slowing growth of the Asian economy, the start of the tapering process in the US with the OPEC announcement under an oversupplied shale oil market and the start of the divesting process from fossil fuels. Pairs trading profitability has also been volatile during the 2020 period. Profitability decreases during the COVID crisis reaching minimum levels around March 2020 in Europe and in April 2020 in Asia. This is just around the time that WTI front month future dropped by 306% in a session re reached negative levels. Pairs trading profitability has been volatile in the aftermath of the COVID crisis possibly reflecting supply bottlenecks and the first energy crisis of the green transition.

4.2 Sorting portfolios with CAPEX

In what follows we present pairs trading profitability when pairs are sorted by investment in capital expenditure CAPEX as well as by industry and geographical area. The strategy builds on the idea introduced in FFPT under which it is demonstrated that pairs trading profitability increases when sorting cointegrated portfolios by firm fundamentals such as book-to-market ratio, market capitalization, and turnover. Filtering pairs with common corporate fundamentals give rise to stronger stationarity and pairs trading profitability. We consider the CAPEX ratio because we want to capture changes in investment capacity over our sample period. This has varied substantially specially in the aftermath of the 2014 crude oil price shock which coincided with the start of the US tapering period (see (Cervera and Figuerola-Ferretti 2021) and (Sengupta, Marsh, and Rodziewicz 2017)). Here we argue that CAPEX is key measure due to two main arguments: a) firms with similar patterns of CAPEX investment are expected to share common credit constraints; b) under the transition to the net zero objectives initiated with the signature of the Paris Agreement the evolution of CAPEX investment within energy corporates can be used as a measure of adaptation to the energy transition. Energy corporates are expected to set investment policies that are compliant with the green transition. Firms that do not invest in green technologies will find that their assets become stranded (See Atanasova and Schwartz 2019) and will fail to transform their economic models to achieve climate neutrality.

Table 8: Number of Firms After Controlling for CAPEX

Sector	Total
US Energy	40
EU Energy	48
Asia Energy	138

Note: This table presents the number of firms after controlling for CAPEX for the period between January 2002 and November 2021.

Table 9: Number of Cointegrated Pairs After Controlling for CAPEX

Sector	Mean	Standard Deviation	Maximum	Minimum
US Energy	19	22	110	6
EU Energy	68	53	186	13
Asia Energy	110	79	427	20

Note: This table presents descriptive statistics of the number of pairs, controlling for CAPEX. Pairs are identified over a 3-year period according to the Johansen cointegration test at the 5% significant level. The Johansen test is conducted on a rolling-window basis. The sample period is January 2002 to November 2021.

Table 9 presents the number of cointegrated pairs under each geographical area once the CAPEX filter is imposed. We can see that the European sample falls due to the lack of continuous CAPEX data for 20 of the 68 companies initially considered. The number of cointegrated pairs is therefore also reduced with Europe and Asia reporting 45% and 29% of the number of pairs found under the benchmark case.

Table 10 presents slope coefficient estimations by percentiles while Table 11 presents estimates of trading triggers for the three geographical areas considered. Results demonstrate that there is lower dispersion in the cointegrating vector slope coefficient and higher speed of mean reversion due to increased commonality arising from the CAPEX filter.

Table 10: Cointegration Slope Coefficient Estimations After Controlling For CAPEX

		Percentiles				
Sector	Parameter	5^{th}	25^{th}	Median	75^{th}	95^{th}
US Energy	γ_1	0.44	0.67	0.98	3.08	13.22
EU Energy	γ_1	0.41	0.63	1.34	3.13	18.51
Asia Energy	γ_1	0.07	0.39	1.28	6.17	36.53

Note: The summary statistics of the estimated values of γ_1 are reported. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021.

Table 11: Persistency Linked Trading Trigger (ρ) After Controlling For CAPEX

		Percentiles				
Sector	Parameter	5^{th}	25^{th}	Median	75^{th}	95^{th}
US Energy	ρ	0.71	0.77	0.82	0.90	0.98
EU Energy	ρ	0.86	0.89	0.92	0.94	0.98
Asia Energy	ρ	0.90	0.96	0.98	0.98	0.99

Note: This table presents the values of persistency-linked trading trigger $\rho = 1 + \alpha_1 - \alpha_2$, which is computed using vector error correction model estimates obtained from the Johansen cointegration methodology. As the trading strategy is conducted on a rolling-window basis, these reported values are an average value computed from a series of threshold numbers of each percentile. The sample period is January 2002 to November 2021.

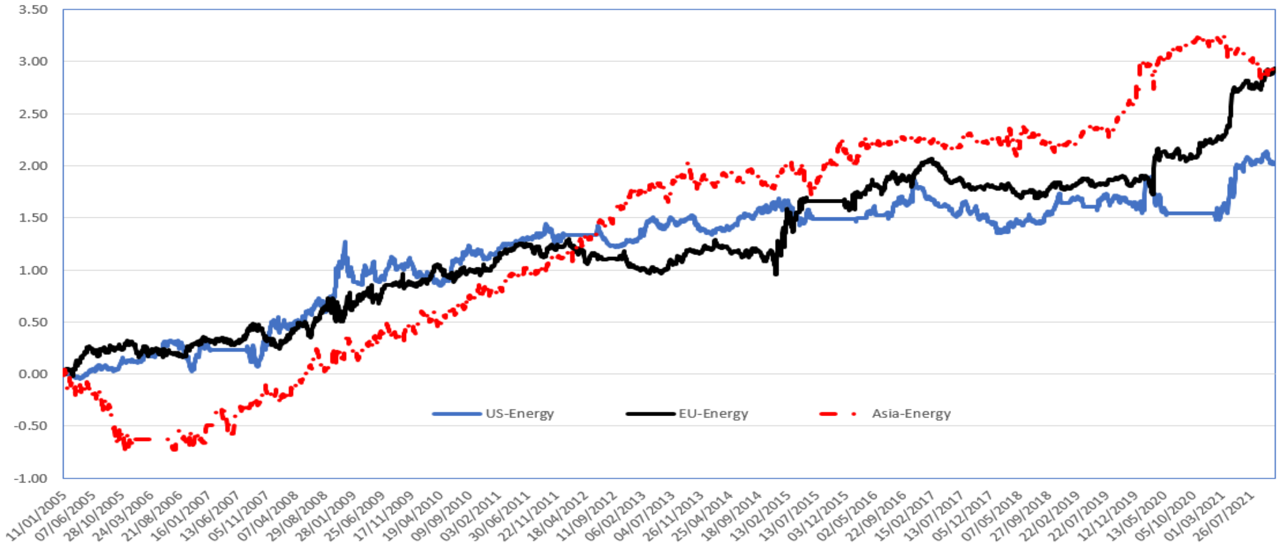
Pairs trading profitability estimates under the CAPEX restriction are reported in Table 12. Results show that filtering by CAPEX ratios deliver significant out-performance when compared to benchmark pairs trading strategies and to corresponding equity indexes. CAPEX restricted pairs trading strategies deliver positive and significant mean returns that outperform the benchmark pairs trading strategies by 2.06%, 5.13% and 7.51%, respectively. Similar conclusions can be obtained when we compare the Sharpe ratios reported in tables 12 and 6 suggesting that the CAPEX measure succeeds in capturing commonalities across energy corporates. This effect is maximized in the Asian portfolio which decreases volatility from 18.5% under the benchmark case to 11.4% under the CAPEX filtered example. The time series evolution of pairs trading profitability for the three areas is depicted in Figure 2. We can see that the cumulative return pattern across EU, US and Asia evolves more closely than in the benchmark case. However, the Asian portfolio outperforms the rest from 2011 up to the end of the sample which shows a decline in profitability possibly driven by the property driven crisis in China. Europe supersedes US profitability since April 2015 and achieves the same level of cumulative returns as its Asian counterpart towards the end of the sample period. The CAPEX factor is therefore highly important in explaining pairs trading profitability.

Table 11: Pairs Trading Profitability

			Percentiles					
Sector	Mean	Median	Stdev	Skewness	Kurtosis	Max	Min	Sharpe Ratio
US Energy	0.1185 (2.03)**	0.000	0.1646	0.65	12.73	0.15	-0.10	0.72
EU Energy	0.1704 (2.961)**	0.000	0.2077	1.27	15.91	0.16	-0.08	0.82
Asia Energy	0.1688 (2.23)**	0.0000	0.1851	0.60	10.58	0.17	-0.09	0.91

*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of excess returns for pairs trading strategies, controlling for CAPEX. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Figure 2: Time Series Evolution of Pairs Trading Profitability in US, EU, and Asia with CAPEX Filter Applied



5. Conclusions

Recent episodes of turmoil in energy markets have hit companies in the oil and gas sector strongly. The 2014 oil price collapse and the transition away from fossil fuels fostered under the Paris Agreement in (2015) have led to a high degree of uncertainty in the sector. The widespread volatility has only been enhanced by the pandemic in 2020 and during the posterior fast recovery. In this paper, we examine market mispricings in energy corporates applying a pairs trading algorithm. In doing this we shed light to the question of whether there are efficient market valuations of fossil fuels.

This question is of great importance as many regulators and financial institutions have identified the mispricing of stranded asset risk as a potential systemic risk and threat to financial stability.

The pairs trading methodology of FFPT is applied for this purpose to the US, European, and Asian energy stock data.

We find evidence of long-term profitability in the three areas considered. The time series evolution of pairs trading performance is enhanced in the aftermath of the 2008, 2010-2012, 2014-2016, 2020 economic crises.

The performance of the European and Asian portfolios beats its US counterpart in the aftermath of the 2014-2016 crisis suggesting that the shale revolution of the US monetary tightening has negatively affected pairs trading profitability.

CAPEX investment is an important metric for filtering stocks on the basis as fundamentals in a context in which commitments to the net zero objectives has constrained investment in fossil fuels. Sorting portfolios on the basis of CAPEX measures delivers higher profitability than that under the benchmark case.

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