When Cryptomining Comes to Town: High Electricity-use Spillovers to the Local Economy

Matteo Benetton¹, Giovanni Compiani², Adair Morse¹

¹University of California, Berkeley ²University of Chicago

Fall 2023

Cryptomining: The Physical Footprint of Digital Currencies

- Technology processing (AI, large language models, ...) consumes large quantities of electricity: 1% of world energy in 2010 and is on trajectory to increase to 6%by 2030 (Masanet et al., 2020)
- Our focus: cryptocurrency mining ("cryptomining")
 - Proof-of-work cryptos require solving increasingly complex computational puzzles
 - $\blacktriangleright\,$ An arms race in processing \rightarrow massive buildup and use of cryptomining processing
 - ▶ No central agent, rather, free entry into cryptomining

Bitcoin network now consumes more electricity than the Netherlands

Paper Contribution: Community Spillovers

- ▶ This paper: Externalities on local community through electricity markets
 - Other papers: Gobal negative externalities of cryptomining in the form of carbon emissions [De Vies (2018), Bandin et al. (2020), Goodkind et al. (2020)]
- ▶ Our story: entrance of cryptoming into a community causes
 - Small businesses and households
 - \blacktriangleright \uparrow prices for other community members ... OR
 - ▶ ↓ availability of electricity for constrained grids (grid and congestion)
 - Electricity producers
 - ↑ revenues (market expansion, higher prices)
 - ► Governments
 - tax revenues (more locally profitable than other sources of electricity)
- Partial welfare punchline... other factors: pollution, innovation, etc)

FRAMEWORK

Electricity Market: Flexible Prices



local energy costs for community Provider profits Added tax revenues (not shown)

Electricity Market: Flexible Prices + Cryptomining



Local energy costs for community Provider profits Added tax revenues (not shown)

Electricity Market: Flexible Prices + Cryptomining



- : Local energy costs for community
- : Provider profits
- : Added tax revenues (not shown)

Setting and Data

The Electricity Market of Upstate NY

NYstate emits 1 out of every 200 tons of energy-related carbon dioxide in the world

- Cold temperatures, hydro & coal power plants, cheap industrial electricity
 A number of highly publicized cryptomining facilities
- Location-Based Marginal Pricing (LBMP)
 - Electricity generators input supply schedules (prices and quantities)
 - Grid system dynamically decides what generator is at the margin for each demand by a local provider at each hour
 - ▶ LBMP = reference price + adjustments for transmission distance and congestion
 - \Rightarrow electricity supply charge shows up on residential and small business electricity bills
 - \Rightarrow A demand shock transmits throughout the system

Data

- Electricity consumption data at the town-month level from New York State Energy Research and Development Authority (NYSERDA), and high-frequency data on electricity prices from New York Independent System Operator (NYISO).
 - Electricity consumption by month, provider, town and user type (residential, business)
 Prices at the month and generator level
- ► Government data at the town-year level from the Office of State Comptroller
 - Local tax revenues and expenditures per capita
- Hand-collected data on cryptomining locations
 - ▶ Keywords search in Google for local news about crytomining for each town in energy dataset
 - ▶ 13 out of 62 counties with at least one cryptomining facility

HOUSEHOLDS AND SMALL BUSINESSES

#1) Spillovers to Electricity Consumers: Identification Strategy

Electricity consumption q by user type u (household or small business) in community c from provider p in month t.

$$OLS: \quad \log q_{pct}^u = \beta^u \log p_{ct} + \gamma^u X_{ct} + \mu_p^u + \mu_c^u + \epsilon_{pct}^u$$

Classic endogeneity problem: supply+demand

- Approach:
 - ↑ BTC price ⇒ ↑ electricity demand by cryptominers ⇒ exogenous effect on portion of supply curve faced by local community (residual supply)
 - Bitcoin price as instrument for LBMP NY Prices

$$FS: \quad \log p_{ct} = \alpha^u \log p_t^{BTC} + \gamma^u X_{ct} + \mu_p^u + \mu_c^u + \varepsilon_{pct}^u$$

$$IV: \ \log q^u_{pct} = \beta^u \widehat{\log p_{ct}} + \gamma^u X_{pct} + \mu^u_p + \mu^u_c + \epsilon^u_{pct}$$

#1) Spillovers to Electricity Consumers: Results

	Small Businesses			I	Residential			
	\mathbf{FS}	OLS	IV	\mathbf{FS}	OLS	IV		13.
BTC price (log)	0.139**** (0.005)			0.145*** (0.006)				OLS
	(*****)			(****)				1\/-
Temperature (log)	-0.195*** (0.020)			-0.233*** (0.020)				cf. (
Community Fixed Effects	Y	Y	Y	Y	Y	Y	-	
Year Fixed Effects	Y			Y				
Provider Fixed Effects	Y			Y				Rob
Mean Y	3.23			3.23				
SD Y	0.35			0.36				
F stat	713.88			656.89				. 1
Obs.	2977			3251				orth
R2adj	0.37			0.39				

FS: expected sign, High F-stat

OLS: upward sloping demand

- IV: residential elasticity = 0.07
 cf. 0.071-0.088, Ito (2014)
- Robust to different controls for seasonality (winter-summer, orthogonalized demand)

#1) Spillovers to Electricity Consumers: Results

	SMA	ALL BUSINE	SSES]	Residentia	L		ES: expected sign High E-stat
	\mathbf{FS}	OLS	IV	\mathbf{FS}	OLS	IV		1.5. expected sign, right -stat
BTC price (log)	0.139*** (0.005)			0.145*** (0.006)				OLS: upward sloping demand
Price (log)		0.056***			0.155***			
		(0.021)			(0.015)			IV: residential elasticity $= 0.07$
Temperature (log)	-0.195***	-0.088***		-0.233***	-0.093***			
	(0.020)	(0.024)		(0.020)	(0.020)			cf. 0.071-0.088, Ito (2014)
Community Fixed Effects	Y	Y	Y	Y	Y	Y	-	
Year Fixed Effects	Y	Y		Y	Y			
Provider Fixed Effects	Y	Y		Y	Y			Robust to different controls for
Mean Y	3.23	5.70		3.23	7.56			
SD Y	0.35	2.00		0.36	1.34			seasonality (winter-summer,
F stat	713.88			656.89				
Obs.	2977	2977		3251	3251			orthogonalized demand)
R2adj	0.37	0.98		0.39	0.98			

#1) Spillovers to Electricity Consumers: Results

	Sma	Small Businesses			RESIDENTIAL			
	\mathbf{FS}	OLS	IV	FS	OLS	IV		
BTC price (log)	0.139***			0.145***				
	(0.005)			(0.006)				
Price (log)		0.056***	-0.179***		0.155***	-0.074**		
		(0.021)	(0.057)		(0.015)	(0.031)		
Temperature (log)	-0.195***	-0.088***	-0.133***	-0.233***	-0.093***	-0.145***		
	(0.020)	(0.024)	(0.031)	(0.020)	(0.020)	(0.024)		
Community Fixed Effects	Y	Y	Y	Y	Y	Y	-	
Year Fixed Effects	Y	Y	Y	Y	Y	Y		
Provider Fixed Effects	Y	Y	Y	Y	Y	Y		
Mean Y	3.23	5.70	5.70	3.23	7.56	7.56		
SD Y	0.35	2.00	2.00	0.36	1.34	1.34		
F stat	713.88			656.89				
Obs.	2977	2977	2977	3251	3251	3251		
R2adj	0.37	0.98	0.98	0.39	0.98	0.97		

- FS: expected sign, High F-stat
- OLS: upward sloping demand
- IV: residential elasticity = 0.07
 cf. 0.071-0.088, Ito (2014)
- Robust to different controls for seasonality (winter-summer, orthogonalized demand)

Local Consumer Surplus: Steps

1. Use First Stage to predict price of electricity with (2018) and w/o (2016) cryptomining:

$$\log p_{ct,nocrypto} = \alpha^u \log p_{2016}^{BTC} + \gamma^u X_{pct} + \mu_p^u + \mu_c^u$$

$$\log p_{ct,crypto} = \alpha^u \log p_{2018}^{BTC} + \gamma^u X_{pct} + \mu_p^u + \mu_c^u$$

2. Use predicted prices and IV estimates to construct consumer loss

$$\Delta \text{Consumer Surplus} = - \frac{p_{ct,crypto}}{p_{ct,nocrypto}} D_{community}(p) dp = -\frac{\exp\left(\alpha + \gamma X\right)}{1 - \beta} \quad p_{ct,crypto}^{1 - \beta} - p_{ct,nocrypto}^{1 - \beta}$$

3. Scale up estimates by number of exposed households, small businesses, communities

Local Consumer Loss: Results

Use first stage to obtain predicted electricity prices pre- and post-entry of cryptominers

	(1)	(2)	(3)	(4)
	Monthly Δ	Annual Δ	Count of	Total Δ
	Consumer	Consumer	Exposed	Consumer
	Surplus (\$)	Surplus (\$)	(,000)	Surplus (\$M)
Households	-7.3	-88	2,321	-204
Small businesses	-14.0	-168	550	-92
				-296



Electricity Market: Flexible Prices + Cryptomining



- : Local energy costs for community
- : Provider profits
- : Tax revenues (not shown)

GOVERNMENT REVENUES

#2) Government Revenues: Identification Strategy

• Effect of cryptomining on local tax revenues in community *c* when price of Bitcoin is high:

 $Y_{ct} = \alpha \times cryptomining_c \times \log p_t^{BTC} + \mu_c + \mu_t + \epsilon_{ct}$

- $cryptomining_c$: dummy for hosting cryptomining operations in the county • μ_c, μ_t : community and time fixed effects
- Concern: Non-parallel trends due to selection of locations
- Approach:
 - Logit model for mining location:

 $cryptomining_c = f(average \ temperature, Distance \ to \ closest \ power \ stations) + \xi_c$

DinD with Inverse probability weighting (IPW)

#2) Government Revenues: Identification Strategy

• Effect of cryptomining on local tax revenues in community *c* when price of Bitcoin is high:

 $Y_{ct} = \alpha \times cryptomining_c \times \log p_t^{BTC} + \mu_c + \mu_t + \epsilon_{ct}$

- cryptomining_c: dummy for hosting cryptomining operations in the county
 μ_c, μ_t: community and time fixed effects
- Concern: Non-parallel trends due to selection of locations
- Approach:
 - Logit model for mining location:

 $cryptomining_c = f(average \ temperature, Distance \ to \ closest \ power \ stations) + \xi_c$

DinD with Inverse probability weighting (IPW)

#2) Government Revenues: Results

	LOCATION	TAXES		F	Robustness	3
	(1)	(2)	(3)	(4)	(5)	(6)
		OLS	IPW	2016	2017	2018
Capacity mw (log)	0.302***					
	(0.051)					
Temperature	-0.406***					
	(0.059)					
BTC price (log) X Cryptomining		4.110***	6.087***			
		(0.983)	(1.155)			
Post X Cryptomining				33.982***	29.461***	27.074**
				(7.639)	(8.894)	(12.501)
Community Fixed Effects		Yes	Yes	Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Mean Y		524.37	498.60	498.60	498.60	498.60
SD Y		505.92	426.95	426.95	426.95	426.95
Observations	719	6851	6135	6135	6135	6135
Adjusted R-squared		0.97	0.96	0.96	0.96	0.96
Pseudo R-squared	0.10					
Area under ROC Curve	.71					

Social Local Welfare: Updated Results

	(1)	(2)	(3)	(4)
	Monthly Δ	Annual Δ	Count of	Total Δ
	Consumer	Consumer	Exposed	Consumer
	Surplus (\$)	Surplus (\$)	(,000)	Surplus (\$M)
Households	-7.3	-88	2,321	-204
Small businesses	-14.0	-168	550	-92
				-296
Taxes		29	1,340	39
				-257

Calculation

Provider Profits

#3) Electricity Provider Revenues: Results

	INDUS	TRIAL	Residential	+ Small business
	(1) Sales (log(MWh))	(2) Revenues (log(\$.000))	(3) Sales (log(MWh))	(4) Revenues (log(\$.000))
Cryptomining	-2.161	-1.826	2.894***	5.570***
	(6.560)	(5.162)	(0.767)	(1.519)
$Cryptomining \times Post$	0.121*	0.136**	-0.008	0.053**
	(0.067)	(0.056)	(0.013)	(0.022)
Temperature controls	Y	Y	Y	Y
Provider Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Mean Y	11.62	8.68	12.13	9.54
SD Y	2.32	2.12	1.96	2.23
Obs.	50	50	116	116
Adjusted R-squared	0.907	0.921	0.999	0.999

► Hosting cryptomining ⇒ 3.6% higher revenues for treated electricity providers for industrial users (also increase in sales volume).

Sales unchanged and revenues go up for residential and small business users

Local Community Surplus

Economic magnitude of provider results

- ► Assuming a profit margin of 15% for electric utilities (Froelich and McLagan II,2008), the increase in revenues leads to a \$62 million increase in profits
 - ▶ Presumably a lower bound, since average profit margin < at the margin
 - To offset the net \$257 million in community losses, profit margin would have to be >58% (very unlikely)

China Analysis, summary

Cryptomining in China





China Analysis



China

- ▶ Prices are fixed within provinces ⇒ Capacity constraints more likely to bite
- ▶ We find evidence of crowding out of local "next best" use of electricity
 - Fixed asset investment, GDP and wage rates tend to decrease as a result of cryptomining locating, within a location selection model

CONCLUSION

Conclusions

- ► We provide new local-level evidence that cryptomining:
 - ► increases local consumption of energy ⇒ higher prices for small businesses and households (indirectly "paying for" cryptomining)
 - increases tax revenues \Rightarrow incentive for local governments to attract cryptominers
 - \blacktriangleright Causes consumer surplus loss of pprox \$260 million per year in Upstate NY
- Measurement and policy implications:
 - Local spillovers effects need to enter full "welfare" analysis of cryptocurrencies (together with pollution costs, transaction benefits - outside the scope of this paper)
 - Consider less energy-intensive non-PoW protocols? Taxes? Some communities considering surcharge for high-usage customers (e.g., cryptominers)
- Local energy supply effects may be important for technology processing beyond cryptocurrencies (e.g., data centers)

Limited Variation over Time in Electricity Prices



Appendix

#3) Electricity Provider Revenues: Identification Strategy

Effect of cryptomining on electricity provider p's revenues after 2016 for user type u:

 $Y_{pt}^{u} = \alpha \times cryptomining_{p} \times Post_{t} + X_{pt} + \mu_{p}^{u} + \mu_{t}^{u} + \epsilon_{pt}^{u}$

- cryptomining_p: fraction of communities hosting cryptomining
- Post_t: after 2016 dummy
- \blacktriangleright X_{pt} : high and low temperature
- μ_p^u, μ_t^u : provider and time fixed effects
- Theory predicts:
 - ↑ sales and revenues for industrial users
 - \blacktriangleright \downarrow sales and \uparrow revenue for residential and small business users (inelastic demand)

Drivers of Location Choice

	Dummy = 1 if mining evidence in coun				
	(1)	(2)	(3)	(4)	
High power plant	1.833**			2.046*	
	(0.868)			(1.103)	
High temperature		-1.511*		-3.098*	
		(0.864)		(1.782)	
High electricity price			-2.028*	-0.846	
			(1.108)	(1.355)	
Macro controls	No	No	No	Yes	
Mean Y	0.19	0.19	0.19	0.19	
SD Y	0.39	0.39	0.39	0.39	
Obs.	48	48	48	48	
Pseudo R2	0.12	0.08	0.11	0.30	

Graphical "First Stage": China



Average Electricity price per Province in Mainland China





Number of Power Plants per Province in Mainland China



Framework: Electricity Market with Fixed Prices



Quantity of Electricity

Framework: Electricity Market with Fixed Prices



Quantity of Electricity

Framework: Electricity Market with Fixed Prices

