Bitcoin Bites: Ambient pollution and labor market outcomes in Pennsylvania

Douglas Almond, Junho Choi, and Anna Papp*

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Abstract

Demand for electricity to "mine" crypto currencies is growing rapidly, driven by record prices and the increasing complexity of requisite "proof of work". This surging energy demand is primarily met by increased fossil-fuel combustion, often from economically-marginal power plants. While environmental externalities from cryptomining may be large, they have not previously been linked causally to mining incentives.[1] This is likely due the scarcity of data on rapidly expanding crypto mining activities, particularly at the crypto-firm level. Here we exploit daily variation in mining incentives as a natural experiment in local air pollution from a coal-fired power plant in Pennsylvania. We consider how mining incentives drive coal use and the emissions of local pollutants (NOX and SO2), as captured by EPA's continuous emissions monitoring system data. After confirming a resulting deterioration in local air quality, we combine our pollution data with daily administrative payroll data. Analyzing 400 unique workers over 1,034 days (413,600 observations) employed within 20 km of the Northampton power plant, IV results indicate a significant reduction in local labor supply when local air quality deteriorates due to expanded cryptomining. An exception to this pattern is the healthcare industry, where the quantity of labor supplied increases with increased pollution, likely due to greater healthcare demand. We conclude that expanded Bitcoin mining has large and previously undocumented externalities on both air quality and labor markets. From a policy perspective, many US states have been encouraging miners to initiate or expand cryptocurrency mining through tax incentives/rebates; federal policy is likewise poised to be more accommodating towards cryptocurrencies. Our future work will expand this "proof of concept" analysis to additional coal-fired Bitcoin mining facilities and integrate predictions from an atmospheric transport model (HYSPLIT) to reduce measurement error in the assignment of crypto-induced air pollution to workers.

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[1] With the exception of A. Papp, D. Almond, S. Zhang (2023)'s analysis focused on carbon emissions and climate forcing.

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Bitcoin Benefits and Costs

- Cryptocurricients offer multidimensional benefits
  - transaction speed, privacy, security, and decentralization
- Power generation is main cost of Bitcoin mining
  - Fossil-fuel generated electricity is thought to power most of cryptomining (Blandin et al., 2021)
  - as difficulty continues to increase, electricity required to mine Bitoin increases
- Meanwhile, many US states have been inducing miners to initiate or expand cryptocurrency mining.3 For example, Texas offers miners a 10-year tax abatement and sales tax credits (Malik, 2021)
- Ours is first paper to directly estimate local pollution effects of cryptomining at firm level

Data

- Systematic data on US cryptomining activity do not exist
- Weak reporting requirements in USA
- Leverage 1,020 price movements over y years
- Powerplant emissions from EPA Clean Air Markets program
- Payroll data from HOMEBASE
  - Over half of US workers are paid hourly. We have obtained labor market microdata come from Homebase
  - derived from its employee scheduling and time tracking tools used by more than 100,000 local business across the USA.
  - These businesses are predominantly in the restaurant, food & beverage, retail and services industries.
  - This generates large sample, daily labor market outcome data that are geo-identified down to the zipcode.

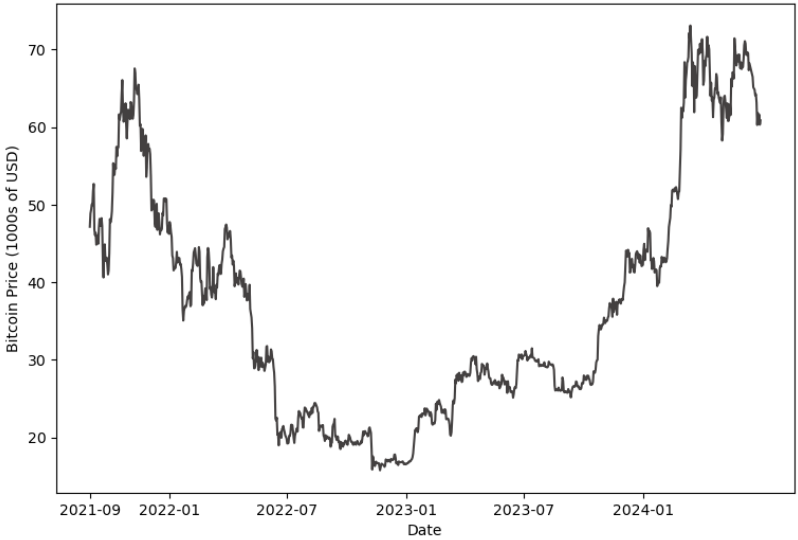
Administrative Payroll Data – daily by worker (Homebase)

1. company_id: unique ID associated with a company (no PII included)
2. location_id: unique ID associated with a company's location (no PII included). Note: One company can have several locations or establishments
3. user_id: unique ID for each employee (no PII included)
4. industry for company
5. zip: zip code for location
6. naics_code for company
7. business _type: Category for business
8. Level: For user, his/her hierarchical rank
9. job_created_date: Date employee hired
10. job_archived_date: Date employee separated from location
11. Total_wages_earned: For employees, weekly earnings in US dollars
12. Hours_worked: For employees, # of hours worked (from timesheets)
13. avg_hourly_wage_rate:

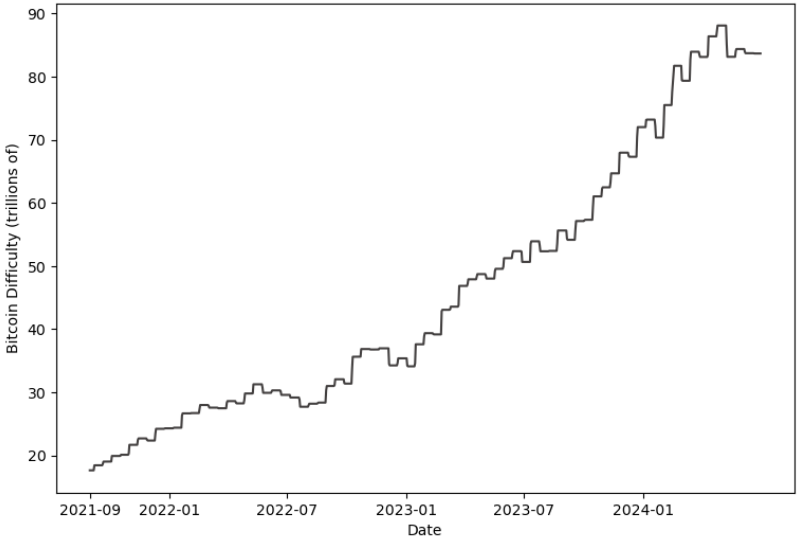
Bitcoin Mining Basics

- Bitcoin miners validate transactions in the network by solving complex mathematical problems known as the " "hashes" item In return for successfully solving a hash, the miner receives a reward of Bitcoins
- Potential drivers of mining activity:
  - Bitcoin price,
  - Mining difficulty,
  - total transaction fee,
  - average block size,
  - median transaction confirmation time,
  - BTC-USD trade volume.
- We will use the above as instrumental variables
  - 1st stage relationship to coal use, pollution emissions
  - Will look at impact of coal use and pollution emissions on worker outcomes within 20km of source

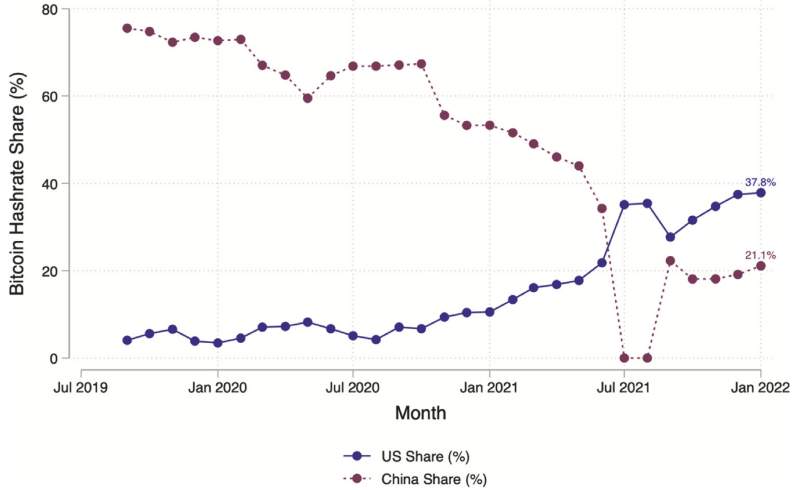
Bitcoin Market Price Over Time



Bitcoin Mining Difficulty Over Time

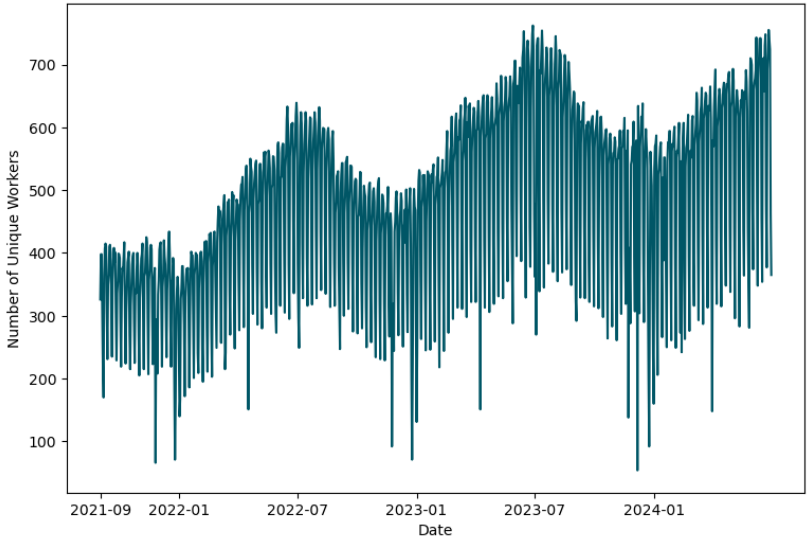


Relocation of Bitcoin Mining Activity to USA



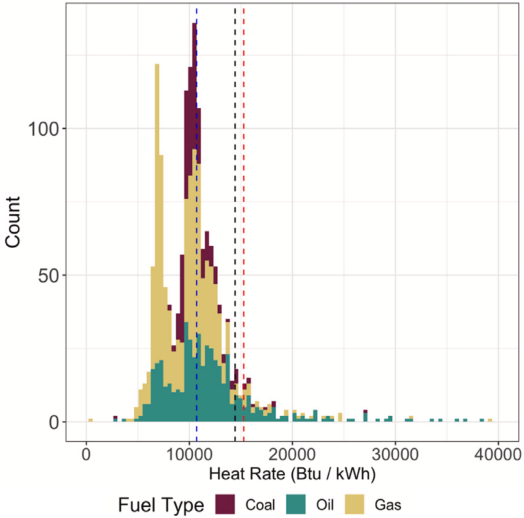
source: Papp, Almond, and Zhang (2023)

Northhampton: Unique Workers within 20km

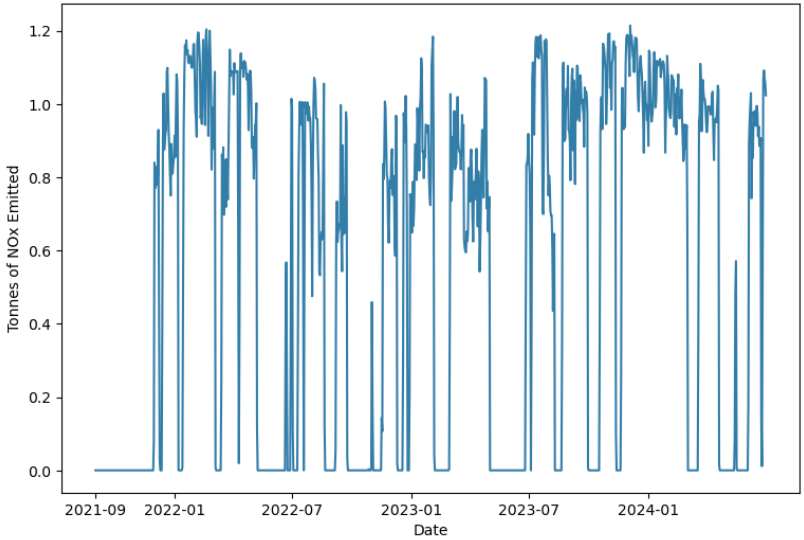


US Powerplants by heat rate – Northampton in Blue

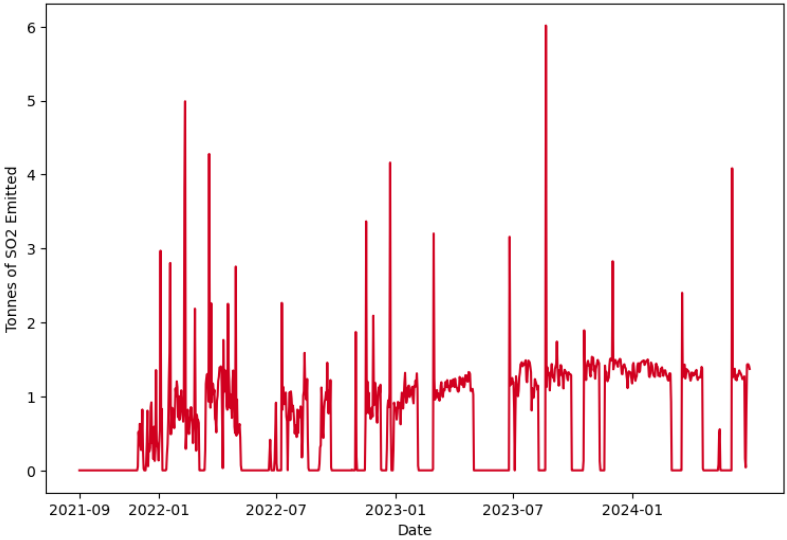
All powerplants active in 2022



Northhampton: NOX emissions (from CEMS)



Northhampton: SO2 emissions (from CEMS)



"The Impact of Pollution on Worker Productivity"

- Zivin and Neidell in AER, 2012
- Central Valley of California (farm)
- piece-rate compensation
- Ozone levels well below federal air quality standards have a significant negative impact on productivity 10 parts per billion (ppb)
- decrease in ozone concentrations increases worker productivity by 5.5 percent

"The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City "

CEEP

- Hanna and Oliva in Journal of Public Economics, 2015
- Use closure of a refinery in Mexico City as a natural experiment
- Closure caused a 19.7% decline in pollution, as captured by SO2, in the surrounding neighborhoods.
- The closure caused a 1.3 h (or 3.5%) increase in work hours per week.
- Effects appeared on the following week

"Bitcoin and carbon dioxide emissions: Evidence from daily production decisions"

CEEP

- Papp, Almond, and Zhang in Journal of Public Economics, 2023
- First paper to link cryptomining causally to externalities
- Focused exclusively on carbon dioxide emissions $\longrightarrow$ climate change
- Carbon emissions respond swiftly to mining incentives
  - Price elasticities of 0.69–0.71 in the short-run and 0.33–0.40 in the longer run.
  - A \$1 increase in Bitcoin price leads to \$3.11–\$6.79 in external damages from carbon emissions alone, well exceeding cryptomining's value added
- Focussed on Scrubgrass power plant in western Pennsylvania

For convenience, we are using the following notations for the bitcoin variables:

- b1 refers to Bitcoin price,
- b2 to difficulty,
- b3 to total tx. fee,
- b4 to average block size,
- b5 to median tx. confirmation time,
- and finally b6 to BTC-USD trade volume.

Table 1: F-statistics under various specifications of the first-stage

DV	PO	Method	F-stat	Terms involved
Heat input (billions BTU)	2	all	15.06	all terms
		LASSO	**18.25**	b_1^2, b_3^2, b_4^2, b_6^2, b_1b_6
		low p	18.13	b_1^2, b_2^2, b_3^2, b_4^2, b_1b_2, b_1b_4, b_2b_3, b_2b_5, b_2b_6, b_4b_6
	3	all	15.04	all terms
		LASSO	19.50	b_1^3, b_6^2, b_1b_4, b_3b_5, $b_1^2b_3$, $b_1^2b_6$, $b_1b_3^2$, b_2^3, $b_3b_5^2$, $b_3b_6^2$, b_4^3, $b_4^2b_6$
		low p	**22.40**	b_2^2, b_2b_4, b_3b_4, b_3b_5, b_4^2, b_4b_5, b_1^3, $b_1^2b_6$, $b_1b_3b_5$, b_2^3, $b_2^2b_6$, $b_2b_3b_5$, $b_2b_3b_6$, $b_2b_4^2$, $b_2b_4b_5$, $b_3^2b_5$, $b_3b_4b_5$ $b_3b_4^2$, b_4^3, $b_4^2b_5$, $b_4^2b_6$, $b_4b_5^2$, $b_4b_5b_6$ b_5^3, $b_5^2b_6$

NOTE 1: "DV" refers to dependent variable and "PO" refers to polynomial order. For method, "all" refers to using all possible polynomial terms for a given polynomial order, "LASSO" refers to selection of terms via LASSO with the regularization parameter of $\alpha = 0.1$, and "low p" refers to selection of terms from the "all" specification with those terms with p-values less than 0.15. For "terms involved," we are omitting linear Bitcoin variable terms (i.e., Bitcoin price, difficulty, total tx. fee, average block size, median tx. confirmation time, BTC-USD trade volume). "Tx." refers to transaction.
NOTE 2: For convenience, we are using the following notations for the bitcoin variables: b_1 refers to Bitcoin price, b_2 to difficulty, b_3 to total tx. fee, b_4 to average block size, b_5 to median tx. confirmation time, and finally b_6 to BTC-USD trade volume.

First stage – SO2

DV	PO	Method	F-stat	Terms involved
SO_2	2	all	12.65	all terms
(tonne, CEMS)		LASSO	2.72	only linear terms
		low p	**13.19**	b_1^2, b_2^2, b_2b_6, b_3^2, b_3b_5, b_4b_5, b_4b_6
	3	all	12.00	all terms
		LASSO	2.72	only linear terms
		low p	**12.21**	b_1b_2, b_2^2, b_3b_4, b_3b_5, b_4^2, b_4b_5, b_6^2, $b_1b_2^2$, $b_1b_3b_5$, b_2^3, $b_2^2b_6$, $b_2b_3b_5$, $b_3b_4b_5$, $b_3b_4^2$, b_4^3, $b_4b_5^2$, $b_4b_5b_6$, b_5^3, $b_5^2b_6$

Ordinary Least Squares (OLS)

In all sections, the "regression equations" refer to the OLS equations.
The regression equation for results in Table 15 is as follows:

$$Y_t = \beta_1(\text{Heat input}_t) + \underbrace{\beta_2(\text{Heat input}_t)^2}_{\text{only in (2)}} + \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \varepsilon_t$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, and t is the time (day) subscript.

Ordinary Least Squares (OLS)

Table: Day-level results

	(1)	(2)
Heat input	-0.0403***	-0.115***
	(0.00455)	(0.0217)
Heat input^2		0.00290***
		(0.000788)
Observations	19,766	19,766
R-squared	0.677	0.677
Adj. R2	0.676	0.676

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

The regression equation for results in Table 2 is as follows:

$$Y_{i,t} = \beta_1(\text{Heat input}_t) + \underbrace{\beta_2(\text{Heat input}_t)^2}_{\text{only in (2)}} + \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \iota_i + \varepsilon_{i,t}$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, i is the industry subscript, and t is the time (day) subscript.

Table: Industry-day-level results

	(1)	(2)
Heat input	-0.00656	0.509***
	(0.00899)	(0.102)
Heat input^2		-0.0192***
		(0.00377)
Observations	19,766	19,766
R-squared	0.097	-0.088
Adj. R2	0.0774	-0.113
KP rk. LM (Under)	2973***	984.7***
KP rk F (Weak)	469	101.2
Hansen J (Over)	58.86***	36.38***

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

The regression equation for results in Table 3 is as follows:

$$Y_{z,t} = \beta_1(\text{Heat input}_t) + \underbrace{\beta_2(\text{Heat input}_t)^2}_{\text{only in (2)}} + \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \zeta_z + \varepsilon_{z,t}$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, z is the zip-code subscript, and t is the time (day) subscript.

Table: Zip-code-day-level results

	(1)	(2)
Heat input	-0.0525***	-0.106***
	(0.00405)	(0.0189)
Heat input^2		0.00206***
		(0.000689)
Observations	24,328	24,328
R-squared	0.643	0.644
Adj. R2	0.643	0.643

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

The regression equation for results in Table 3 is as follows:

$$Y_{i,z,t} = \beta_1(\text{Heat input}_t) + \underbrace{\beta_2(\text{Heat input}_t)^2}_{\text{only in (2)}} + \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \zeta_z + \iota_i + \varepsilon_{i,z,t}$$

Ordinary Least Squares (OLS)

Ordinary Least Squares (OLS)

Table: Industry-zip-code-day-level results

	(1)	(2)
Heat input	-0.0351***	-0.0650***
	(0.00254)	(0.0126)
Heat input^2		0.00116**
		(0.000472)
Observations	65,634	65,634
R-squared	0.385	0.385
Adj. R2	0.384	0.384

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

For Tables 5, 6 7, the regression equation is the same as that for Table 2, but we limit it to the following industries respectively: clinical healthcare (e.g., physicians), automotive repair and maintenance, and all industries except the two.

Table: Clinical healthcare industry

	(1)	(2)
Heat input	-0.0165	-0.254***
	(0.0156)	(0.0700)
Heat input^2		0.00919***
		(0.00252)
Observations	1,030	1,030
R-squared	0.600	0.605
Adj. R2	0.592	0.597

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table: Auto repair industry

	(1)	(2)
Heat input	-0.0543**	-0.312***
	(0.0226)	(0.0943)
Heat input^2		0.00996***
		(0.00329)
Observations	1,021	1,021
R-squared	0.534	0.538
Adj. R2	0.525	0.528

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

Table: All industries except healthcare and auto repair

	(1)	(2)
Heat input	-0.0406***	-0.0955***
	(0.00469)	(0.0225)
Heat input^2		0.00212***
		(0.000817)
Observations	17,715	17,715
R-squared	0.667	0.667
Adj. R2	0.666	0.666

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ordinary Least Squares (OLS)

The regression equation for results in Table 8 is as follows:

$$Y_t = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \varepsilon_t$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, and t is the time (day) subscript.

Table: Day-level results

	(1)	(2)	(3)	(4)
SO_2	-0.969*	-2.728***	0.482	0.612
	(0.566)	(0.796)	(0.847)	(1.558)
SO_2^2		0.654**		0.0123
		(0.278)		(0.267)
Heat input			-0.124***	-0.295***
			(0.0414)	(0.0953)
Heat input^2				0.00640**
				(0.00278)
Observations	1,034	1,034	1,034	1,034
R-squared	0.311	0.320	0.324	0.326
Adj. R2	0.297	0.305	0.309	0.310

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p <$

The regression equation for results in Table 9 is as follows:

$$Y_{i,t} = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \iota_i + \varepsilon_{i,t}$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, i is the industry subscript, and t is the time (day) subscript.

Table: Industry-day-level results

	(1)	(2)	(3)	(4)
SO_2	-0.396***	-1.120***	0.166	0.0952
	(0.0862)	(0.134)	(0.121)	(0.272)
SO_2^2		0.272***		0.0414
		(0.0397)		(0.0526)
Heat input			-0.0474***	-0.132***
			(0.00649)	(0.0243)
Heat input^2				0.00328***
				(0.000773)
Observations	19,766	19,766	19,766	19,766
R-squared	0.676	0.677	0.677	0.677
Adj. R2	0.675	0.676	0.676	0.676

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p <$

The regression equation for results in Table 10 is as follows:

$$Y_{z,t} = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \zeta_z + \varepsilon_{z,t}$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, z is the zip-code subscript, and t is the time (day) subscript.

Table: Zip-code-day-level results

	(1)	(2)	(3)	(4)
SO_2	-0.488***	-1.334***	0.245**	0.427*
	(0.0767)	(0.119)	(0.110)	(0.249)
SO_2^2		0.312***		-0.0245
		(0.0366)		(0.0476)
Heat input			-0.0629***	-0.141***
			(0.00596)	(0.0217)
Heat input^2				0.00277***
				(0.000677)
Observations	24,328	24,328	24,328	24,328
R-squared	0.641	0.643	0.644	0.644
Adj. R2	0.641	0.642	0.643	0.643

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p <$

The regression equation for results in Table 10 is as follows:

$$Y_{i,z,t} = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \iota_i + \zeta_z + \varepsilon_{i,z,t}$$

Table: Industry-zip-code-day-level results

	(1)	(2)	(3)	(4)
SO_2	-0.376***	-0.891***	0.0756	0.124
	(0.0465)	(0.0742)	(0.0684)	(0.167)
SO_2^2		0.192***		-0.00140
		(0.0234)		(0.0350)
Heat input			-0.0384***	-0.0767***
			(0.00379)	(0.0153)
Heat input^2				0.00140***
				(0.000484)
Observations	65,634	65,634	65,634	65,634
R-squared	0.384	0.385	0.385	0.385
Adj. R2	0.383	0.384	0.384	0.384

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p <$

Ordinary Least Squares (OLS)

For Tables 12, 13 14, the regression equation is the same as that for Table 9, but we limit it to the following industries respectively: clinical healthcare (e.g., physicians), automotive repair and maintenance, and all industries except the two.

Table: Clinical healthcare industry

	(1)	(2)	(3)	(4)
SO_2	-0.155	-0.616	0.0784	0.323
	(0.304)	(0.454)	(0.431)	(0.922)
SO_2^2		0.171		0.00859
		(0.132)		(0.163)
Heat input			-0.0199	-0.285***
			(0.0222)	(0.0733)
Heat input^2				0.00984***
				(0.00232)
Observations	1,030	1,030	1,030	1,030
R-squared	0.600	0.601	0.600	0.606
Adj. R2	0.591	0.592	0.591	0.596

NOTE: Robust standard errors in parentheses. ***$p < 0.01$,

Table: Auto repair industry

	(1)	(2)	(3)	(4)
SO_2	-0.221	-1.603**	0.833	1.321
	(0.445)	(0.670)	(0.609)	(1.250)
SO_2^2		0.513**		-0.0335
		(0.208)		(0.215)
Heat input			-0.0898***	-0.427***
			(0.0319)	(0.100)
Heat input^2				0.0123***
				(0.00298)
Observations	1,021	1,021	1,021	1,021
R-squared	0.531	0.535	0.536	0.541
Adj. R2	0.521	0.525	0.526	0.530

NOTE: Robust standard errors in parentheses. ***$p \leq 0.01$,

Table: All industries except healthcare and auto repair

	(1)	(2)	(3)	(4)
SO_2	-0.416***	-1.113***	0.133	0.00693
	(0.0886)	(0.138)	(0.124)	(0.278)
SO_2^2		0.262***		0.0483
		(0.0408)		(0.0541)
Heat input			-0.0462***	-0.105***
			(0.00666)	(0.0250)
Heat input^2				0.00236***
				(0.000800)
Observations	17,715	17,715	17,715	17,715
R-squared	0.666	0.667	0.667	0.667
Adj. R2	0.665	0.666	0.666	0.666

NOTE: Robust standard errors in parentheses. $***p < 0.01$, $**p <$

Instrumental Variables (IV)

In all sections, the "regression equations" refer to the structural or second-stage equations. The first-stage equation used for all cases, where X_t is an endogenous variable (e.g., SO_2 emissions) is as follows:

$$X_t = f(\text{price}_t, \text{difficulty}_t, \text{tx-fee}_t, \text{bk-size}_t, \text{confirm}_t, \text{volume}_t) + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \varepsilon_t$$

where t is the time (day) subscript. price_t refers to Bitcoin price, difficulty_t to Bitcoin difficulty, tx-fee_t to total transaction fee in Bitcoins, bk-size_t to average block size, confirm_t to median transaction confirmation time, and volume_t to BTC-USD trade volume.
$f(\cdot)$ is a 2nd-order polynomial function that always includes first-order terms of the said Bitcoin variables and selected squared and interaction terms. 2nd-order was chosen as there was no meaningful improvements in the fit by testing higher polynomial orders.

The regression equation for results in Table **??** is as follows:

$$Y_t = \beta_1(\text{Heat input}_t) + \underbrace{\beta_2(\text{Heat input}_t)^2}_{\text{only in (2)}} + \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \varepsilon_t$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, and t is the time (day) subscript.

Table: Day-level results

	(1)	(2)
Heat input	-0.0403***	-0.115***
	(0.00455)	(0.0217)
Heat input^2		0.00290***
		(0.000788)
Observations	19,766	19,766
R-squared	0.677	0.677
Adj. R2	0.676	0.676

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table: Industry-day-level results

	(1)	(2)
Heat input	-0.00656	0.509***
	(0.00899)	(0.102)
Heat input^2		-0.0192***
		(0.00377)
Observations	19,766	19,766
R-squared	0.097	-0.088
Adj. R2	0.0774	-0.113
KP rk. LM (Under)	2973***	984.7***
KP rk F (Weak)	469	101.2
Hansen J (Over)	58.86***	36.38***

NOTE: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Instrumental Variables IV

For Tables 17, 18 19, the regression equation is the same as that for Table 16, but we limit it to the following industries respectively: clinical healthcare (e.g., physicians), automotive repair and maintenance, and all industries except the two.

Table: Clinical healthcare industry

	(1)	(2)
Heat input	0.145***	0.0984
	(0.0267)	(0.317)
Heat input^2		0.00174
		(0.0119)
Observations	1,030	1,030
R-squared	0.132	0.137
Adj. R2	0.113	0.118
KP rk. LM (Under)	153.4***	51.26***
KP rk F (Weak)	24.22	5.247
Hansen J (Over)	15.75	14.03

NOTE: Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table: Auto repair industry

	(1)	(2)
Heat input	0.155***	0.411
	(0.0353)	(0.446)
Heat input^2		-0.00951
		(0.0166)
Observations	1,021	1,021
R-squared	0.187	0.162
Adj. R2	0.169	0.142
KP rk. LM (Under)	153.4***	48.99***
KP rk F (Weak)	23.57	5.097
Hansen J (Over)	10.58	9.163

NOTE: Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table: All industries except healthcare and auto repair

	(1)	(2)
Heat input	-0.0237**	0.532***
	(0.00938)	(0.107)
Heat input^2		-0.0207***
		(0.00395)
Observations	17,715	17,715
R-squared	0.095	0.053
Adj. R2	0.0920	0.0505
KP rk. LM (Under)	2667***	885.2***
KP rk F (Weak)	419.9	90.65
Hansen J (Over)	57.74***	32.36***

NOTE: Robust standard errors in parentheses. *** < 0.01, ** < 0.05, * < 0.1

The regression equation for results in Table 20 is as follows:

$$Y_t = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \varepsilon_t$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, and t is the time (day) subscript.

Table: Day-level results

	(1)	(2)	(3)	(4)
SO_2	-1.251*	-2.315	-2.514	-21.01*
	(0.694)	(3.508)	(4.258)	(11.06)
SO_2^2		0.647		3.845
		(2.182)		(3.434)
Heat input			0.0627	2.297***
			(0.211)	(0.699)
Heat input^2				-0.0609***
				(0.0182)
Observations	1,034	1,034	1,034	1,034
R-squared	0.085	0.096	0.059	-0.322
Adj. R2	0.0649	0.0754	0.0373	-0.355
KP rk. LM (Under)	113.1***	8.284	15.24	7.041
KP rk F (Weak)	15.76	0.765	1.338	0.573

The regression equation for results in Table 21 is as follows:

$$Y_{i,t} = \beta_1 SO_{2t} + \underbrace{\beta_2 (SO_{2t})^2}_{\text{only in (2), (4)}} + \underbrace{\beta_3 (\text{Heat input}_t)}_{\text{only in (3), (4)}} + \underbrace{\beta_4 (\text{Heat input}_t)^2}_{\text{only in (4)}}$$
$$+ \sum_{j=1}^{3} \tau_j t^j + \phi_{\text{month}(t)} + \psi_{\text{DOW}(t)} + \iota_i + \varepsilon_{i,t}$$

where Y_t is the weighted (by $\ln(\#\text{ of workers} + 1)$) average hours worked, i is the industry subscript, and t is the time (day) subscript.

Table: Industry-day-level results

	(1)	(2)	(3)	(4)
SO_2	-0.140	0.338	-0.412	-6.431**
	(0.182)	(0.861)	(1.222)	(2.879)
SO_2^2		-0.291		0.765
		(0.515)		(0.731)
Heat input			0.0137	0.925***
			(0.0605)	(0.187)
Heat input^2				-0.0252***
				(0.00445)
Observations	19,766	19,766	19,766	19,766
R-squared	0.076	0.069	0.075	-0.024
Adj. R2	0.0739	0.0664	0.0723	-0.0268
KP rk. LM (Under)	2294***	163.7***	252.7***	135.1***
KP rk F (Weak)	310.9	14.71	24.32	11.74

Robustness

1. Tested for stationarity of variables to ensure we are not recovering a spurious relationship
2. Falsification tests?
3. E.G. doing first stage on 5 non-Bitcoin plants in appendix table A14 PAZ23
4. TBA

Next steps

1. Consider analogous impacts at other on-site cryptominers, like Scrubgrass in western PA
2. Indoor air quality data? Purple Air monitors
3. Use atmospheric transport model to better match pollution from power plant to zipcode of worker
4. TBA

Discussion

1. TBA
2. Externality substantially greater than carbon alone (GHG and climate forcing)
3. Proof-of-stake mechanism for cryptocurrency. Ethereum switched to proof-of-stake consensus mechanism in Spet. 2022
4. $\exists$ crypto benefits without these externalities