Is There an Impact of the Ethereum Merge on the Relationship Between Ethereum and Energy Portfolios?[⋆]

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ABSTRACT

The mining of cryptocurrencies consumes energy in a way similar to that of small countries. This raises the question of the sustainability of cryptocurrency investing. Ethereum, the second-largest cryptocurrency by market capitalization, changed the energy-intensive proofing mechanism, Proof-of-Work, to a more sustainable Proof-of-Stake in September 2022. The network update to the transition was called Merge and was said to enable a 99% reduction in energy costs associated with transaction processing. This paper aims to show if and how this transition has affected the dependencies between Ethereum and different energy portfolios, including green or dirty assets. As a proxy for dirty energy, we include Brent oil futures prices, West Texas Intermediate crude oil prices, and the MSCI World Energy Index. The clean energy sector is approximated by clean energy ETFs such as the First Trust NASDAQ Clean Edge Green Energy Index Fund, SPDR S&P Kensho Clean Power ETF and S&P Global Clean Energy Index. Our data sample covers three years, with the date of the Merge at the centre of the sample. We find that the correlations between Ethereum prices and the prices of clean energy sources decrease after the Merge. For the dirty energy assets, no change was observed. Investors' reaction to the Merge in the short term was negative and significant. Our results have implications for both practitioners and regulators.

1. Introduction

In today's world, obtaining and using energy sources is of great importance. As indicated by Digiconomics the power demand used by Bitcoin miners for ongoing operations caused gigantic carbon emissions. Proof-of-work under which Bitcoin operates offers a high level of security and decentralization, which makes a hostile attack on the network almost impossible (Bake). On the disadvantages side, apart from huge energy consumptions related to PoW, there are several other drawbacks to be named: the environmental impact in the form of greenhouse gas emissions, limited speed of network's growth and high hardware requirements. In 2022 the second huge player in the cryptoassets market, Ethereum, changed the proofing mechanism from proof-of-work to proof-of-stake. In consequence, it was able to reduce the power demand by at least 99.85% (SAXO).

The environmental issue has become important enough to launch special indices, describing the estimated usage of energy, such as the Cambridge Blockchain Network Sustainability Index, which is calculated for Bitcoin[1] and Ethereum [2], respectively. Those indices are provided by the Cambridge Center for Alternative Finance (CCAF). The comparison between the Bitcoin and Ethereum network annualized energy consumption available on the CCAF website shows a dramatic difference in the energy consumption since the Merge. Apart from that these two cryptocurrencies are also heavily discussed and compared in the literature also in other aspects (M'bakob, 2024; Gaies, Chaâbane, Arfaoui and Sahut, 2024; Będowska-Sójka and Kliber, 2021).

This paper aims to show if and how the transition from proof-of-work to proof-of-stake has affected the dependencies between Ethereum and different energy portfolios, including green or dirty assets. We are also interested in how this change impacted the dependency structure with other cryptocurrencies. As a proxy for dirty energy, we include Brent oil futures prices, West Texas Intermediate crude oil prices, and the MSCI World Energy Index. The clean energy sector is approximated by clean energy ETFs such as the First Trust NASDAQ Clean Edge Green Energy

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[1]https://ccaf.io/cbnsi/cbeci
[2]https://ccaf.io/cbnsi/ethereum

Index Fund, SPDR S&P Kensho Clean Power ETF and S&P Global Clean Energy Index. Our data sample covers three years, with the date of the Merge, the 15th of September 2022, at the centre of the sample.

Our analysis consists of several approaches. In the beginning, we conduct the event analysis and we calculate the cumulative abnormal returns around the Merge. Then, we compare networks for returns built before and after the Merge and verify the structure of dependence between cryptocurrencies and the energy portfolios. Next, we obtain the correlations between ETH and energy portfolios by applying the dynamic conditional correlation models. To verify if the correlations change after the Merge, we conduct the causal impact test based on Bayesian structural time series approach (Brodersen, Gallusser, Koehler, Remy and Scott, 2014).

Since the Merge has happened relatively recently, there are not many scientific papers analysing its impact on the cryptocurrency market and investors. From these papers, we can mention Baur and Karlsen (2024) who investigated returns, volatility, correlations and volume of ETH, ETC and BTC for all the events that led up to the change. These authors revealed that although some investors seemed to value the "green" mining mechanism and invest in ETH, the overall effect was rather weak. Jain, Jain and Krystyniak (2023) examined the changes in transaction fees in two blockchains, Bitcoin and Ethereum caused by the Merge. They found that fees increased nonlinearly as the blockchain was becoming congested. For both BTC and ETH a fee reduction after the Merge was observed. Kapengut and Mizrach (2023) examine the impact of the Ethereum's switch from PoW to PoS on the competing platforms. They focus on the two-months window around the Beacon chain merge. They found that miners were not eager to become validators, and the total block reward decreased by 97%. Contrary to Jain et al. (2023) they indicated that the transaction fees have increased by nearly 10%.

We contribute to the existing literature in several ways. First, instead of focusing on other cryptocurrencies (Baur and Karlsen, 2024; Jain et al., 2023) or other platforms (Kapengut and Mizrach, 2023), we examine the interdependence with the energy assets, treating dirty and green portfolios separately. We estimate the dynamic conditional correlations and build the networks for unconditional correlations. Both approaches confirm the change in the strength of the dependency, which is observed not only in the case of ETH, but also for the bitcoin and our equally weighted portfolio. Second, we show that the short-term reaction to the Merge itself is negative. The cumulative abnormal returns around the event are below -8%. Third, we examine the causal effects of the Merge on energy assets. To the best of our knowledge, no work focuses on the event study approach to the Merge itself. Third, we contribute to the strand of the literature related to the causal dependencies between cryptocurrencies and other markets (Lu, Huang and Mo, 2024; Huang, 2024; Zhu, Xing, Ren, Chen and Hau, 2023; Lee, Yu and Zhang, 2023). In addition to this work, we focus on causal inference, looking at what would have happened if the merge had not occurred.

The rest of the paper is organized in the following way. In the second section, we describe the methodological approaches. In the third one, we present the data used in the study. The fourth section shows the empirical analysis and the final section concludes the study.

2. Methodology

We apply several different methodological tools. First, we conduct the classical event analysis around the Merge, to answer the question of investor's reaction to the change of proofing mechanism. Next, we verify if the correlations between ETH and the dirty or clean energy assets before and after the Merge is the same. Due to the fact that some correlations represented as edges in the networks disappeared after the proofing mechanism was changed, we estimate the dynamic conditional correlation and verify what is the direction of the potential change. In the last step, we apply the casual inference with Bayesian structural tune series modelling. It allows us to verify if the change from PoW to PoS has an impact on the change in the correlation structure.

2.1. Event analysis

In the first step, to assess the reaction of investors to the Merge itself, we apply the event analysis commonly used in the literature (Allee, Speitmann, Stenzel and Wu, 2024; Kočenda and Moravcová, 2018). We calculate abnormal returns as the difference between ETH returns and the cryptocurrency portfolio returns. The latter is an equally-weighted portfolio of cryptocurrencies, which consists of 12 top capitalized crypto assets described in the section 3.

More specifically, the abnormal return is calculated within the market model as follows (Brown and Warner, 1980):

$$AR_t = R_{ETH,t} - (\beta_0 + \beta_1 \cdot R_{PORT,t}) \tag{1}$$

where AR_{it} is the abnormal return on day t, $R_{ETH,t}$ is the return of ETH on day t, $R_{PORT,t}$ is the return of an equally-weighted portfolio on day t and β_0 and $beta_1$ are the coefficients in the linear regression. We further use the abnormal returns to obtain the cumulative abnormal return over a given window:

$$CAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} AR_t. \tag{2}$$

In the next step, we verify if the cumulative abnormal returns are significantly different from zero using the following statistic:

$$t = CAR_{t_1,t_2}/\sigma_{ETH} \tag{3}$$

where σ_{ETH} is a standard deviation of residuals from the market model regression from the pre-event window (t running from -365 to -6).

We enrich the classic event-study approach by considering returns' networks of assets under consideration before and after the Merge. The financial network analysis combined with event study analysis approach enables us to get insight into multiple dependencies between assets in the network and to compare them before and after the change of the proofing mechanism. We utilize correlation matrices obtained based on returns and compare networks' features.

2.2. DCC

Let us denote by y_t a vector of time series, and by Ω_{t-1} - the set of information available up to the moment $(t-1)$. Let us denote the conditional mean of y_t as:

$$y_t = E\left(y_t \mid \Omega_{t-1}\right) + \epsilon_t, \tag{4}$$

where $E(\cdot \mid \cdot)$ is the conditional expectation operator, and ϵ_t - the disturbance term with $E\left(\epsilon_t\right) = 0, E\left(\epsilon_t, \epsilon_s\right) = 0, \forall t \neq s$. In the case of daily financial time-series, conditional mean is typically modelled with one of AR, MA or ARMA models, while the ϵ_t can be decomposed in the following way:

$$\epsilon_t = z_t \sigma_t, \tag{5}$$

where $z_t \sim iid$ with mean 0 and unit variance. If σ_t can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{6}$$

we say that it follows a GARCH(p,q) process (see: Bollerslev (1986) for details).

To estimate time-varying correlation between assets, we apply bivariate volatility specification, which allows us to calculate co-variance between assets and later on- correlation.

We apply the specification of Engle and Sheppard (2001), according to which the covariance matrix is specified in the following way:

$$H_t = D_t R_t D_t \tag{7}$$

where in the case of the conditional constant correlation $R = (\rho_{ij})$ is a symmetric positive definite matrix with $\rho_{ii} = 1$ for each i, and

$$D_t = diag(h_{11,t}^{1/2}, ..., h_{NN,t}^{1/2}). \tag{8}$$

In the general case $h_{ii,t}$ can be defined by any univariate GARCH model. In our case that were each time plain-vanilla GARCH(1,1) models.

The introduction of the dynamics into the conditional correlation requires R to be specified in the following way (Laurent, 2018):

$$R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \Psi_{t-1} + \theta_2 R_{t-1}. \tag{9}$$

where Q_t is a symmetric positive definitive matrix such as:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha a_{t-1} a'_{t-1} + \beta Q_{t-1}, \tag{10}$$

$\overline{Q}$ is the $N \times N$ unconditional variance matrix of a_t, which are the residuals from the conditional mean equations, while α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$.

Based on the estimates from DCC models, we calculate the time-varying betas for ETH versus both energy portfolios and an equally weighted portfolio.

$$\beta_{ETH} = \sigma_{P,ETH} / \sigma_P^2 \tag{11}$$

where $\sigma_{P,ETH}$ stands for the conditional covariance between returns of portfolio and ETH, while σ_P^2 stands for the conditional variance of the portfolio under consideration.

2.3. Causal Inference with Bayesian Structural Time Series Modelling

To verify whether the change of the protocol influenced the dynamics of conditional correlation between Ether and the different energy sources, we use causal inference analysis applying Bayesian structural time series modelling. Based on a state-space model, we predict the counterfactual response of correlation in a synthetic control that would have occurred if no change took place.

Let us denote by y_t a vector of observed data, by α_t - the vector of latent variables, which further be called "state". A structural time series model is defined by two equations. The first one is called observation equation (Brodersen et al., 2014):

$$y_t = Z_t^T \alpha_t + \epsilon_t, \tag{12}$$

and the second - transition equation:

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t. \tag{13}$$

Z_t is d-dimensional output vector, T_t is $d \times d$ transition matrix and R_t is $q \times q$ control matrix ($q \leq d$), while ϵ_t and η_t are uncorrelated random terms: $\epsilon_t \sim (0, \sigma_t)$ and $\eta_t \sim (0, Q_t^{1/2})$.

One can accommodate various assumptions about the latent state and process underlying the observed data by including e.g. trend or seasonality. In our approach, we use a local level model with no covariates, i.e. (Brodersen et al., 2014):

$$\begin{aligned} y_{t+1} &= \mu_t + \epsilon_t, \\ \mu_{t+1} &= \mu_t + \eta_t, \end{aligned} \tag{14}$$

where $\eta_{\mu,t} \sim N(0, \sigma_\mu)$ and $\eta_t \sim N(0, \sigma_\eta)$, $\alpha_t = \mu_t$, $Z_t = G_t = R_t = \mathbf{1}$. The observations are modelled as noisy observations of a level μ_t which is subject to random changes over time, described by a random walk (Campagnoli, Petrone and Petris, 2009).

The model is estimated using the Bayesian approach and R package "CausalImpact" (Brodersen et al., 2014). The model assumes that:

$$\begin{aligned} y_t &\sim N(\mu_t, \epsilon_t) \\ \mu_t &\sim N(\mu_{t-1}, \eta_t) \end{aligned} \tag{15}$$

When it comes to the variance of the state, it is assumed that:

$$\sigma \sim G(\frac{v}{2}, \frac{s}{2}) \tag{16}$$

where $G(a, b)$ is the Gamma distribution with expected value a/b. The prior parameter s can be interpreted as a prior sum of squares, and therefore s/v is a prior estimate of σ^2, and v is the weight assigned to the prior estimate. The parameters are obtained by sampling from the conditional distribution $f(\mu|\mathbf{y})$ using the MCMC technique.

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Table 1
Descriptive statistics of data

	mean	median	sd	min	max
ETH	0.0001	0.0005	0.0455	-0.3175	0.2256
BTC	0.0003	-0.0005	0.0384	-0.1741	0.1358
PORT	0.0001	0.0027	0.0486	-0.3970	0.2316
Brent	0.0001	0.0025	0.0237	-0.1411	0.0843
WTI	0.0001	0.0024	0.0250	-0.1293	0.0802
MSCI	0.0005	0.0013	0.0157	-0.0713	0.0483
CNRG	-0.0009	-0.0017	0.0209	-0.0599	0.0821
QCLN	-0.0011	-0.0018	0.0251	-0.0828	0.0921
ICLN	-0.0008	-0.0016	0.0185	-0.0616	0.0735

3. Data

We analyse log-returns of Ether, three dirty-energy assets (Brent and WTI futures together with the MSCI-Energy index[3]) and three clean-energy ETFs: CNRG (SPDR S&P Kensho Clean Power ETF - designed to capture companies whose products and services are driving innovation behind clean power), QCLN (First Trust NASDAQ Clean Edge Green Energy Index Fund, designed to track the Nasdaq Clean Edge Green Energy index which captures companies worldwide which operate in the clean energy sector) and ICLN (iShares Global Clean Energy ETF which track the SP Global Clean Energy index comprising of the largest and most liquid stocks worldwide which are involved in clean energy business) from 15.03.2021 to 15.03.2024. We are interested in the Ether protocol change's effect on ETH's relationships with clean and dirty energy sources. The event took place in the middle of the period which we analyse. As a robustness check, we study the relationships of ETH with the cryptocurrency market - therefore we include an equally weighted portfolio of twelve cryptos. Among the crypto-assets included in the portfolio, we use Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), Monero (XMR), Stellar (XLM), Ethereum Classic (ETC), Neo (NEO), EOS (EOS), Bitcoin Cash (BCH), Tron (TRX), Cardano(ADA) which where considered in Bengtsson and Gustafsson (2023) and Binance (BNB), DOGE (DOGE) and Solana (SOL) often considered in other studies. These cryptocurrencies are of different proofing mechanisms and various capitalizations. They accounted for 80% of the total cryptocurrency market capitalization as of 15th of March, 2024 (`https://coinmarketcap.com/historical/20240315/`. Thus they might be considered representatives of the entire cryptocurrency trading market.

In Table 1, we present descriptive statistics of the data. We observe that the median return of clean energy indices was negative in the studied period. The most volatile was the cryptocurrency portfolio weighted by capitalisation.

Figure 1 shows the log-prices of dirty and clean energy sources with respect to the returns of Ether, while Figure 6 - respective returns.

4. Results

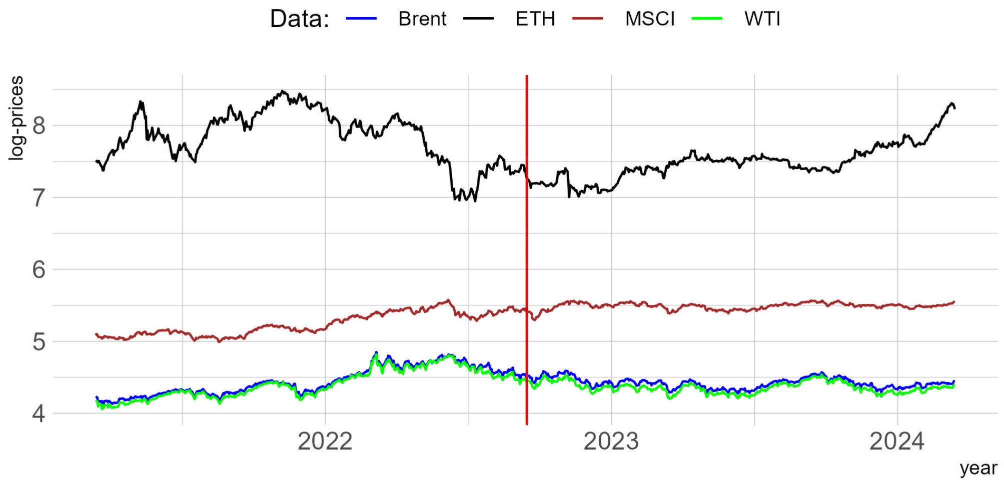
4.1. Abnormal returns around the Merge

The event analysis shows that the reaction to the Merge around the event day is negative and statistically significant. The cumulative abnormal return accounts for -8% within the window $(-1; +1)$ for both the market model (MM) and the market-adjusted approach (MA). Raw returns of ETH at the same time are even lower, -10%, while raw returns of the largest competitor on the market, BTC, are -3%. In the longer 30-day period, the cumulative abnormal returns for ETH range from -11% to -8% depending on the approach used. All cumulative abnormal returns are statistically significantly different from zero, confirming investors' lack of enthusiasm just after implementing the change.

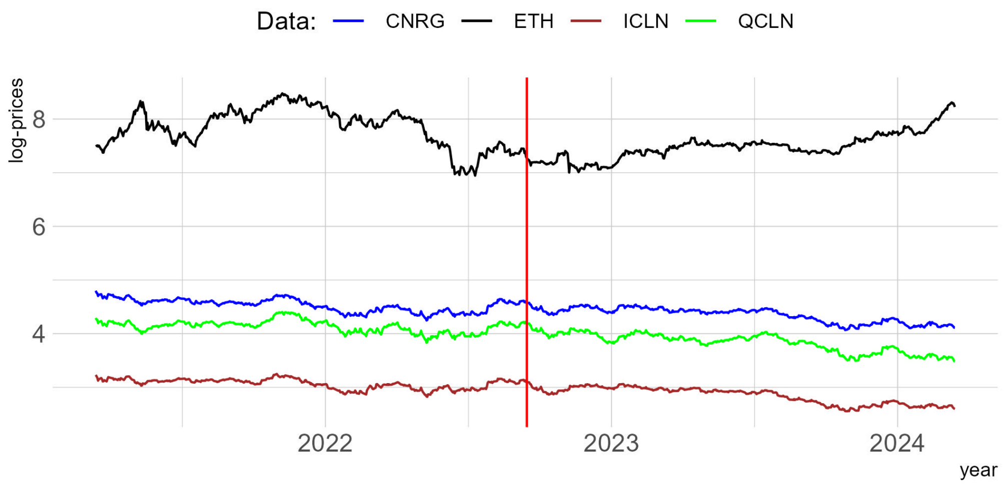
We also present abnormal returns of ETH from both approaches, the market model and market-adjusted model as well as returns of ETH and BTC as the largest competitor, that did not change the proofing mechanism. Figure 3 presents the event window from -10 day to $+10$ day around the Merge. We find that at the day of the Merge, the return of ETH was the lowest (dropped by 10%), but if we correct it for the market conditions the loss diminishes to around 6%. BTC itself lost on that day 2.7%.

[3] `https://www.msci.com/documents/10199/de6dfd90-3fcd-42f0-aaf9-4b3565462b5a`

Figure 1: Log prices of Brent, WTI and MSCI-Energy versus ETH (upper panel) and green ETFs versus ETH (lower panel)



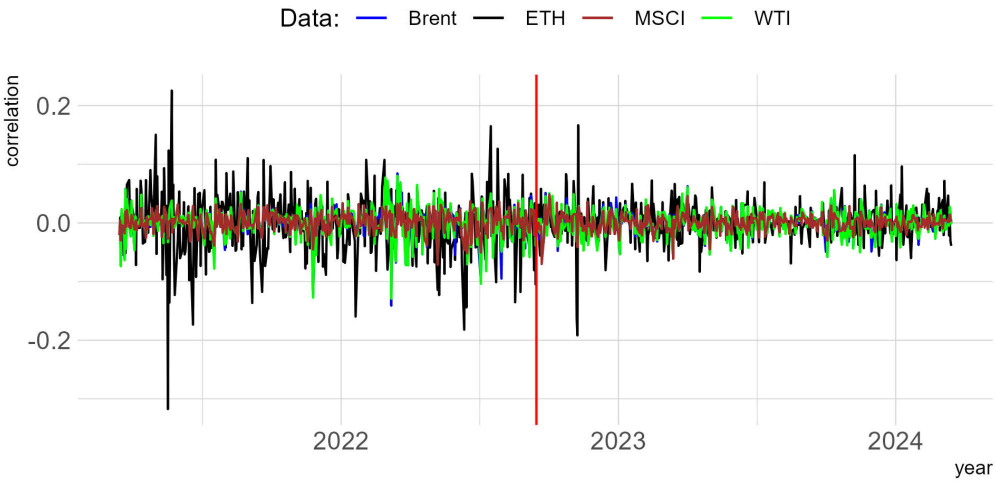
(a) Log-prices of dirty energy sources and ETH



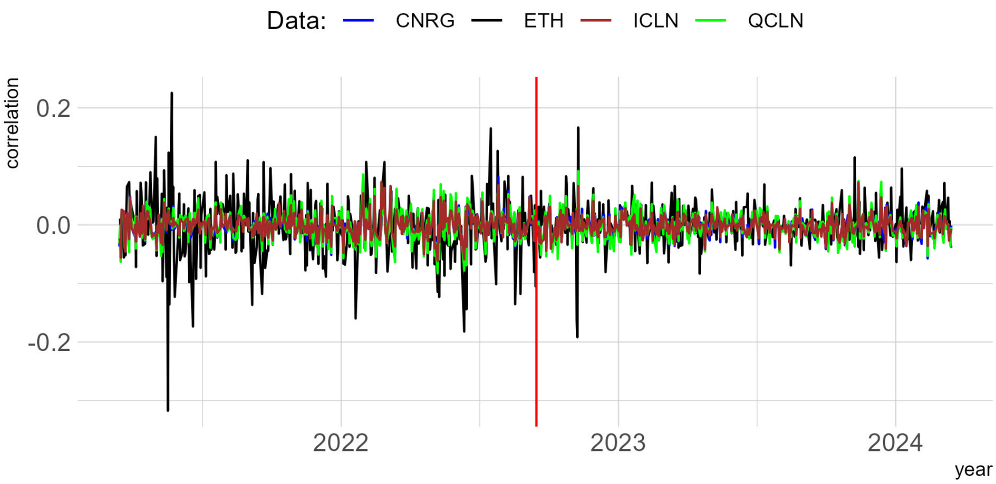
(b) Log-prices of clean energy sources and ETH

Note: The upper panel shows the log prices of dirty energy sources. The bottom panel presents the log prices of the clean energy sources. A logarithmic transformation is applied only to allow the series to be presented on single graphs. The red vertical line is drawn on the Merge day, September 9, 2022.

Figure 2: Log returns of Brent, WTI and MSCI-Energy versus ETH (upper panel) and green ETFs versus ETH (lower panel)



(a) Returns of dirty energy sources and ETH



(b) Returns of clean energy sources and ETH

Note: The red horizontal line is drawn on the Merge day, September 9, 2022.

4.2. The application of networks to the event study approach

First, we verified the unconditional correlations in two subperiods, before and after the Merge. Both subperiods include the same number of days. We consider three portfolios of green energy sources, CNRG, QCLN and ICLN,

Table 2
Cumulative abnormal returns over the Merge day

	(-1;+1)	(-2,+2)	(-3,+3)	(0,+30)
CAR ETH MM	-0.084	-0.093	-0.150	-0.114
t-stat	-4.130	-4.622	-7.419	-5.662
CAR ETH MA	–0.080	-0.084	-0.133	-0.081
t-stat	-2.805	-2.956	-4.673	-2.850
raw ETH returns	-0.099	-0.154	-0.277	-0.233
raw BTC returns	-0.026	-0.106	-0.114	-0.055

Note: CAR ETH MM is the cumulative abnormal return from the market model. CAR ETH MA is the cumulative abnormal return from the market-adjusted model. Raw ETH and BTC returns are cumulative returns of Ethereum and Bitcoin, respectively, within the event window

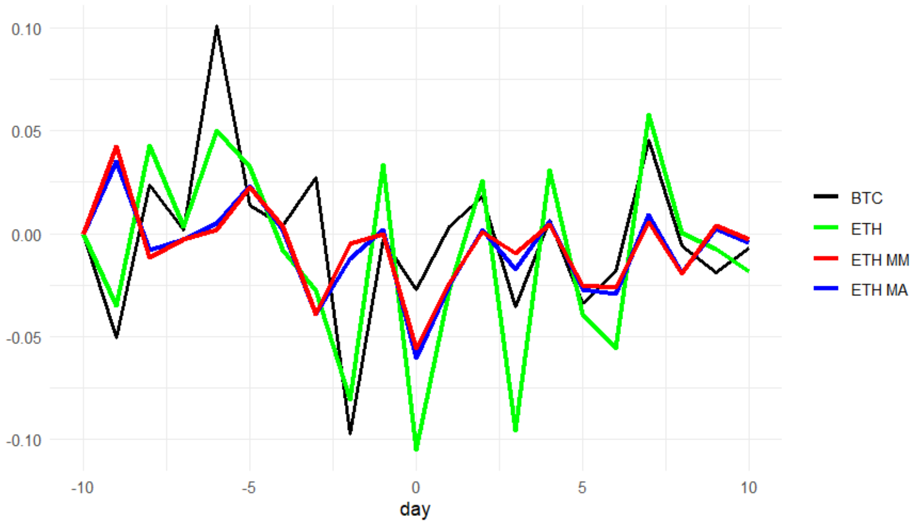


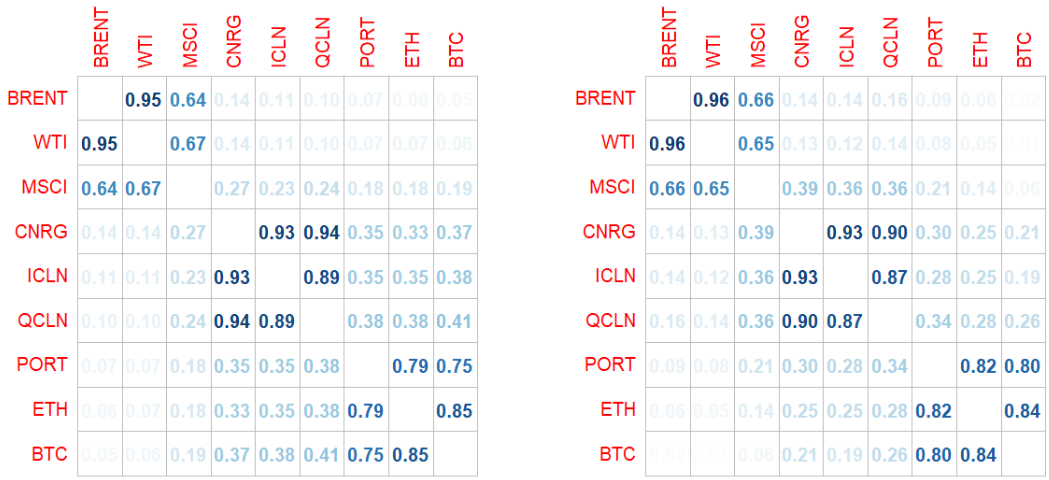
Figure 3: Returns around the event day

Note: ETH MM represents the abnormal returns from the market model, ETH MA from the market-adjusted model, ETH shows the returns of ETH, while BTC returns from BTC. All abnormal returns are presented in the event window of 21 days from -10 to 10 day $(-10, +10)$.

three dirty energy sources, BRENT, WTI and MSCI, and three cryptocurrency-based assets, ETH, BTC and an equally-weighted portfolio of 12 assets. The correlation matrices are presented in Figure 4. We focus mostly on the potential changes in correlations with ETH. Correlations with green energy sources decreased after the Merge (from 33%, 35% and 38% to 25%, 25% and 28%). Concerning the dirty portfolios, the differences are not significant. We find that the decrease in the correlations with green portfolios is not related to the Merge, as if we look at BTC, which has constantly used the proof-of-work mechanism, the correlations with the same green portfolios also dropped. A similar observation is found for the equally weighted portfolio.

We visualize the return dependencies using networks, which allows us to present the multidimensional phenomena better. Figure 5 shows that the strongest dependencies are within each group of assets. The green portfolios denoted by the green colour of nodes are strongly interdependent (the edges are solid), the dirty energy assets denoted by red colour are also strongly interconnected, and the same is observed for the cryptocurrencies denoted by blue colour. The missing edges on the graphs signify correlations lower than 10%. Thus all cryptos are not correlated with BRENT and WTI, while ETH is (weakly) correlated with MSCI both in the period before and after the Merge, and BTC is weakly correlated only in the first period.

Figure 4: Correlations between returns before and after the Merge



(a) A correlation matrix for returns before the event (b) A correlation matrix for returns after the event

Note: The correlations are obtained for two subperiods, from 2021-03-18 to 2022-08-15 and from 2022-10-16 to 2023-03-15.

4.3. Volatility models, dynamic correalations and time-varying betas

In Tables 4 - 9, we present the estimates of multivariate volatility models. In all the cases we used GARCH(1,1) model with Student or GED distributions and variance targetting options. We estimated the parameters of the dynamic correlation models. We note that the parameter α was significant only for the models where green indices were included. That suggests that the correlation between Ether and dirty energy sources may be not time-varying. We present the respective plots in Fig 6. We note the difference in the scales of both figures. The correlation between Ether and Brent/WTI oscillated around 0.1, while ETH-MSCI - around 0.2. The correlations between Ether and green energy indices took values from 0.2 to 0.6.

4.4. Causal impact in correlations

To verify whether the change of the protocol changed the relationship between Ether and different energy sources, we apply causal impact analysis. In Figures 7 -11 we present the results. We fit the state-space model to the correlations for the period up to the protocol change.

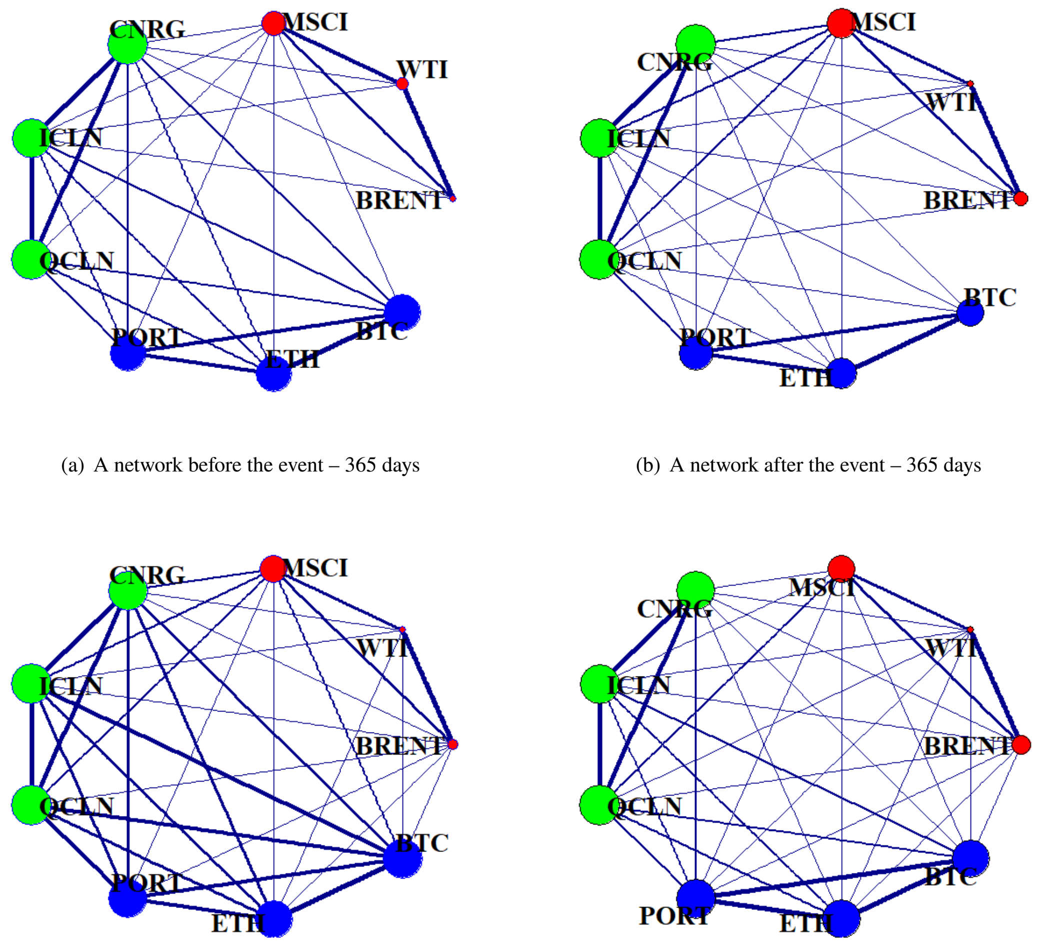
In Table 3, we present the summary of the results. Actual denotes the actual average value of the correlation in the post-merge period. Prediction - is the predicted value (we provide standard deviation in brakets). The absolute effect is the difference between the actual and predicted value, while relative - the relative deviation from the forecast. In each case we present also the 95% credibility interval for the prediction and the effect. In the last row, we present the posterior probability of the causal effect.

We observe that the statistically significant change in the relationships occurred for ETH and clean evergy ETFs, but not for dirty energy. That may also result from the fact that the conditional correlation was in fact stable for ETH-Brent, ETH-WTI and ETh-MSCI.

5. Robustness check

To verify if the dynamics observed in the previous section are not caused by the market conditions, we estimate the additional models with equally-weighted portfolios of cryptocurrencies, dirty energy and clean energy. Table 10 shows the estimates of these models. In Fig. 13, we present the conditional correlations. We observe, that ETH was highly correlated with the cryptocurrency market for most of the time. There were two episodes of the correlation drops: at the beginning and at the end of the analysed period. Yet, none of the drops could be attributed to the "Merge". The correlation of ETH with green energy was higher than its correlation with dirty energy. Starting from mid-2021 the correlation with green energy was steadily growing, but after the "merge", it began to fall down. We also observe a

Figure 5: Networks before and after the Merge



(a) A network before the event – 365 days

(b) A network after the event – 365 days

(c) A network before the event – 100 days

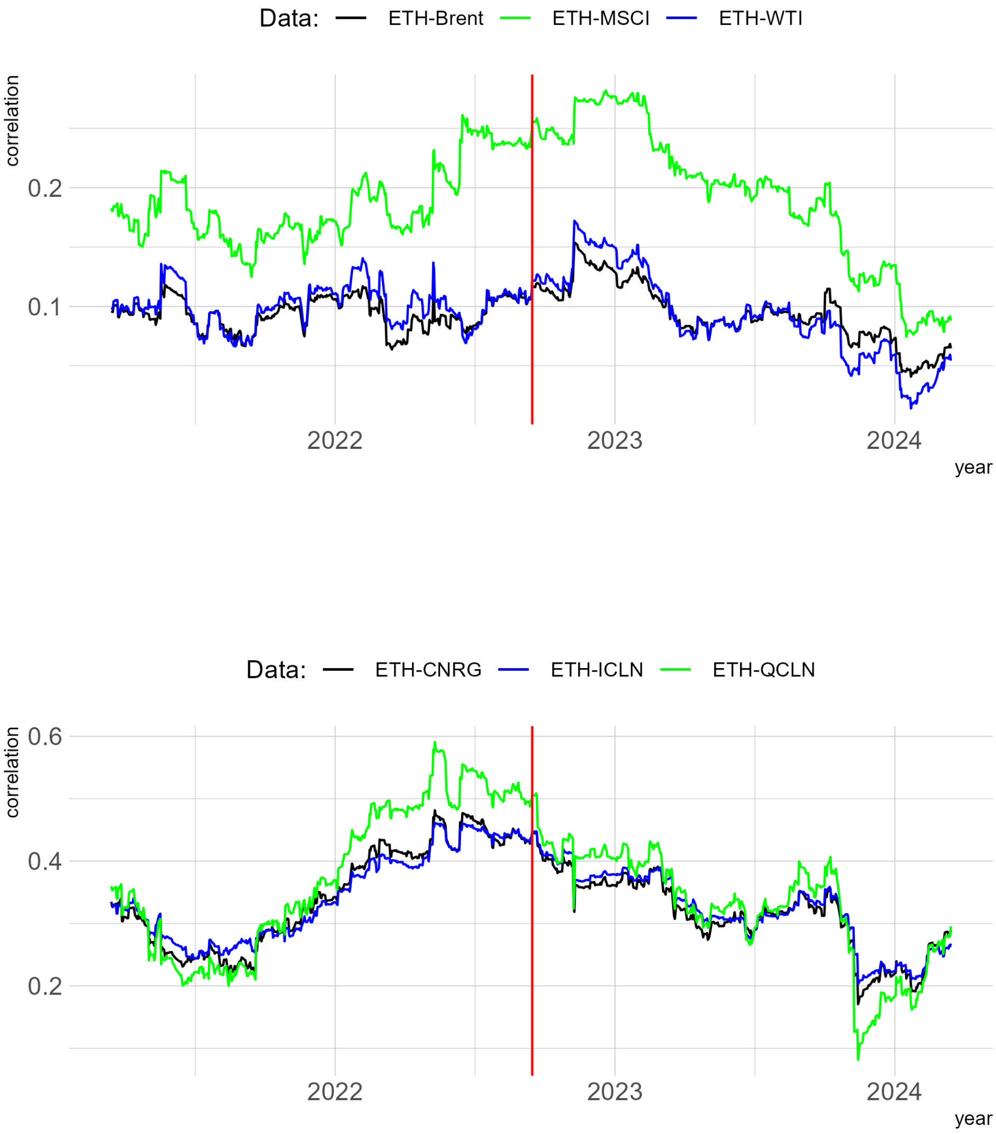
(d) A network after the event – 100 days

Note: Nodes represent dirty energy assets for which nodes are coloured in red, BRENT, WTI and MSCI, green energy assets with green nodes (CNRG, ICLN and QCLN) and cryptocurrencies coloured in blue, a crypto portfolio PORT, and two separate cryptos, ETH and BTC. Edges represent the correlations between particular assets. The darker the line, the higher the correlation is. Correlations below 10% are not presented on the graph. The size of a node is proportional to the node's eigenvector centrality measure. The bigger the size is, the more important a node in the network. The networks are calculated on the correlations obtained for two subperiods, from 2021-03-18 to 2022-08-15 (365 days in the before period) and from 2022-10-16 to 2023-03-15 (365 days in the after period). In the bottom row, we obtain the networks based on shorter periods of 100 days, from 2022-03-22 to 2022-08-15 and from 2022-10-06 to 2023-03-12.

drastic decline at the end of 2023, which overlaps with the decline in correlation with the cryptocurrency portfolio. Thus, we can suppose that this event was specific for ETH, not for the whole cryptocurrency market. Eventually, ETH was relatively weakly correlated with the dirty energy portfolio, with the maximal value of the correlation slightly exceeding 0.25, following the Merge.

Next, we calculate time-varying betas based on the estimates from DCC models. Figure 14 present estimated betas for ETH with three different reference equally-weighted portfolios, dirty energy (upper panel) , clean energy (middle panel) and cryptocurrency (bottom panel). Again, we added a red vertical lines to each chart to indicate the day of the

Figure 6: Time-varying correlations between Brent, WTI and MSCI-Energy and ETH (upper panel) and green ETFs and ETH (lower panel)



Note The red vertical line is drawn at 15.09.2022

'Merge'. Beta measures the expected move in ETH relative to movements in the investigated markest. A beta greater than 1.0 suggests that ETH is more volatile than the market, and a beta less than 1.0 - its lower volatility.

We conclude that ETH was less volatile than the dirty portfolio for most of the time, apart from two episodes in 2021 and at the end of 2022. We observe no visible reaction of the beta to the 'Merge'.

Yet, for the green energy market, the values of beta were higher up to the change of the protocol - as compared to the dirty energy. We notice a deep decline just after the merge, a spike at the end of 2022 and a gradual decline afterwards.

Figure 7: Causal effect - ETH-Brent

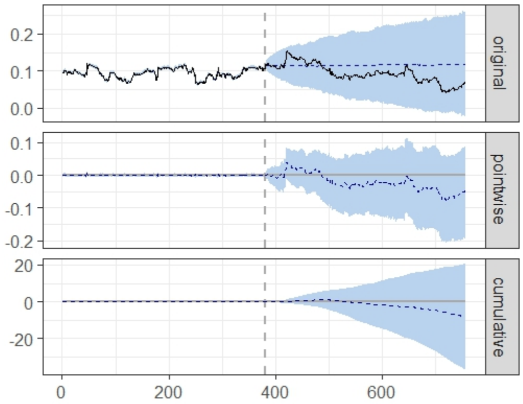
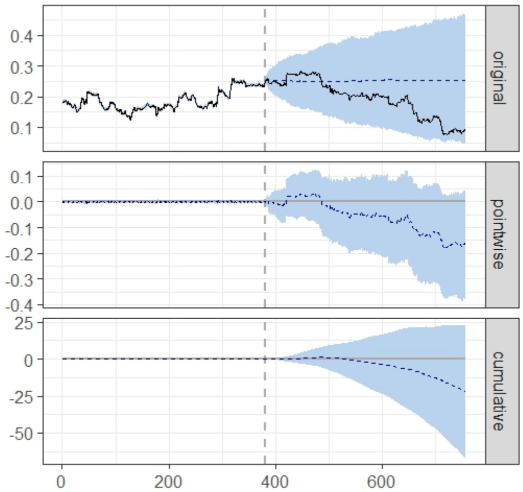


Figure 8: Causal effect - ETH-MSCI



Beta between Ether and the cryptocurrency market was the least varying and after the protocol change its trend was downward sloping, indicating lower variance than the market one.

6. Discussion and conclusions

To summarise, we analyse the relationships between Ether and clean and dirty energy assets around the change of the ETH protocol from proof-of-work to proof-of-stake. We expected that the change would result in the weakening of the relationships between this cryptocurrency and dirty energy assets and strengthen the linkages with clean energy assets. We apply different econometric and statistical techniques, starting from event analysis, through dynamic conditional correlation, network analysis and intervention analysis.

Our results indicate that the relationships between dirty energy and Ether did not change significantly. However, there was a statistically significant change in the relationships between Ether and clean energy portfolios. Contrary to our expectations, the relationship weakened. That result supports the findings reported by Baur and Karlsen (2024) who documented that although some investors seemed to value the eco-friendly mining mechanism of Ether, the overall effect of the Merge was rather weak. It might be caused by the fact that the introduction of the new system was a long-term process and thus the reaction was extended in time.

Figure 9: Causal effect - ETH-WTI

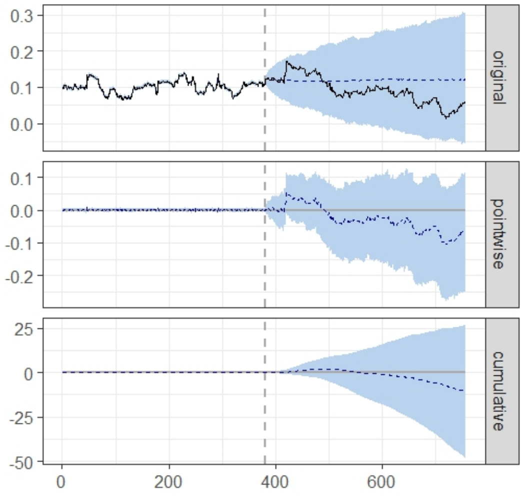
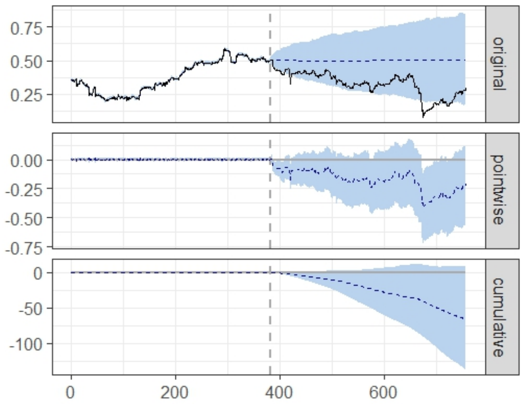


Figure 10: Causal effect - ETH-QCL



The policy implications of our study could be summarised as follows. The invisible hand of the market is unable to encourage investors to switch to green investment. Firstly, special campaigns should be implemented to encourage investors to go green. Secondly, the market does not perceive ether as a green investment. It could therefore be used to diversify a green portfolio, especially as its beta is less than 1, which means it is less volatile than the market. The same applies to the "dirty" energy market, which also has a beta of less than one. Finally, the time-varying beta between ether and the cryptocurrency market has been gradually decreasing since the moment of the merger, making it a safer investment compared to the overall market.

CRediT authorship contribution statement

Barbara Będowska-Sójka: Conceptualization of this study, Methodology, Software, Data curation, Writing - Original draft preparation. **Agata Kliber:** Conceptualization of this study, Methodology, Data curation, Software, Writing - Original draft preparation.

Figure 11: Causal effect - ETH-ICL

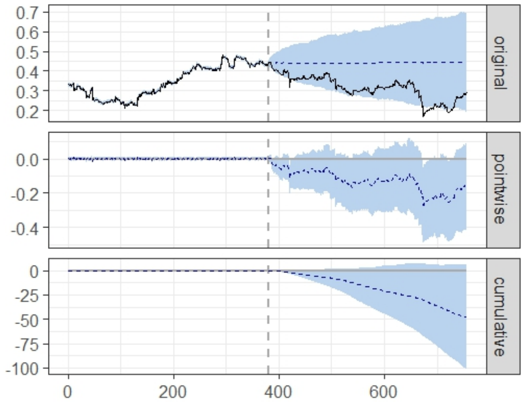


Figure 12: Causal effect - ETH-CRG

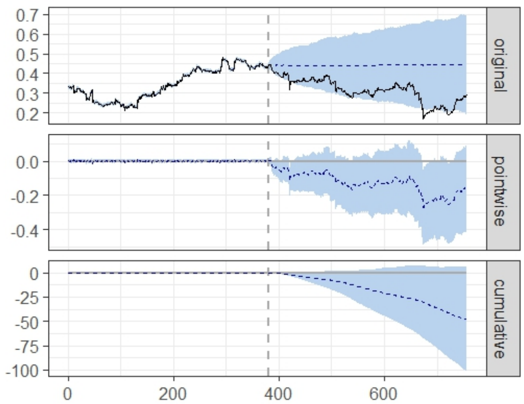
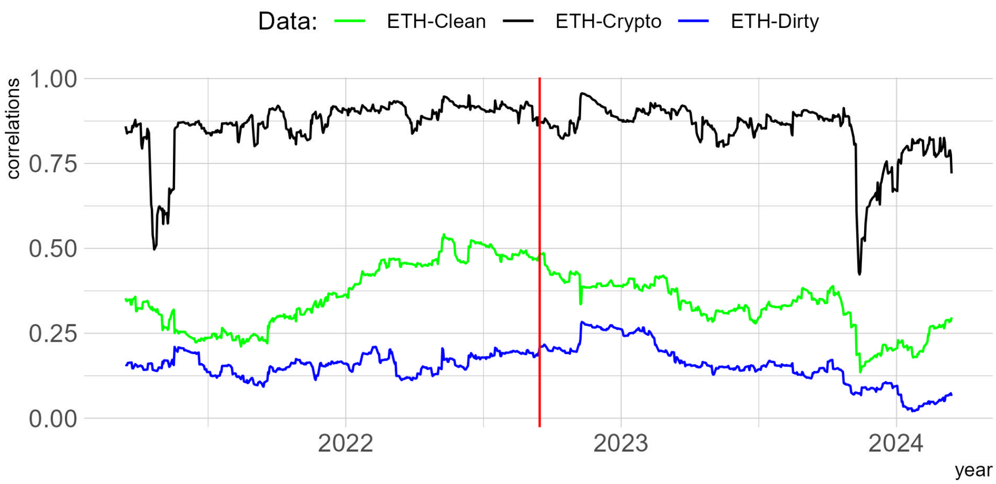


Table 3
Causal inference analysis

	Clean		Dirty	
	Average	Cumulative	Average	Cumulative
	CRG		Brent	
Actual	0.31	117.76	0.094	35.129
Prediction (s.d.)	0.44 (0.072)	165.76 (26.878)	0.12 (0.039)	43.28 (14.774)
95% CI	[0.3, 0.58]	[111.4, 219.11]	[0.039, 0.19]	[14.509, 72.19]
Absolute effect (s.d.)	-0.13 (0.072)	-48.00 (26.878)	-0.022 (0.039)	-8.150 (14.774)
95% CI	[-0.27, 0.017]	[-101.35, 6.405]	[-0.099, 0.055]	[-37.059, 20.621]
Relative effect (s.d.)	-27% (13%)	-27% (13%)	-16% (461%)	-16% (461%)
95% CI	[-46%, 5.8%]	[-46%, 5.8%]	[-52%, 132%]	[-52%, 132%]
Posterior prob. of causal effect	95.84%		70%	
	QCL		WTI	
Actual	0.33	122.6	0.092	34.456
Prediction (s.d.)	0.5 (0.097)	188.3 (36.462)	0.12 (0.051)	44.91 (19.150)
95% CI	[0.3, 0.69]	[114.4, 259.65]	[0.021, 0.22]	[7.764, 82.52]
Absolute effect (s.d.)	-0.18 (0.097)	-65.73 (36.462)	-0.028 (0.051)	-10.455 (19.150)
95% CI	[-0.37, 0.022]	[-137.05, 8.236]	[-0.13, 0.071]	[-48.07, 26.692]
Relative effect (s.d.)	-32% (15%)	-32% (15%)	-104% (2495%)	-104% (2495%)
95% CI	[-53%, 7.2%]	[-53%, 7.2%]	[-63%, 182%]	[-63%, 182%]
Posterior prob. Of causal effect	95.94%		70%	
	ICL		MSCI	
Actual	0.32	120.62	0.19	72.77
Prediction (s.d.)	0.44 (0.054)	166.75 (20.118)	0.25 (0.061)	94.59 (22.694)
95% CI	[0.34, 0.55]	[126.08, 206.37]	[0.13, 0.37]	[50.09, 139.54]
Absolute effect (s.d.)	-0.12 (0.054)	-46.13 (20.118)	-0.058 (0.061)	-21.819 (22.694)
95% CI	[-0.23, -0.015]	[-85.76, -5.460]	[-0.18, 0.06]	[-66.77, 22.69]
Relative effect (s.d.)	-27% (9.3%)	-27% (9.3%)	-18% (25%)	-18% (25%)
95% CI	[-42%, -4.3%]	[-42%, -4.3%]	[-48%, 45%]	[-48%, 45%]
Posterior prob. Of causal effect	98.25%		83%	

Figure 13: Time-varying correlations between cryptos and energy portfolios and ETH



Ethereum merge

Figure 14: Time-varying betas for dirty portfolio and ETH (upper panel), green ETFs portfolio and ETH (middle panel) and cryptocurrency portfolio and ETH (bottom panel)

Table 4
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and Brent: ARMA(0,0)-GARCH(1,1) with Student distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5269	0.5983
α_{ETH}	0.0530	0.0011	47.5442	0.0000
β_{ETH}	0.9414	0.0003	3341.9227	0.0000
$shape_{ETH}$	1.1851	0.0759	15.6180	0.0000
μ_{Brent}	0.0018	0.0008	2.0916	0.0365
α_{Brent}	0.0820	0.0073	11.2370	0.0000
β_{Brent}	0.8950	0.0120	74.2939	0.0000
$shape_{Brent}$	6.1002	1.0953	5.5695	0.0000
$Joint : dcc_{\alpha}$	0.0042	0.0074	0.5680	0.5700
$Joint : dcc_{\beta}$	0.9760	0.0144	67.8475	0.0000
$Joint : shape$	6.2192	0.7317	8.4995	0.0000

Table 5
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and WTI: ARMA(0,0)-GARCH(1,1) with Student distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5270	0.5982
α_{ETH}	0.0530	0.0011	47.5688	0.0000
$beta_{ETH}$	0.9414	0.0003	3325.9792	0.0000
$shape_{ETH}$	1.1851	0.0759	15.6215	0.0000
μ_{WTI}	0.0016	0.0008	1.9664	0.0493
α_{WTI}	0.0947	0.0371	2.5566	0.0106
β_{WTI}	0.8689	0.0559	15.5338	0.0000
$shape_{WTI}$	8.7393	2.3193	3.7681	0.0002
$Joint : dcc_{\alpha}$	0.0052	0.0072	0.7229	0.4697
$Joint : dcc_{\beta}$	0.9797	0.0184	53.2983	0.0000
$joint : shape$	7.1019	0.9286	7.6481	0.0000

Table 6
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and MSCI: ARMA(0,0)-GARCH(1,1) with GED distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5271	0.5981
α_{ETH}	0.0530	0.0011	47.5792	0.0000
β_{ETH}	0.9414	0.0003	3337.4801	0.0000
$shape_{E}TH$	1.1851	0.0759	15.6178	0.0000
μ_{MSCI}	0.0008	0.0005	1.4414	0.1495
ϕ_{MSCI}	0.0668	0.0297	2.2484	0.0245
α_{MSCI}	0.0292	0.0013	22.0966	0.0000
β_{MSCI}	0.9698	0.0007	1476.4593	0.0000
$shape_{MSCI}$	1.5604	0.1182	13.2065	0.0000
$Joint : dcc_{\alpha}$	0.0056	0.0042	1.3321	0.1828
$Joint : dcc_{\beta}$	0.9912	0.0034	289.1487	0.0000
$joint : shape$	6.9063	1.0192	6.7761	0.0000

7. Appendix

Table 7
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and QCLN: ARMA(0,0)-GARCH(1,1) with Gaussian distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5267	0.5984
α_{ETH}	0.0530	0.0011	47.4699	0.0000
β_{ETH}	0.9414	0.0003	3304.3510	0.0000
$shape_{ETH}$	1.1851	0.0759	15.6205	0.0000
μ_{QCLN}	-0.0008	0.0008	-1.0129	0.3111
α_{QCLN}	0.0414	0.0023	17.6640	0.0000
β_{QCLN}	0.9480	0.0029	330.7749	0.0000
$Joint : dcc_\alpha$	0.0133	0.0051	2.6157	0.0089
$Joint : dcc_\beta$	0.9783	0.0076	128.4813	0.0000
$joint : shape$	8.1645	1.2259	6.6597	0.0000

Table 8
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and ICLN: ARMA(0,0)-GARCH(1,1) with Student distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5260	0.5989
α_{ETH}	0.0530	0.0011	47.4026	0.0000
β_{ETH}	0.9414	0.0003	3331.9327	0.0000
$shapeETH$	1.1851	0.0759	15.6068	0.0000
μ_{ICLN}	-0.0012	0.0006	-1.9315	0.0534
α_{ICLN}	0.0391	0.0096	4.0566	0.0000
β_{ICLN}	0.9465	0.0129	73.3497	0.0000
$shape_{ICLN}$	8.8398	2.4942	3.5441	0.0004
$Joint : dcc_\alpha$	0.0071	0.0034	2.0850	0.0371
$Joint : dcc_\beta$	0.9861	0.0073	134.8205	0.0000
$Joint : shape$	6.6617	1.0133	6.5743	0.0000

Table 9
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and CNRG: ARMA(0,0)-GARCH(1,1) with Gaussian distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5266	0.5985
α_{ETH}	0.0530	0.0011	47.4862	0.0000
β_{ETH}	0.9414	0.0003	3317.0318	0.0000
$shape_{ETH}$	1.1851	0.0759	15.6180	0.0000
μ_{CNRG}	-0.0009	0.0007	-1.2442	0.2134
α_{CNRG}	0.0260	0.0025	10.4668	0.0000
β_{CNRG}	0.9639	0.0044	219.1681	0.0000
$Joint : dcc_\alpha$	0.0093	0.0044	2.1133	0.0346
$Joint : dcc_\beta$	0.9805	0.0076	128.5422	0.0000
$joint : shape$	7.9584	1.1377	6.9953	0.0000

Table 10
Estimates of DCC model for ETH: ARMA(0,0)-GARCH(1,1) with GED and equally-weighted portfolio: ARMA(0,1)-APARCH(1,1) with GED distribution

	Estimate	Std. Error	t value	Pr(>|t|)
μ_{ETH}	0.0008	0.0016	0.5245	0.5999
α_{ETH}	0.0530	0.0011	47.2485	0.0000
β_{ETH}	0.9414	0.0003	3346.6907	0.0000
$shape_{ETH}$	1.1851	0.0760	15.5948	0.0000
μ_{PORT}	0.0016	0.0011	1.5005	0.1335
θ_{PORT}	-0.0587	0.0521	-1.1252	0.2605
α_{PORT}	0.0999	0.0206	4.8442	0.0000
β_{PORT}	0.8990	0.0042	216.1834	0.0000
γ_{PORT}	-0.0981	0.0978	-1.0028	0.3160
δ_{PORT}	1.3820	0.4716	2.9301	0.0034
$shape_{PORT}$	1.2083	0.0745	16.2153	0.0000
$Joint : dcc_{\alpha}$	0.0612	0.0141	4.3462	0.0000
$Joint : dcc_{\beta}$	0.9132	0.0213	42.8282	0.0000
$joint : shape$	4.7654	0.3206	14.8659	0.0000

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