CryptoMining: Energy Use and Local Impact

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Agenda

Motivation:

- Cryptomining uses a tremendous amount of electricity
- Potentially making electricity a scarce resource for local economies
- We wanted to know why local governments allow / lobby for cryptomining

Contributions:

- What is the impact of cryptomining on local economies? Two Arenas:
  - What governments say: Positive spillovers
    i. Taxes
    ii. Wages / Consumption
  - Unintended consequences
    iii. Pollution: Establish lower bound on fossil-fuel energy used by cryptomining globally
    iv. Energy crowding out of other industries
- In the process, we study location decision of cryptominers

SETTING

A few slides to set the stage of energy use

Setting 1: Total consumption of electricity is large

Digiconomist:

- Current use: **0.3% of world energy**
- Could power **6.3M US households**

De Vries (2018) in *Joule*

- ST Projection: **0.5% of world energy**
- Implication: **10.5M US households**

Bitmain IPO , Cambridge (2018)

- Manufacturer – market share: 67%
- Recent sales: 4.2 million machines
- Energy use of these machines > Digiconomist estimate

Comparison:

UN Emissions Gap Report 2018:

- Emissions from Bitcoin energy use **unwind 5-12% of carbon reduction commitments** (private and sub-national government)

Why so much energy use?

Setting 2: *Proof of work* to clear transactions

Why people like it?

- *Proof of Work* is the only completely democratized system now in place without a central agent (banks, government) to keep account and prevent fraud

Why does it use so much energy? *Cryptominers* (firms with computing power) compete to clear a block of transactions (winner takes all rewards).

- Reward: newly minted coins
- Winning requires solving a very complex mathematical problem
- Result: Cryptominers engage in an arms race in computing power

Why can't problem be simplified or transactions be bundled for energy efficiency?

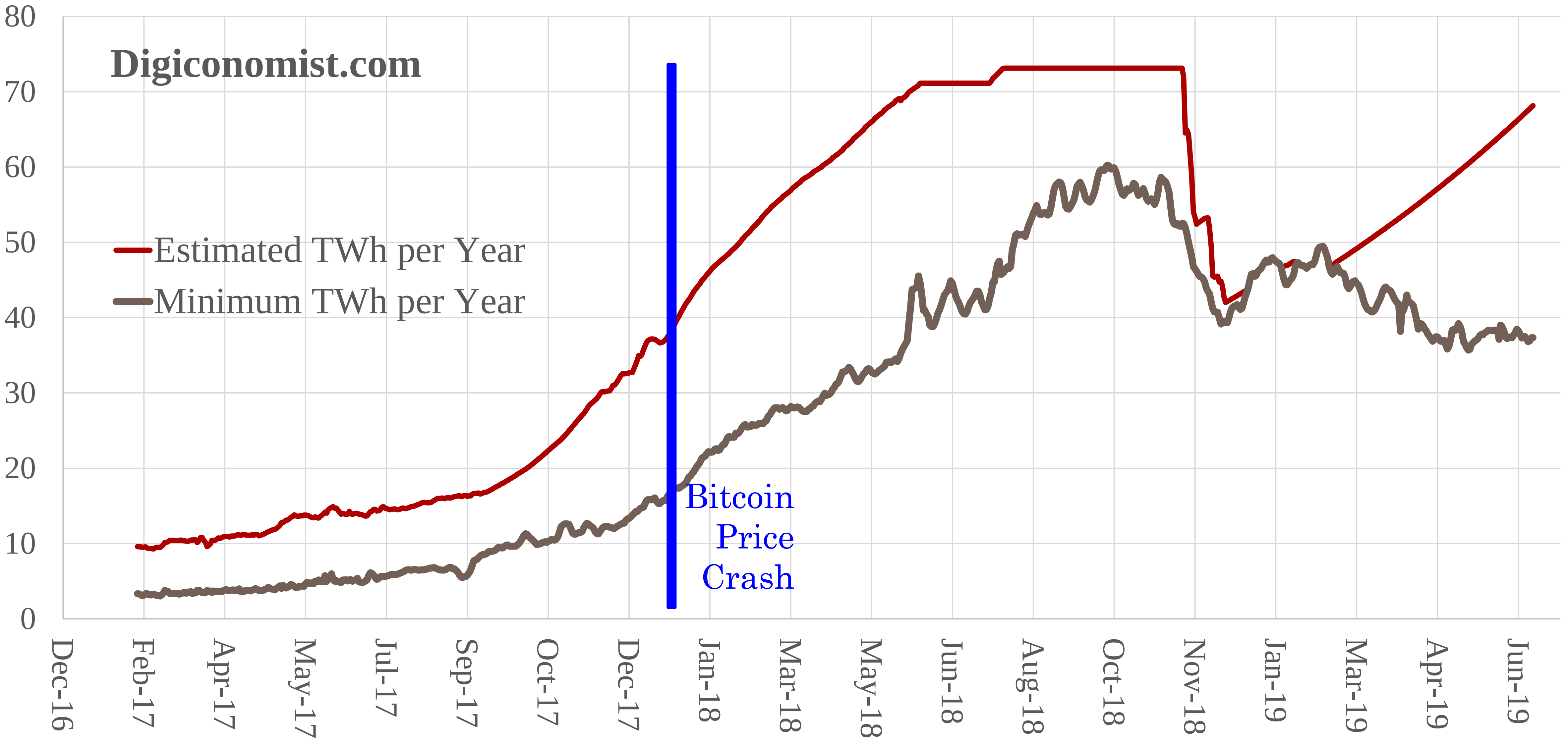
- Need scarcity in ultimate number of coins. System relies on a block being validated successfully only every ten minutes (on average).
- Need automatic ***Difficulty Adjustment*** to keep miner marginal profit (and thus amount of mining) in line with 10 minute goal.

Setting 3: Scaling-up under proof of work is environmentally infeasible

- **1 transaction cleared by bitcoin uses the equivalent daily energy of 15 U.S. households.**
  - Cannot be a system to clear "daily life" payments system
  - New stablecoin digital currencies do not use proof of work validation.

	Transactions / day	Equivalent in U.S. daily household energy use if transactions occurred in bitcoin
Paypal	16.7 M	16.7 M transactions /day * energy use of 15 households / transaction = Energy use equivalent: **250 million US households-days**
Visa	144 M	Energy use equivalent: **2.16 billion US households-days**

Setting 4: Energy consumption did not crash with price of Bitcoin



THEORETIC UNPINNING

Establishing the pollution externality problem

Pollution externality is not priced.

- Standard free-entry equation for cryptomining (Ma, Gans, Tourky, 2018):

$$Nc\,(x^*) = P$$

x^*: electricity use by a cryptominer

$Nc\,(x^*)$: expected private hashing cost for a successful mine given N miners

P: the exogenously-priced reward for a successful mine

  - Total private cost $Nc\,(x^*)$ equals reward in equilibrium

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- But if electricity use x causes pollution externality $\varphi(x)$ social optimum requires:

$$N[c\,(x^*) + \varphi(x^*)] = P$$

  - Social optimum involves lower N and/or lower x^*: Lower energy consumption.
  - Not easy to solve via tax; need global restriction on quantity.

Where we are going

$$N[c(x^*) + \varphi(x^*)] = P$$

- Government gets some of P through taxes
- Entry of new miners (N) may bring local economy spillovers
- Local governments and advocates say x^* is clean (hydropower)

We will take each of these claims to the data

DATA

China

New York State

Data from China & New York State

China:

- Hosted 70-83% of cryptomining in 2015-2018
  - For incidence, China is most important market to study
  - Yet, pollution has global consequences
- But China pricing of electricity is provincial

New York State:

- Multiple electricity providers
- Commercial electricity prices float ("dirty float")
  - Household and corporate contract pricing are sticky

Inland Cities in China: Statistics

	Mean Statistics	
Cryptomining	No	Yes
Unique Cities	164	54
Population (1,000s)	356	376
GDP (million CNY)	13,550	18,770
Energy (10,000 Kwh)	513,162	956,075
Business Taxes (million CNY)	214	282
Wages (CNY annual)	46,171	51,337
Value-Add Taxes (million CNY)	149	239
Fixed Asset Invest. (million CNY)	111,974	154,877

Note: All statistically different except population

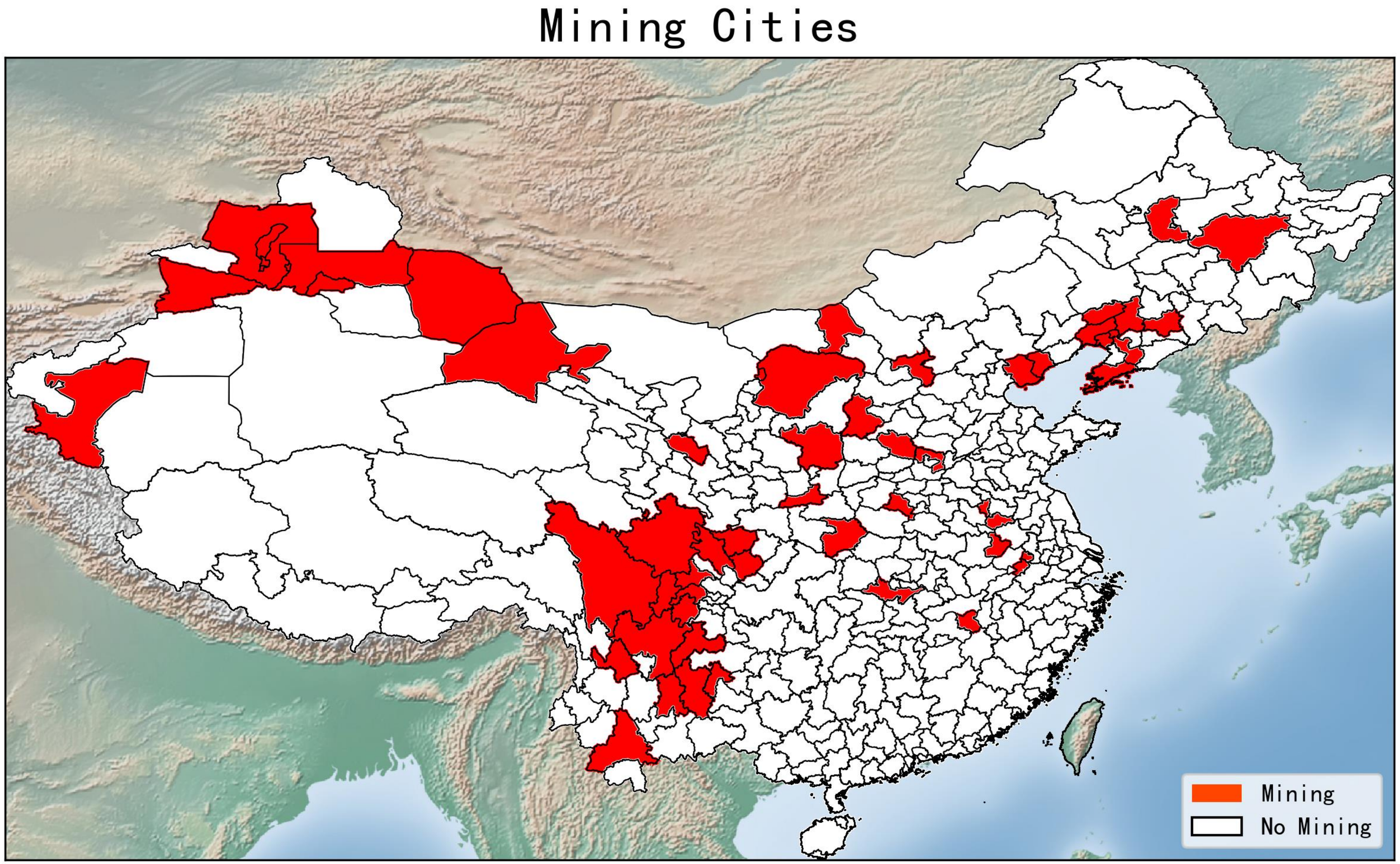
- Manually gathered data from each province's Statistical Yearbook
- Observation level: city-year
  - a city is the city-seat and covers surrounding rural areas
  - Statistics to left are collapsed first to city
- Drop coastal provinces (export economies)

What is the energy source used in cryptomining?

Contribution #1

Where are cryptomines?

For each city-seat in inner provinces in China, we conducted local news searches (focusing but not exclusively on local newspapers) in Baidu and Google to find evidence of cryptomining facilities



A similar picture is found in: 2018, Cambridge Center for Alternative Finance, 2nd Global Cryptoasset Benchmarking Study with a punchline:

"The majority [globally]... use some share of renewable energy … in their energy mix"

Energy Source

Closest Power Plant Type:

Cryptomining	No	Yes
Unique Cities	164	54
Coal	61%	48%
Gas	8%	11%
Hydro	20%	28%
Oil	1%	0%
Solar	2%	0%
Wind	9%	13%

Contribution #1: Cryptomining primarily uses fossil fuels, in particular, coal

- Coal (48%) + gas (11%) account for 59% of Chinese locations
- Anecdotes suggest that new coal-based cryptomines in Inner Mongolia are large (larger than average) **=> Lower Bound**

- If China represented 80% of cryptomining during period:

	Assume rest of world has no coal crypto	Assume rest of world has proportionate
Coal-powered cryptomining	39%	48%
Fossil fuel cryptomining	47%	59%

Our estimate:

- **39-48% of world cryptomining has been coal-powered**
- **47%-60%, fossil-fuel powered**

HOW DO CRYPTOMINERS CHOOSE LOCATIONS?

Important results in general and also for selection

Location decision model

Motivation:

> *On the way to Bitmain's Ordos mine, I ask Su what he looks for when he surveys new locations. He's like Bitmain's real estate developer, scoping out places that fill the right criteria for a mine. It's not quite "location, location, location" but there is a rough checklist: climate, cost of electricity, distance to a power station, and lastly, whether or not there are opportunities to partner with the local government."*

- Tech in Asia, August 22, 2017

Model:

$$logit(city\ has\ miners) = splines\ (average\ temperature, electricity\ price, distance\ to\ closest\ power\ station)$$

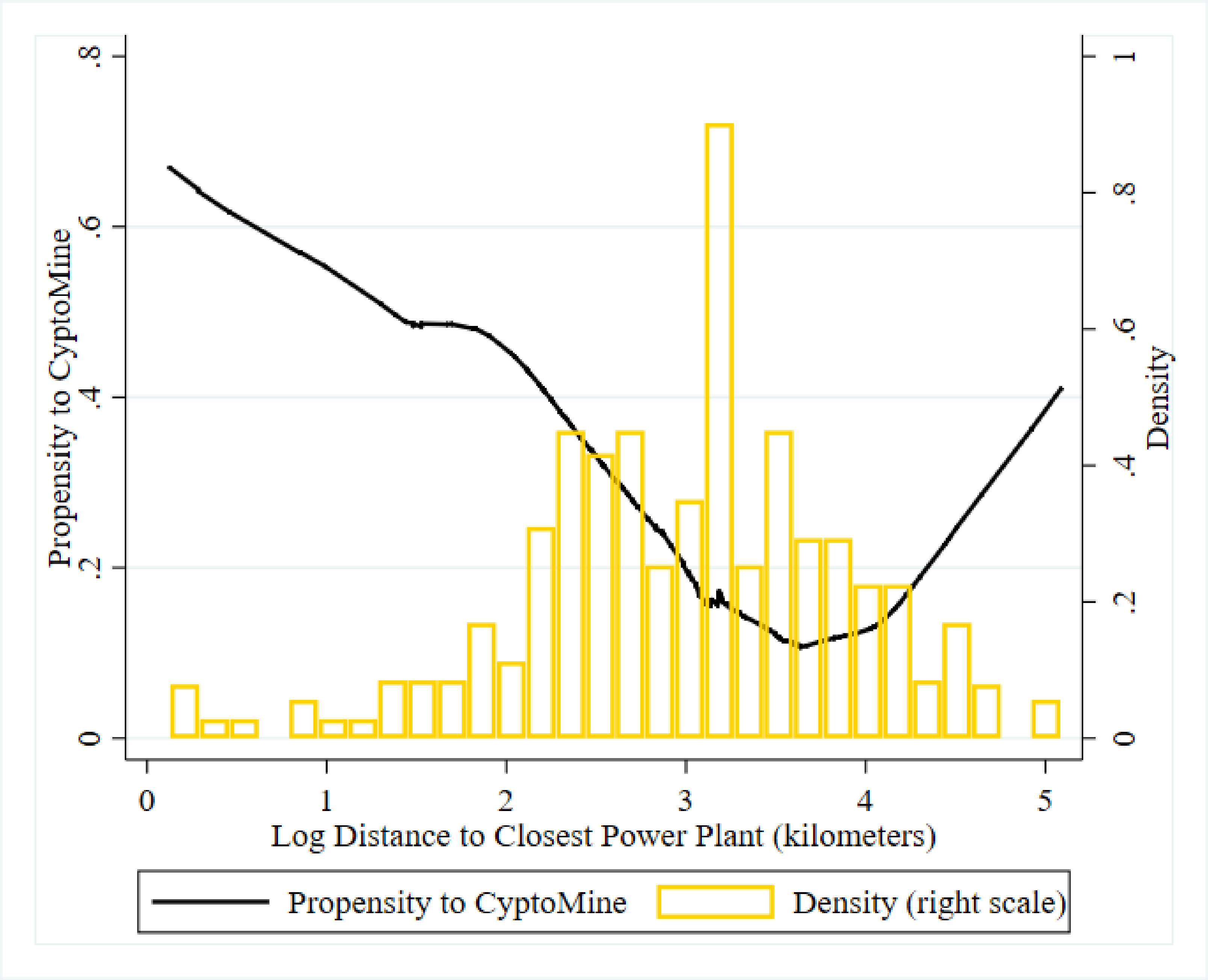
Location Decision Results

	Logit (City has CryptoMining)		
X Spline, where X independent variable is:	Distance to Closest Power Plant	Temperature	Electricity Price
Quintile 2	-16.39*	14.39***	-48.6
	[9.156]	[5.233]	[47.01]
Quintile 3	-64.19*	14.73***	-25.47
	[34.98]	[4.133]	[15.64]
Quintile 4	9.848	13.83***	-28.85*
	[14.52]	[3.897]	[15.97]
Quintile 5	-13.55**	12.61***	-27.67*
	[6.136]	[3.837]	[16.00]
Slope Quintile 1 to 2	0.022	2.195***	0.0640*
	[illegible]	[illegible]	[illegible]5]
Slope Quintile 2 to 3	5.763*	0.132	0.0426
	[3.488]	[0.265]	[0.0831]
Slope Quintile 3 to 4	19.34*		
	[10.91]		
Slope Quintile 4 to 5	-3.636		
	[4.292]		
Slope Quintile 5 to 6	2.562*		
	[1.403]		

This is too hard to read. Let's plot it instead

Also included: year, log population
Estimation sample: 2013, 2014

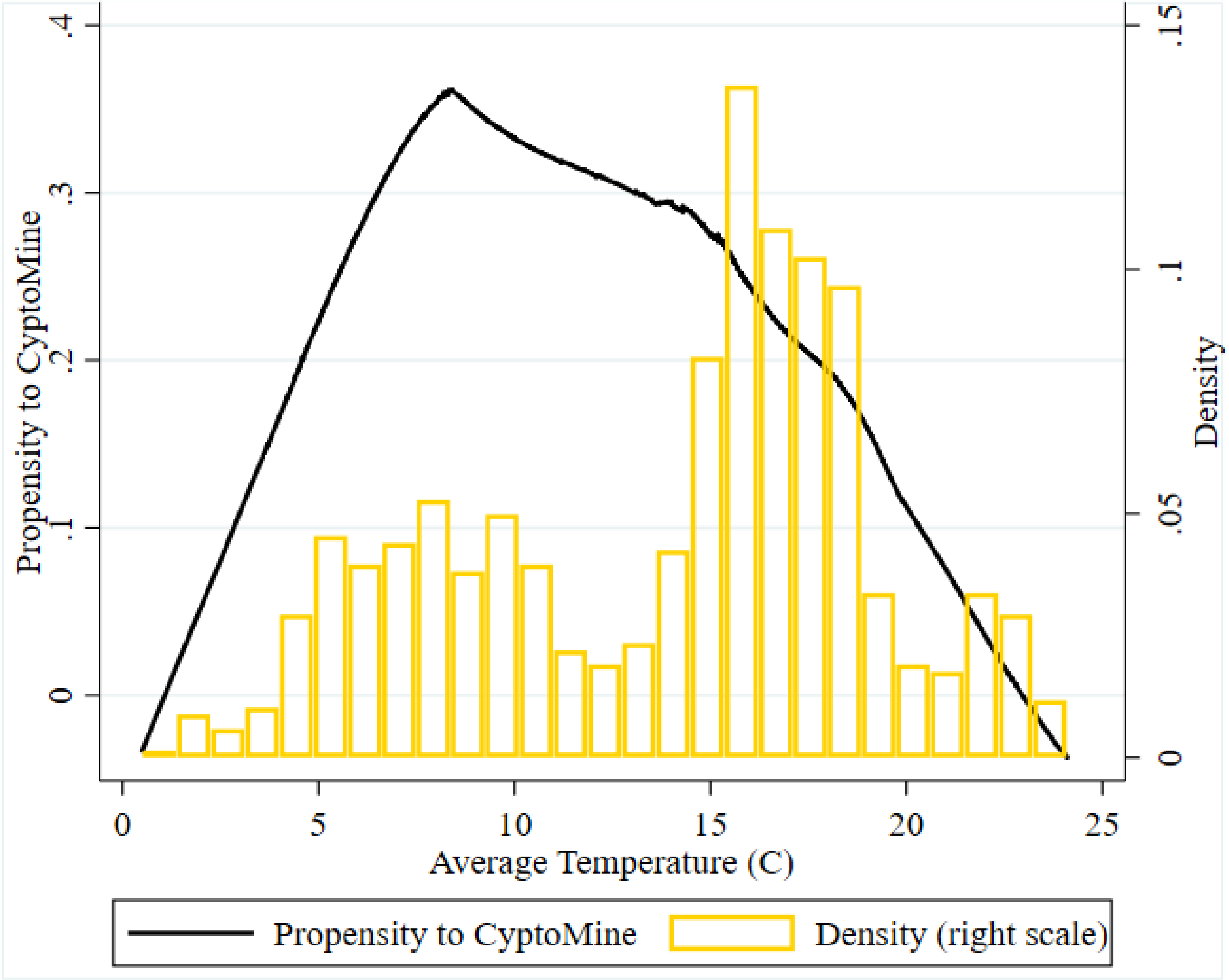
Observations	276
Pseudo R-squared	**0.387**



Predicted Propensity of a City to Host CrytoMining by Distance to Power Plant

Plotted from estimation predicted values (R-square 0.387) of:

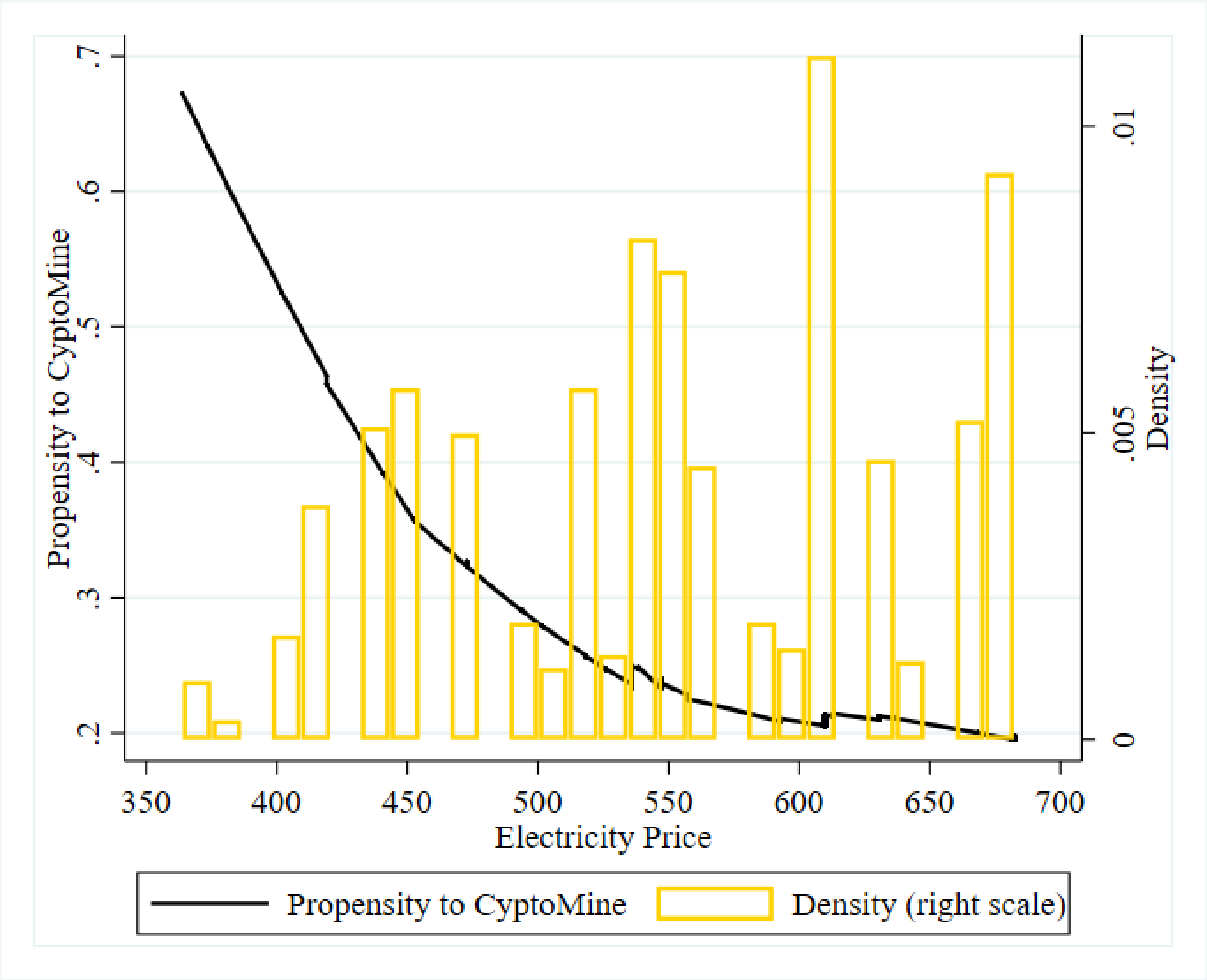
$$logit(city\ has\ miners) = splines\ (average\ temperature, electricity\ price, distance\ to\ closest\ power\ plant)$$



Predicted Propensity of a City to Host CrytoMining by Temperature

Plotted from estimation predicted values (R-square 0.387) of:

$$logit(city\ has\ miners) = splines\ (average\ temperature, electricity\ price, distance\ to\ closest\ power\ plant)$$



Predicted Propensity of a City to Host CrytoMining by Electricity Price

Plotted from estimation predicted values (R-square 0.387) of:

$$logit(city\ has\ miners) = splines\ (average\ temperature, electricity\ price, distance\ to\ closest\ power\ plant)$$

LOCAL ECONOMY IMPACTS

Results on positive motivations for hosting and unintended consequences

Local Government Motivations & Unintended Consequences

Collected news stories from local media…

What governments say:

- Anecdotes from China, Caucasus: Tax Revenues
- Anecdotes from Caucasus, Canada, U.S. and Scandinavia: Local Economy Spillovers to workers and consumers

Unintended consequences:

- Anecdotes from Montana, Australia, Texas: Re-opening coal mines or forestalling closure
- Anecdotes from Oregon, NY State: Rising energy costs for businesses because utilities have to buy electricity from other counties to provide to industry
- Anecdotes from Caucasus, Venezuela: Blackouts

Local Economy Analysis –1

Difference-in-Difference Baseline Specification (2012-2017)

$$outcome_{city,t} = \alpha\, post * M_{city} + \mu_{city} + \mu_{year} + covariates_{city,t} + \varepsilon_{city,t}$$

M_{city} : indicator for the city being in a cryptomining city

$post$: 2015-2017

$covariates_{city,t}$: includes population (level and growth), GDP (level and growth), and electricity price (level and growth)

Remaining Concern: Non-parallel trends due to selection of locations

Local Economy Analysis - 2

Difference-in-Difference Specification with **Inverse Probability Weighting (IPW)**

- Levels observations on the probability of selection into treatment
- Including pre-trends based on covariate growth variables

1. Pre-period: $logit(M_{city}) = splines\,(average\ temperature, electricity\ price, distance\ to\ closest\ power\ plant) + covariates_{city,t} + \xi_{city,t}$

2. [IPW]: $outcome_{city,t} = \alpha\, post * M_{city} + \mu_{city} + \mu_{year} + covariates_{city,t} + \varepsilon_{city,t}$

   weighted by normalized IPW of being treated, taking the propensity score as the balancing score (Rosenbaum and Rubin (1983))

Remaining concern: Unobservables related to trends in outcomes.

Example: cities A and B have the same observables, but A is close to a highway while B is not. If proximity to a highway affects the trend (not level) in outcomes (e.g. tax revenue growth), then highway selection may be confounding.

Local Economy Analysis - 3

Control Function (Wooldridge) Difference-in-Difference Specification with IPW

- By including $\beta\ post * resid_{city}$ in the outcome estimation, we can interpret α as only the change in outcomes in cryptomining cities related to the observables selection

1. Pre-period: $logit\ (M_{city}) = splines\ (average\ temperature, electricity\ price, distance\ to\ closest\ power\ plant) + covariates_{city,t} + \xi_{city,t}$

   Define: $\widehat{M_{city}}$, *predicted probability*

   $resid_{city}$, *residual probability*

2. [IPW]: $outcome_{city,t} = \alpha\ post * \widehat{M_{city}} + \beta\ post * resid_{city} + \mu_{city} + \mu_{year} + covariates_{city,t} + \varepsilon_{city,t}$

Remaining concern (unlikely but always possible in observational studies): Outcome trends experience a kink only for cryptomining cities. The IPW cannot forecast changes in trends.

Energy Use Results

	(1)	(2)	(3)
Dependent Variable:	Log (Energy Consumption)		
Diff-in-diff Model:	OLS	IPW	IPW-CF
Post * MiningCity * Clean	-0.148*	-0.0977	
	[0.0858]	[0.0730]	
Post * MiningCity * Fossil	0.0964**	0.106**	
	[0.0446]	[0.0484]	
Post * MiningCity			
Post*Predicted MiningCity* Clean			0.0752
			[0.122]
Post*Predicted MiningCity* Fossil			0.246*
			[0.129]
Control Variables	Y	Y	Y
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	595	595	590
R-squared	0.954	0.947	0.948

Energy / Pollution Take Away:

Cryptomining increases energy consumption by at least 10% in fossil fuel-powered cities, with large pollution implications.

Business Tax Results

	(1)	(2)	(3)
Dependent Variable:	Log (Business Tax Rev. /GDP)		
Diff-in-diff Model:	OLS	IPW	IPW-CF
Post * MiningCity * Clean	0.0566	0.0576	
	[0.0468]	[0.0427]	
Post * MiningCity * Fossil	0.117*	0.124*	
	[0.0628]	[0.0644]	
Post * MiningCity			
Post*Predicted MiningCity* Clean			0.242**
			[0.115]
Post*Predicted MiningCity* Fossil			0.281**
			[0.130]
Control Variables	Y	Y	Y
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	255	255	255
R-squared	0.904	0.891	0.893

Government
Take Away:

Cryptomining increases business taxes per unit of GDP by at least 10% in ALL cryptomining cities.

Governments in clean and fossil-fuel powered cities have incentives to lure cryptomining.

Wages Results

	(1)	(2)	(3)
Depedent Variable:		Log (Wages)	
Diff-in-diff Model:	OLS	IPW	IPW-CF
Post * MiningCity * Clean	-0.0113	-0.00331	
	[0.0369]	[0.0461]	
Post * MiningCity * Fossil	-0.0768**	-0.0608*	
	[0.0335]	[0.0341]	
Post * MiningCity			
Post*Predicted MiningCity* Clean			-0.0104
			[0.0619]
Post*Predicted MiningCity* Fossil			-0.112**
			[0.0439]
Control Variables	Y	Y	Y
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	698	698	693
R-squared	0.871	0.891	0.893

Household
Take Away 1:

Cryptomining does *not* benefit workers. In fact, wages decrease in fossil fuel-powered cities, probably because of low use of labor in cryptomining vis-à-vis other energy-using industries

Household Consumption-Proxy Results

	(1)	(2)	(3)
Dependent Variable:		Log (VA Tax / GDP)	
Diff-in-diff Model:	OLS	IPW	IPW-CF
Post * MiningCity * Clean	0.0452	0.0341	
	[0.119]	[0.139]	
Post * MiningCity * Fossil	-0.108	-0.145	
	[0.106]	[0.0906]	
Post * MiningCity			
Post*Predicted MiningCity* Clean			0.375
			[0.359]
Post*Predicted MiningCity* Fossil			-0.127
			[0.213]
Control Variables	Y	Y	Y
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	301	301	301
R-squared	0.761	0.742	0.751

Household
Take Away 2:

Households do not gain in spillover benefits in consumer spending, as evidenced by value-added tax realizations

Fixed Asset Investment Results

	(1)	(2)	(3)
Dependent Variable:	Log (Fixed Asset Investment)		
Diff-in-diff Model:	OLS	IPW	IPW-CF
Post * MiningCity * Clean	-0.0955	-0.0882	
	[0.148]	[0.186]	
Post * MiningCity * Fossil	-0.222**	-0.153*	
	[0.0955]	[0.0889]	
Post * MiningCity			
Post*Predicted MiningCity* Clean			-0.179
			[0.285]
Post*Predicted MiningCity* Fossil			-0.241*
			[0.135]
Control Variables	Y	Y	Y
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	704	704	699
R-squared	0.897	0.886	0.887

Other Industry
Take Away:

Investment in fossil-fuel cryptomining cites declines, consistent with blackout stories that cryptomining crowds out other industries needing energy.

Conclusion

Our objective: Shed light on the **trade-offs** involved in cryptomining

- Cryptomining consumes huge amounts of fossil fuels worldwide
  - One cannot advocate for both proof-of-work technology democratization and concern for the environment
- In China, cryptoming increases business taxes, but it also has adverse effects on wages and investments
  - Local governments have a lot to gain, but our evidence suggests this gain comes only with an expense to citizens and other industries
- The results have immediate implications for policy
  - Pollution externlaities are a public good
  - Political economy agency costs are strongly at play: media accounts reinforce duplicity in spoken motives and realizes consequences.