

DID

How does cryptocurrency affects energy consumption

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PART ONE

01

cryptocurrency

Background



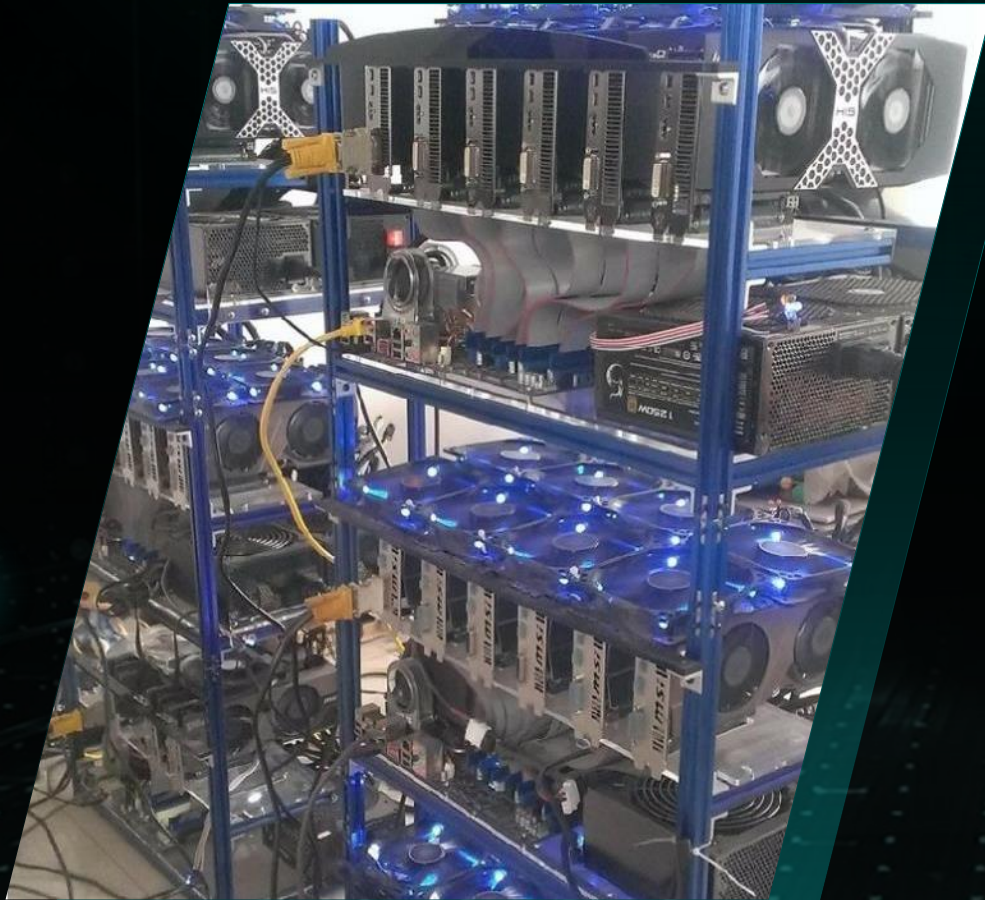
1 Cryptocurrency Mining



Cryptocurrency:

The concept of Bitcoin (BitCoin) was first proposed by Satoshi Nakamoto in 2009. Peer-to-peer transmission means a decentralized payment system

1 Cryptocurrency Mining



Cryptocurrency Miner:

Bitcoin mining machine, is used to earn bitcoin, such computers generally have professional mining chips, mostly use the way of burning graphics cards to work, **power consumption is large.**

Question?

How to measure the
consumption of
Energy?

Introduction



Data

US energy information
administration



Goal

Quantify the impact of cryptocurrency on
the energy consumption in US



Method

Difference in Difference (DID)

1 US energy data



The screenshot shows the EIA website interface. At the top, the EIA logo is on the left, and navigation links for 'Sources & Uses', 'Topics', and 'Geography' are on the right. Below the header, the word 'ELECTRICITY' is prominently displayed. Underneath it, there are tabs for 'OVERVIEW', 'DATA', and 'ANALYSIS & PROJECTIONS'. The 'DATA' tab is selected. The main content area is titled 'Form EIA-861M (formerly EIA-826) detailed data'. It includes release dates: 'Monthly Release Date: April 26, 2023 for February 2023 data', 'Next Monthly Release: End of May 2023 for March 2023 data', and 'Final annual 2021 data released: November 23, 2022'. There is a section for finding detailed data with links to 'net metering', 'small scale PV estimate', 'sales and revenue', 'advanced metering', and 'green pricing'. A paragraph describes the 'Form EIA-861M, Monthly Electric Power Industry Report', stating it collects data from distribution utilities and marketers of electricity from a statistically chosen sample of electric utilities in the United States. It mentions that the respondents to Form EIA-861M are from the larger group of respondents to 'Form EIA-861, Annual Electric Power Industry Report'. It also notes that the methodology is based on the 'Annual Electric Utility Report' and the 'Monthly Electric Power Industry Report'. A link to the 'survey page' is provided, which contains the current survey form, instructions, respondent portal, and frequently asked questions. It states that data from these files can be found throughout publications, usually in aggregated form in the 'Electric Power Monthly (EPM)' report, 'Electricity Data Browser', and in some 'Today in Energy' reports. It also mentions a 'Guide to EIA Electric Power Data' and a contact email 'InfoElectric@eia.gov'. A note states that prior to February 2017, this form was originally Form EIA-826. Below this, there is a section for 'Net Metering' with a 'Timeframe: 2011 to present'. A 'Description' paragraph explains that the data contain the cumulative installation count and capacity of net metered, by technology, state, and sector. It lists technology types: photovoltaic (standard, virtual less than 1 megawatt or greater), wind, and other. It also mentions that storage systems paired with photovoltaic (PV) are captured. A final paragraph states that a state-level adjustment for capacity of non-respondents of PV systems is made, converting state total capacity to AC units for those respondents who report data in DC units, using a conversion factor to change DC to AC. For other energy sources, no such adjustment is made.

Electricity:

EIA website records all the electricity data from power stations across US 51 states and district, including commercial, transportation, residential and industrial electricity data. (In EXCEL)

1 Data Preprocessing

```
In [5]: # 缺失值比例  
df.isnull().sum()/len(df)
```

```
Out[5]: Date                0.000000  
Year                0.000000  
Month              0.000000  
State              0.000000  
Data Status        0.000000  
C_Residential      0.032856  
C_Commercial       0.032061  
C_Industrial       0.208532  
C_Transportation   0.049285  
C_Total            0.027822  
Cu_Residential     0.019343  
Cu_Commercial      0.019343  
Cu_Industrial      0.019343  
Cu_Transportation  0.019343  
Cu_Total           0.019343  
E_Residential      0.019343  
E_Commercial       0.019343  
E_Industrial       0.019343  
E_Transportation   0.019343  
E_Total            0.019343  
dtype: float64
```

```
In [6]: df.State.unique()
```

```
Out[6]: array(['AK', 'AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA',  
              'HI', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME',  
              'MI', 'MN', 'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM',  
              'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC', 'SD', 'TN', 'TX',  
              'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY'], dtype=object)
```

```
# 缺失值比例  
data.isnull().sum()/len(df)  
  
Date                0.0  
Year                0.0  
Month              0.0  
State              0.0  
Data Status        0.0  
C_Residential      0.0  
C_Commercial       0.0  
C_Industrial       0.0  
C_Transportation   0.0  
C_Total            0.0  
Cu_Residential     0.0  
Cu_Commercial      0.0  
Cu_Industrial      0.0  
Cu_Transportation  0.0  
Cu_Total           0.0  
E_Residential      0.0  
E_Commercial       0.0  
E_Industrial       0.0  
E_Transportation   0.0  
E_Total            0.0  
dtype: float64
```

1 Data

. sum

Variable	Obs	Mean	Std. dev.	Min	Max
date	0				
year	8,058	2016.089	3.799602	2010	2023
month	8,058	6.436709	3.476052	1	12
state	0				
r_revenue	8,058	299473.7	334237.3	13064	2932836
r_sales	8,058	2339413	2508844	104574	2.09e+07
r_count	8,058	2585231	2676350	226548	1.46e+07
r_price	8,058	13.39813	4.484965	6.73	45.58
c_revenue	8,058	235391.5	285746.6	20778	2890006
c_sales	8,058	2196315	2349642	126343.7	1.52e+07
c_count	8,058	358684.5	353777.1	23408	1897985
c_price	8,058	11.0317	3.956915	5.52	43.65
i_revenue	8,058	113079.8	114615.9	242.5	984988.8
i_sales	8,058	1613989	1620063	2918.65	1.27e+07
i_count	8,058	17025.82	31181.15	1	340715
i_price	8,058	8.069394	3.859961	2.02	40.19
t_revenue	8,058	649172.6	702999.6	54601	6781119
t_sales	8,058	6161709	6118571	392218.2	4.67e+07
t_count	8,058	2960943	3047764	253016	1.66e+07
t_price	8,058	11.06115	4.145098	5.74	42.76

PART TWO

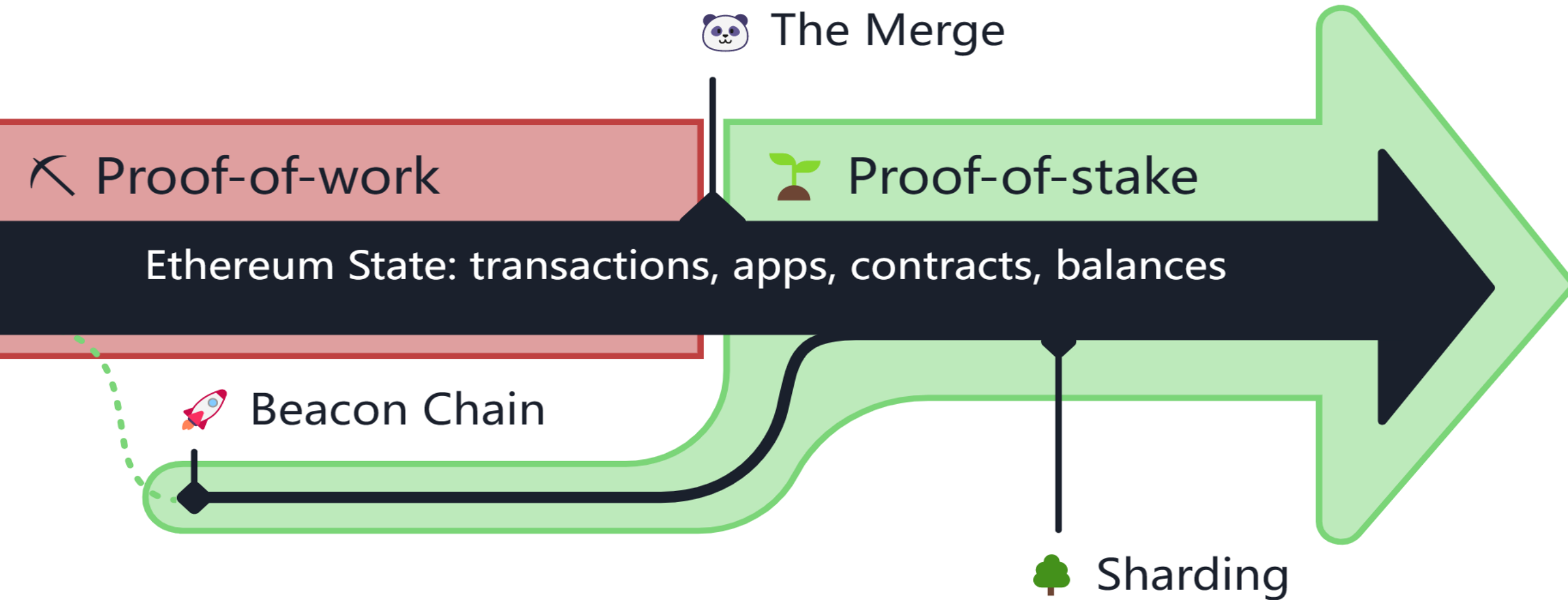
02

Merge Policy **Proposition**

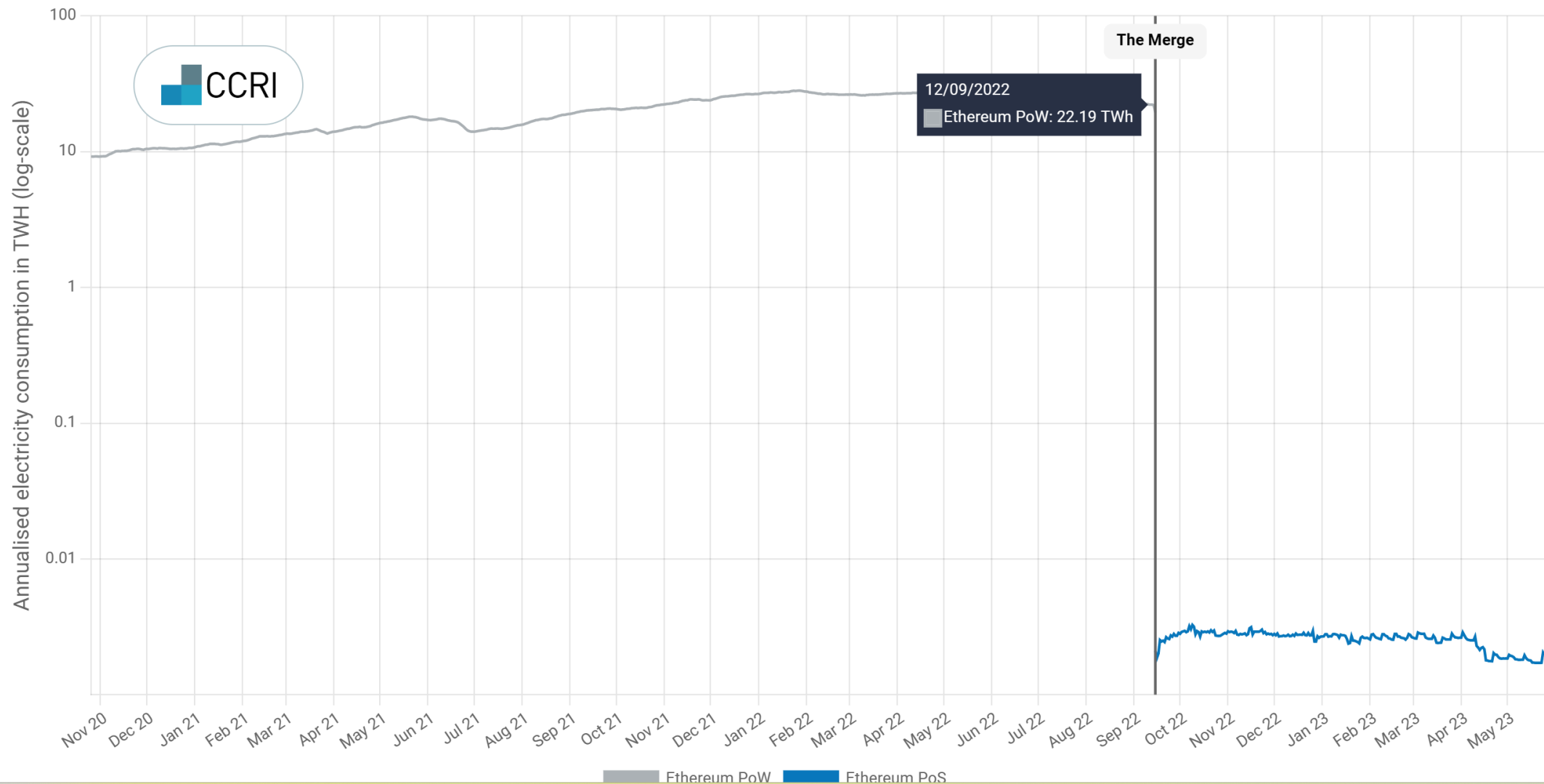


2 Merge Policy


- The Merge reduced Ethereum's energy consumption by ~99.95%.



2 Merge Policy



2 Merge Policy



Products

Resources

Team

Contact

Crypto Sustainability API:
Check out the new pricing tiers

Intelligence sustaina

Proof of Work

Proof of Stake

Tokens

Electricity Consumption

CO₂ Emissions

Ethereum

Cardano

Avalanche

Bitcoin

CCRI

5,000

4,500

4,000

3,500

Watt hours (MWh)

UNIVERSITY OF CAMBRIDGE
Judge Business School

Cambridge
Centre
for Alternative
Finance

Cambridge Blockchain Network Sustainability Index

Home

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CBECI

Choose blockchain network:

Ethereum

Ethereum

Ethereum Merge

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Methodology

Comparisons

Network Analytics

Ethereum 1.0 (PoW)

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Methodology

About

FAQ

About CBECI

consider the publication date and methodology when comparing estimates from other studies.

All comparisons are based on estimated annualised electricity consumption to make comparing estimates more convenient.

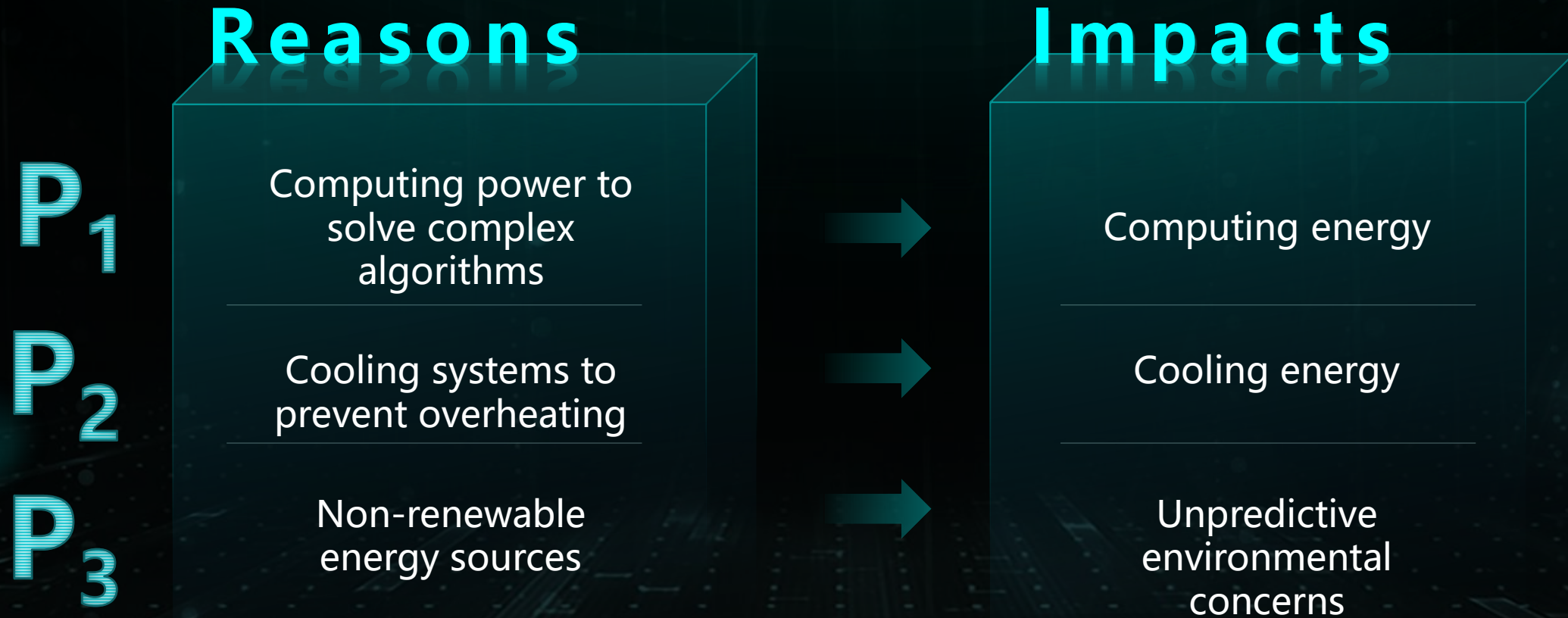
Table 7: Overview of previous studies

Author(s)	Publication date	Title	Ann. electricity consumption
Cambridge Centre for Alternative Finance	Live	Cambridge Ethereum Electricity Consumption Index	6.71 GWh
Digiconomist	Live	Ethereum Energy Consumption Index	12.71 GWh
Crypto Carbon Ratings Institute (CCRI)	Live	CCRI Crypto Sustainability Indices	6.89 GWh
Crypto Carbon Ratings Institute (CCRI)	September 2022	The Merge: Implications on the Electricity Consumption and Carbon Footprint of the Ethereum Network	2.6 GWh
Xiaoyang Shi, Hang Xiao, Weifeng Liu, Xi Chen, Klaus S Lackner, Vitalik Buterin and Thomas F Stocker	December 2021	Confronting the Carbon-footprint Challenge of Blockchain	311.9 GWh
Moritz Platt, Johannes Sedlmeir, Daniel Platt, Jiahua Xu, Paolo Tasca, Nikhil Vadgama and Juan Ignacio Ibañez	September 2021	Energy Footprint of Blockchain Consensus Mechanisms Beyond Proof-of-Work	974.7 GWh

Appendix 1

Hardware configuration

2 Proposition: Cryptocurrency and Energy



2 Proposition: Energy and Electricity

Reasons

P₄

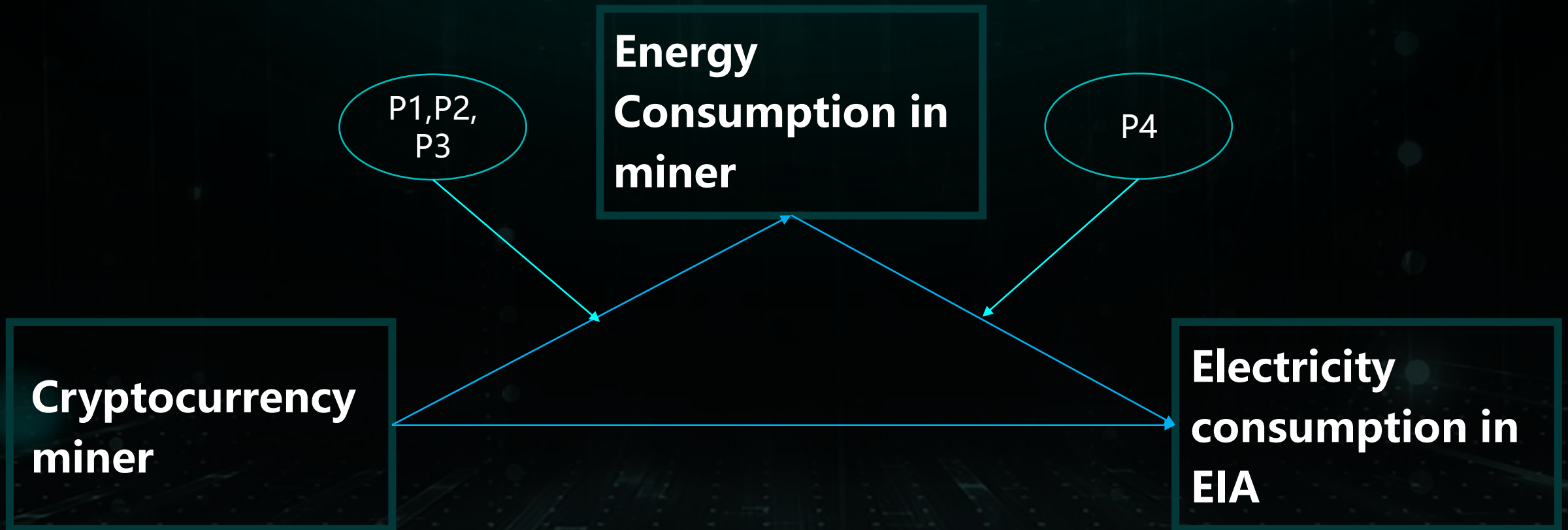
TOTAL			
Revenue	Sales	Customers	Price
Thousand Dollars	Megawatthou	Count	Cents/kWh
275,110	1,099,790	1,504,074	25.01
283,319	1,187,554	1,503,606	23.86
351,343	1,316,440	1,503,157	26.69
384,680	1,360,142	1,502,969	28.28
375,159	1,066,934	1,502,845	35.16
413,823	1,433,132	1,501,807	28.88
451,655	1,443,965	1,501,210	31.28
532,148	1,543,315	1,500,642	34.48

Energy reduction will lead to sales reduction in electricity

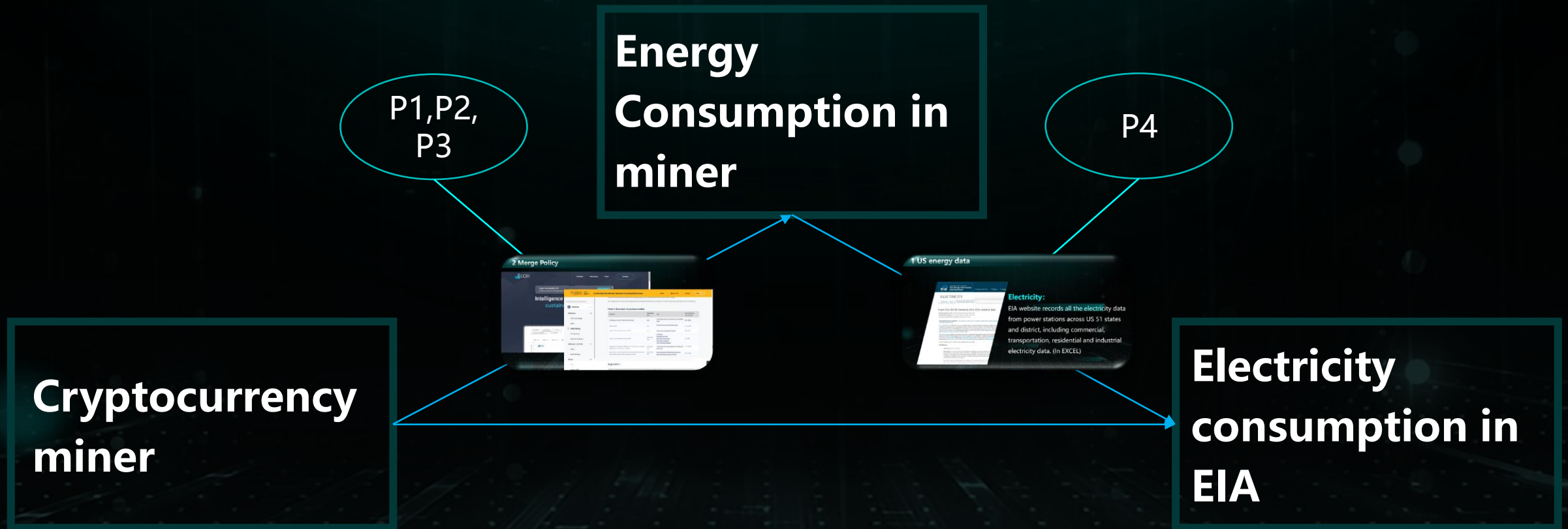
Impacts

Sales in all categories, including residential, industrial, transportation, and commercial

2 Model



2 Model



2 Method

$$\ln(\text{sales}_{it}) = \beta_0 + \beta_1 \text{treat}_i + \beta_2 \text{after}_t + \beta_3 \text{treat}_i * \text{after}_t + a_i + \varepsilon_{it}$$

- *sales_{it} : numerical sales data of electricity from EIA*
- *Treat: proportion of the state's mining activity at 2021*
- *After: binominal data which is 1 after 2022-09-15(merge policy)*
- *a_i: unobserved time-invariant factors(fixed effect)*
- *ε_{it} : other unobserved factors*

2 Method



2 Method

```
. codebook treat_proportion
```

treat_proportion	(unlabeled)
------------------	-------------

Type: Numeric (**float**)

Range: [0,30.76]

Units: .01

Unique values: 35

Missing .: 0/8,058

Mean: 1.96255

Std. dev.: 4.92307

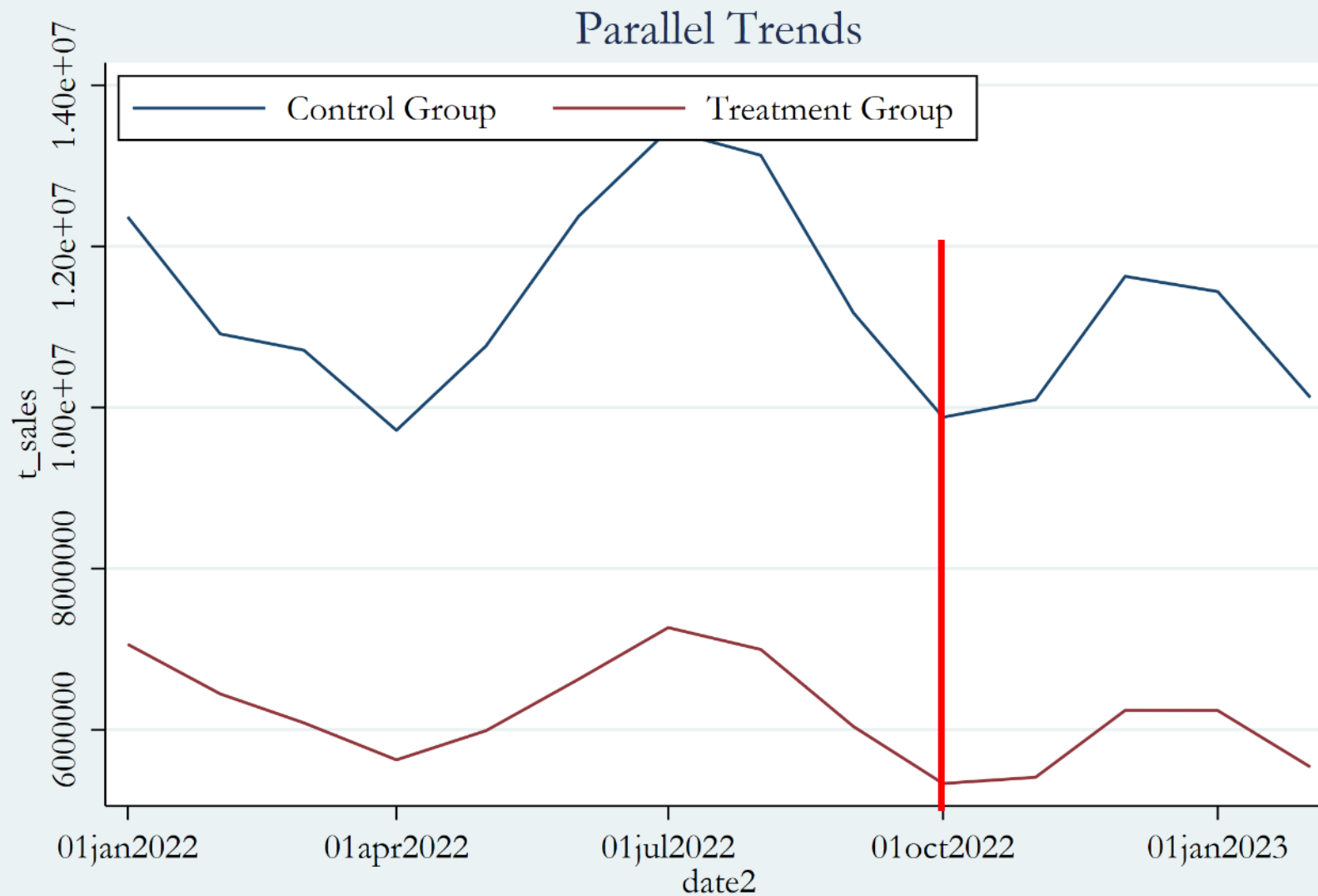
Percentiles:	10%	25%	50%	75%	90%
	0	.03	.12	1.35	4.74

PART THREE

03 DID Results



3 Result



Treatment occurred in Year 2022/09/15

3 Result

```
. reghdfe log_r_sales after_treat_proportion, absorb(date state)
(MWFE estimator converged in 2 iterations)
```

HDFE Linear regression
Absorbing 2 HDFE groups

Number of obs = 3,950
F(1, 3767) = 0.50
Prob > F = 0.4789
R-squared = 0.9821
Adj R-squared = 0.9812
Within R-sq. = 0.0001
Root MSE = 0.1378

log_r_sales	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
after_treat_proportion	-.0008474	.0011966	-0.71	0.479	-.0031934	.0014986
_cons	14.61214	.0022327	6544.52	0.000	14.60777	14.61652

log_c_sales	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
after_treat_proportion	-.0021156	.0006898	-3.07	0.002	-.0034681	-.0007632
_cons	14.56524	.0012871	1.1e+04	0.000	14.56272	14.56777

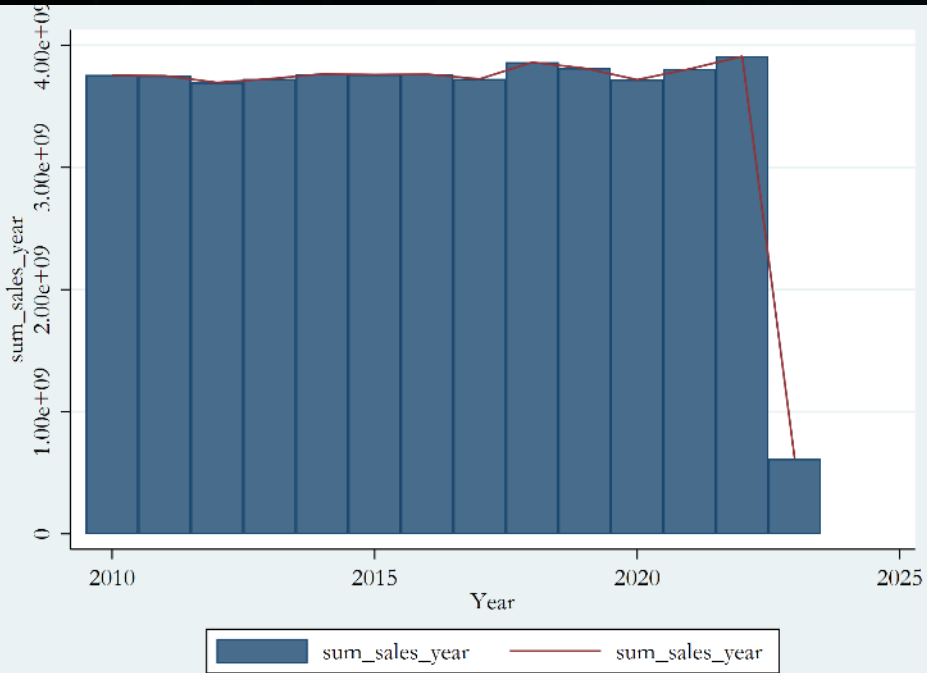
log_i_sales	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
after_treat_proportion	-.0023879	.0009934	-2.40	0.016	-.0043356	-.0004402
_cons	14.37407	.0018536	7754.47	0.000	14.37043	14.3777

log_t_sales	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
after_treat_proportion	-.0020675	.0007592	-2.72	0.006	-.003556	-.0005789
_cons	15.66591	.0014167	1.1e+04	0.000	15.66314	15.66869

3 Result

2022: 3.91e+09

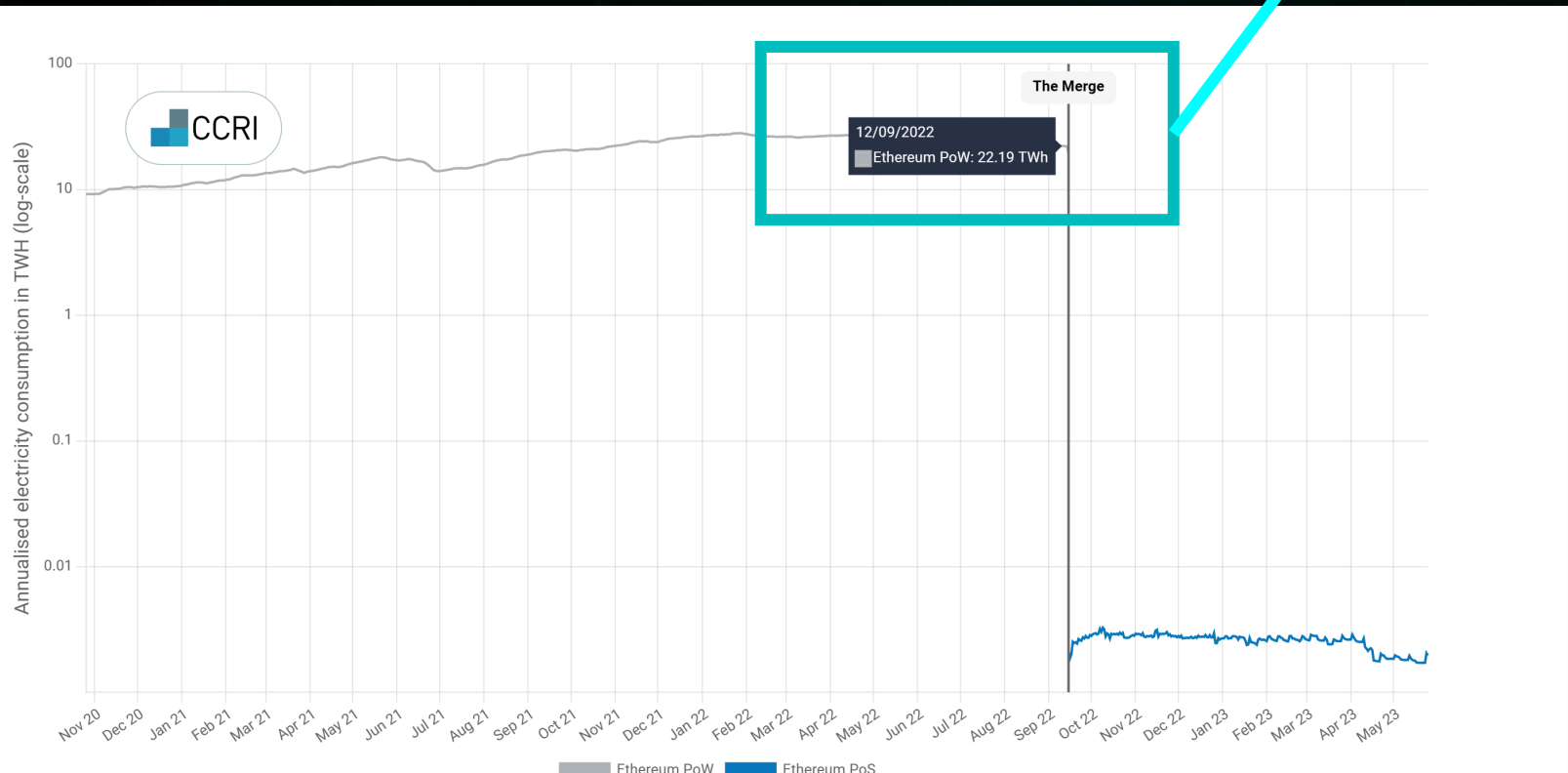
Electricity reduction: $3.91e+09 * 0.0020675 = 8.08 \cdot 10^6 \text{ MWh} = 8.08 \text{ TWh}$



log_t_sales	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
after_treat_proportion	-.0020675	.0007592	-2.72	0.006	-.003556	-.0005789
_cons	15.66591	.0014167	1.1e+04	0.000	15.66314	15.66869

3 Result

Electricity reduction $22.19 * 0.9995 = 21.96$ TWh



DID
8.08

VS Estimate model
VS 21.96

Why?

Limitation

1 US energy data



Electricity:

EIA website records all the electricity data from power stations across US 51 states and district, including commercial, transportation, residential and industrial electricity data. (In EXCEL)

Data



$$\ln(sales_{it}) = \beta_0 + \beta_1 treat_i + \beta_2 after_t + \beta_3 treat_i * after_t + a_i + \varepsilon_{it}$$

- $sales_{it}$: numerical sales data of electricity from EIA
- $Treat$: proportion of the state's mining activity at 2022
- $After$: binominal data which is 1 after 2022-09-15(merge policy)
- a_i : unobserved time-invariant factors(fixed effect)
- ε_{it} : other unobserved factors

Method



Model



Continuous improvement

THANKS FOR YOUR LISTENING!