CryptoMining:
Local Evidence from China and the US*

Matteo Benetton[†], Giovanni Compiani[‡] and Adair Morse[§]

June 19, 2019

Abstract

Cryptomining gives rise to negative externalities through consumption of scarce electricity. Thus why do local governments pursue cryptominers and what are the broader effects of cryptomining on the local economy? Our testimonial evidence supports cryptomining as a source of tax revenues and purported local economy spillovers. Using a novel panel dataset for counties in China and New York State, we take these claims to the data. In Chinese cities, we find that cryptomining substantially increases business tax revenues relative to GDP, thus providing a strong incentive for local governments to attract this type of operations. However, we also find a negative impact on local wages and value added taxes (as a fraction of GDP). In New York State, we find that cryptomining results in substantially higher electricity prices for businesses and commercial operations. These findings suggest that cryptomining leads to crowding-out of other economic activities and point to possibly unintended consequences that local governments should factor in their decisions.

PRELIMINARY AND INCOMPLETE
COMMENTS WELCOME

*We are grateful to Aiting Kuang, Tanvi Shinkre, George Bao Lee, David Bian, Suyash Gupta, Jerry Song, Ethan Teo, and Yuan Xie for excellent research assistance.

[†]University of California, Berkeley. Email: benetton@berkeley.edu.

[‡]University of California, Berkeley. Email: gcompiani@berkeley.edu.

[§]University of California, Berkeley. Email: morse@haas.berkeley.edu.

The functioning of decentralized blockchain-based payment systems, known as cryptocurrencies, requires enormous amounts of world energy. Alex De Vries of PWC estimates that, to clear a paltry 81 million transactions in 2018, Bitcoin consumed more energy than Ireland, even despite the crash in the price of Bitcoin. The energy consumption results from the fully democratized feature, proof-of-work transaction clearing, wherein no central agent is designated to validate and secure transactions. Rather, any person or firm can become a cryptominer, choosing to participate in the solving of increasingly complex computational puzzles in order to verify the validity of the transactions. Because the payoff from mining remains yet uncompetititve due to the organizational structure (Cong, He, and Li, 2018), an arms race has occurred in mining, resulting in massive building and use of cryptomining processing power in the race to validate transactions.

Advocates for the future of proof-or-work protocols stress that "the majority [of mines]... use some share of renewable energy . . . in their energy mix," (Cambridge, 2018). Yet, such a claim struggles with its own proof since much of cryptomining happens in coal or natural-gas producing areas such as Inner Mongolia, Xinjiang, Georgia, Alberta, and Western Australia. If cryptomining is using fossil fuels, then it must be that these fuels have been diverted from other uses or are being extracted at a higher rate than would have occurred. Thus, increased fossil fuel use in cryptomining necessarily gives rise to negative local and global externalities, an insight that has been largely ignored in the economics literature.[1] In addition, anecdotes suggests that energy crowding out is occurring, whereby other firms and households face shortages or heightened costs resulting from local cryptomining industries. For instance, a Missoula, Montana (a cryptomining city) commissioner states "One-third of the county's residential energy used in one factory that employs 19 people to do something that, as of right now, is of dubious social good..." (*CrowdfundInsider*, 3/19/2019).

Our goal is to shed light on the interaction of cryptomining with local economies. In particular we study the economic spillovers and tax incentives faced by governments in promoting cryptomining in their communities. We start by adapting the standard model of cryptomining from Ma, Gans, and Tourky (2018) to allow for externalities. The modeling framework clarifies our concern that governments are not likely to be able to correct the potential negative externality by imposing taxes. The reason is that, since anyone with computing power can engage in cryptomining and the production reward is set externally,

[1] An important exception is Cong, He, and Li (2018), who show how concentration via the mining pools innovation has encouraged a greater arms race in mining. Their study shows that the global increase in mining pools is correlated in time with the increase in energy consumption.

this is a global industry and therefore a tax will be ineffective unless it is levied world-wide. Local taxes are likely to only move the problem elsewhere, akin to the issue of corporate profit shifting to tax-friendly geographies.

We then introduce our main question: given the negative exernality, why would local government allow cryptominers to divert public utility-based electricity generation? Our empirical investigations start with testimonial evidence that governments say that cryptomining will generate more tax revenues and local economy spillovers (investment and jobs) than other uses of the electricity or increased production of electricity. Because testimonies of government intention come from fossil-fuel regions, as well as hydropower regions, it must be that the governments are factoring in the pollution and energy diversion aspects of cryptomining in a cost-benefit frame.

We take these insights to data using a novel dataset constructed from local economies in China and New York State. We focus on China, because China has accounted for 70% to 83% of cryptomining during the last decade. Furthermore, China provides us with the opportunity to study hyrdopower-based cryptomining in Sichuan as distinct from coal power-base cryptomining in the Northern and Western provinces. The analysis for New York State complements the analysis for China with detailed high-frequency data on local consumption and, most importantly, prices of electricity.

Our goal is to study three outcomes emerging from the testimonial evidence concerning government incentives. (1) Is there more energy consumption suggesting either a greater use of fossil fuels in local production or a greater extraction overall? (2) Is there evidence supporting the benefits that governments purport to internalize – namely, tax revenue and more GDP-generating use of electricity? (3) Do we find any evidence of other investment increasing locally (positive spillovers) or decreasing locally (energy crowding-out)?

The answer to these questions needs to address a selection problem concerning cryptominers endogenous choice of locations. For example, a negative relation between cryptomining and energy use of local business other than cryptominers is consistent with both a story of selection (cryptomining emerging in accelerated declining cities) and treatment (cryptomining inducing an energy crowding-out effect on other uses of electricity). We estimate a logit model to predict the location of cryptominers using key determinants of their choice (temperature, distance from power plant and electricity prices) and employ a difference-in-differences identification strategy with inverse probability weighting (IPW) where the weights are the propensity scores obtained from the location model.

First, we start by looking at whether crypto operations lead to higher energy consumption. On the one hand, one would expect energy consumption to increase due to the nature of cryptomining, all else equal; on the other, it could be that crypto operations crowd out energy usage by other economic activities. Thus, the net effect is a priori ambiguous, implying that this is ultimately an empirical question. In China, we find that cryptomining correlates with higher levels of energy consumption at a local level. Importantly, this effect is larger in magnitude in provinces which rely heavily on coal for energy. In New York State, we find evidence of an extreme correlation of Bitcoin prices and energy consumption at local township levels.

Second, we study the incentives for local government in allowing cryptomining. We find strong evidence in local China data that cities engaging in cryptomining generate more business tax revenues relative to GDP. Testimonial evidence, not only from China, but also from the U.S. states of Washington and Oregon, the Canadian province of Alberta, the country of Georgia, and regions of Western Australia, all suggest that this elasticity should be large. Local authorities in regions with cheap energy and declining industrial use of that energy seem to be seeking out and welcoming opportunities to home cryptominers. In other words, local governments are correct in their assessment that cryptomining offers their economies a way to make more business tax revenues from their coal. Local governments trade this benefit against the environmental costs.

Third, we study the potential for positive or negative externalities in terms of local investment and energy crowding-out, potentially through increases in electricity prices. Anecdotes by local media suggest that cryptominers in Oregon are driving up electricity prices, such that cities may be importing electricity from outside suppliers. In a more extreme instance, Venezuelan homes and businesses have been experiencing blackouts while electricity consumption by miners has increased. In China, we find that cryptomining in coal-heavy cities is associated with lower levels of wages, fixed asset investments and value-added tax revenues, although the effects on the last two variables are not statistically significant. In New York State, we find very large elasticities of the price of electricity for businesses relative to the price of Bitcoin as well as some spillover effects on the price of electricity for households. When the price of Bitcoin went from about \$5,000 to more than \$15,000 at the end of 2017 electricity prices raised on average by 16% for business and 6% for households. These crowding out effects constitute an important (possibly unintended) consequence of hosting crypto operations that local governments should weigh against the benefits in terms of increased tax revenues.

Related literature. Our paper contributes to a growing literature on the functioning of the proof-of-work model of the Nakamoto-blockchain innovation, most closely tied to the bitcoin cyptocurrency (see Nakamoto, 2009). However, the economics literature has focused most proof-of-work attention to the features and stability of the proof-of-work protocol itself (Budish (2018), Weinberg (2014)). We instead focus on the implications of proof-of-work for local economies. We build off the literature that models how the mining equilibrium evolves with the bitcoin-blockchain supply structure (Ma, Gans, and Tourky (2018)). Others have studied other aspects of the bitcoin-blockchain supply model including the role of transaction fees (Easley, O'Hara and Basu (2018)). The important model of Alsabah and Capponi (2018) of firm decision-making allows for heterogeneity across miners to study how much investment in R&D emerges for cost reduction. Important for an overlay to our work, these authors then relate how efficiencies gained from R&D investment may increase the total computational power devoted to mining by lowering mining costs. The model also captures the trend towards more concentration in the mining industry that has been observed recently, which is the focus of Cong, He, and Li (2018). Cong et al (2018) show that the rise in mining pools tends to exacerbate the arms race between miners, thus resulting in even higher energy consumption relative to the case of solo mining.

Our work also complements the work by energy engineers and scientists on the energy consumption more directly (Li, Li, Peng, Cui, and Wu (2019), Truby (2018), and de Vries (2018). Finally, the Cambridge report (Cambridge, 2018) referred to a number of times in this paper has excellent statistics on the energy measurement as well as on all aspects of the supply of cyptomining and is generally an excellent read.

The paper is organized as follows. In Section 1, we outline the theoretical framework. Section 2 describes the novel data sets we collected from China and New York State. Section 3 contains the empirical analyses. Section 4 concludes.

1 Model

We model the Bitcoin mining market based on the framework of Ma et al. (2018) (MGT, henceforth). However, relative to this paper, we allow for externalities from mining. We refer to the existing literature for details on the Bitcoin protocol (e.g. MGT, Budish (2018), Alsabah and Capponi (2018), Cong et al. (2018)). Here, we just describe the basic elements of the system. Bitcoin is a decentralized payment system in which transactions are verified by anonymous agents, called miners, as opposed to a third-party entity such as a bank or credit card company. Miners compete to be the first to solve complex computational puzzles. The winner of each competition adds a new block of transactions to the system and in return obtains a reward consisting of newly minted bitcoins as well as a fee. The network sets the complexity of the computational puzzle in order to keep the expected completion time approximately constant.

We consider a network with N identical miners competing to win a reward P. The network sets the number of computations, K, required to solve the puzzle with the goal of keeping the expected completion time at a target level δ^*. Each miner i chooses a computing technology $x_i \in \mathbb{R}_+$. The choice of x_i affects i's expected computing speed and thus the time i expects to take to complete the K computations. In order to acquire x_i, miner i incurs a private cost $c(x_i)$, where the function c is strictly increasing and convex. In addition, the computing technology leads to a social cost $\phi(x_i) \geq 0$ (with ϕ an increasing function) which is not taken into account by miners. This externality represents, for instance, the consequences in terms of pollution and greenhouse emissions of the energy used to power the machines performing the computations.

In this setting, miner i's payoff function takes the form

$$U_i(x_i, x_{-i}, K) = P\pi_i(x_i, x_{-i}, K) - c(x_i) \tag{1}$$

where $\pi_i(x_i, x_{-i}, K)$ denotes the probability that i is the first to solve the puzzle, and the subscript $-i$ denotes all miners other than i. Then, miner i's first-order condition is

$$P\frac{\partial \pi_i(x_i, x_{-i}, K)}{\partial x_i} = \frac{\partial c(x_i)}{\partial x_i} \tag{2}$$

Now, we make assumptions on the winning probability $\pi_i(x_i, x_{-i}, K)$ which will be helpful to establish existence and uniqueness of an equilibrium in this game.

Assumption 1. For each miner i, the winning probability $\pi_i(x_i, x_{-i}, K)$ is strictly increasing and strictly concave in x_i.

Assumption 1 imposes the intuitive restriction that the more each miner invests in the mining technology the more she is likely to win, and that the returns to the technology are decreasing.

Next, we make a mild assumption on the relationship between the expected time to solve the puzzle and the number of computations K.

Assumption 2. All else equal, the expected time that it takes for at least one miner to solve the puzzle increases strictly with the number of required computations K.

Under these assumptions, MGT show existence and uniqueness of a symmetric equilibrium, which we now formalize.

Lemma 1. *Let Assumptions 1 and 2 hold. Then, for any fixed number of miners N and reward P, there exist a unique $x^* \in \mathbb{R}_+$ and a unique $K^* \geq 1$ such that:*

1. $U_i\left(\underbrace{x^*, ..., x^*}_{N\ times}, K^*\right) \geq U_i\left(x_i, \underbrace{x^*, ..., x^*}_{N\text{-}1\ times}, K^*\right)$ *for all $x_i \in \mathbb{R}$ and all i;*
2. *The expected time for at least one miner to solve the K^* required computations is equal to the target level δ^*.*

Proof. See Proposition 4.4 in MGT. □

The result in Lemma 1 treats the number of miners N as exogenous. In order to endogenize N, MGT assume that entry into the mining market is free and show that this leads to the following equation

$$Nc\left(x^*\right) = P \tag{3}$$

In words, the sum of the private costs of mining equals the reward in equilibrium, so that there are zero aggregate private profits.

So far we have assumed that miners maximize their private payoff functions. If, instead, they maximized payoffs inclusive of social costs, then their payoff function would be

$$U_{i,social}\left(x_i, x_{-i}, K\right) = P\pi_i\left(x_i, x_{-i}, K\right) - c\left(x_i\right) - \phi\left(x_i\right) \tag{4}$$

leading to the first-order condition

$$P\frac{\partial \pi_i\left(x_i, x_{-i}, K\right)}{\partial x_i} = \frac{\partial c\left(x_i\right)}{\partial x_i} + \frac{\partial \phi\left(x_i\right)}{\partial x_i} \tag{5}$$

In addition, by the same argument above, in a free-entry equilibrium we would have

$$N\left[c\left(x^*\right) + \phi\left(x^*\right)\right] = P \tag{6}$$

Comparing (2) to (5) and (3) to (6) yields the following comparative statics:

1. All else equal, the level of x_i chosen by i decreases if i internalizes the social cost;

2. In the free-entry equilibrium with internalization of social cost, either N is lower or x^* is lower (or both) relative to the case of no internalization.

In order to correct this market failure, the regulator could decide to impose a tax on consumption of x devoted to crypto-mining. However, note that, since anyone in the world is able to participate in Bitcoin mining, this is a global market and thus the tax would need to be imposed simultaneously world-wide. A local tax would not achieve the goal of remedying the negative externality, since miners from non-taxing countries would make up for the reduced activity from the miners subject to the tax. This is a similar pattern to that of multinational companies shifting their profits to low-tax countries (see, e.g., the recent paper by Tørsløv et al. (2018)).

Finally, it should be noted that the current model does not account for the fact that most of Bitcoin mining is performed by mining pools, as opposed to individual miners (see Cong et al. (2018)). By pooling together, miners share the risk inherent in the mining activity. As shown in Cong et al. (2018), this exacerbates the arms race between miners, i.e. it induces each miner to invest more in her computing technology, which makes the computational problem harder for all other miners and, in turn, prompts them to also invest more. Therefore, accounting for the presence of mining pools would yield even starker model predictions in terms of consumption of input x.

2 Data

Our goal is to anaylze the local consequences of crytpomining, embedding the choice of location. Our analyses thus begin with a study of the location of cryptomining facilities, reflecting attributes that make cryptomining most profitable. We then embed this selection of location into our study of the outcomes. Outcomes on the local economy are of two categories – those refelcting the intended governmental motives in attracting crytominers and those reflecting unintended consequences.

During the last decade, China hosted 70-83% of cryptomining (Cambridge (2018)), making it the most important setting to study cryptomining. It is also a location with little short-term electricity price reaction to pressures and shocks. For this reason, we study a second location with a more flexible price regime, that of New York State (NY). Far away from New York City, most of NY's towns and cities have a historical foundation in farming or manufacturing, and many turned to cryptoming in the mid-2010s. In NY, electricity prices float to some degree, especially for businesses, with pressures of supply and demand. We use these settings to provide complementary evidence on different aspects of the local economy impact of cryptomining.

2.1 Cryptomines and Power Plants at the Chinese City-Seat Level

Our first, and most difficult, task is to uncover the location of cryptomines. No public registries exist globally or in China. Our hand collection process begins with all the city names within all Chinese provinces which are subsequentially reported in the economic statistics Yearbooks. We exclude all coastal provinces and three major urban centers (Beijing, Chongqing, and Tianjin) as their economies are substantially more advanced than those of the rest of China, and they are not likely to host a significant amount of cryptomining operations (Cambridge, 2018). Further, we exclude the autonomous regions of Tibet and Qinghai due to sparse data on economic outcomes. We end up with 206 cities, which have a mean population of 356 thousand people. These city designations are more akin to a county with a city seat of local power; all of the land mass is covered by city divisions.

For each city, we do manual searches in Google and Google news (in English) and, more importantly, in Baidu and Baidu news (in Mandarin) to look for local news articles (or other web references) to any cryptomining facilities. Our search terms include cryptomining (and variation of it, such as crypto mining and crypto-mining), the names of the top crypto currencies (Bitcoin, Ethereum, Ripple), and the names of the top mining pools (BTC.com, AntPool). We coded a mining variable equal to 1 only if an article or webpage explicitly mentioning crypto operations in the city (or the area administered by the city). We find 54 unique cities with cryptomining, and 164 unique cities without cryptomining. Figure 2 shows the location of cryptomining cities. Panel A provides the heat map of to the province level, akin to Cambridge (2018). Panel B presents data at our more granular level of city-seats. Not surprisingly, cryptomining has more intensity in the northern regions with cooler temperatures and coal-based production economies as well as in a central China river valley.

Motivated by the importance of power, we gather data on the location of power plants, in particular focusing on the distance to the closest power plant (calculated using GIS mapping) and the type of power plane (hydro, coal, solar, gas, wind, or oil).[2] Anecdotally, it is interesting that two cities where it is well-publicized that cryptomining is taking place are in Inner Mongolia. These cities — Erdos and Baotou — are located in areas surrounded by a large supply of coal plants. Sichuan, on the other hand, hosted a large volume of cryptomining during its high-river season close to the city of Mianyang, where we identify two coal plants. Table 1 presents statistics to support these observations. In China, the vast majority of the fossil fuel power is based on coal burning, with oil and natural gas being used more in coastal provinces and hydropower in some central river valleys. Nevertheless, those advocating for crytomining argue that the mining is mostly renewables.

We classify a cryptomine as being clean if the closest power plant produces electricity using hydro, solar, or wind energy. We classify a cryptomine as being fossil if the closest power plant generates electricity from coal, oil, or natural gas. As reported in Table 1, only 27.8% of cryptomining cities are powered by hydropower, plus another 13% powered by wind. This leaves just short of 60% of crytomining cities being powered by coal (48.2%) and gas (11.1%). It could be that because we do not see capacity at each cryptomining mine, we are overestimating the importance of the coal; however, given the recent press surrounding media tours of few cryptomines in Inner Mongolia (which is a coal-based province), it is probably more likely that 48.2% is an underestimate of the importance of coal. However, if 48.2% of Chinese cryptomining is powered by coal, and 80% of the world's cryptomining happened in China during this period, this implies that at least 39% of the worlds cryptomining was coal-based or 47.4% was fossil-fuel-based if adding in oil power plants. This is a large underestimate since we assume all other cryptomining is from renewables, which is clearly not the case for the large cryptomines in Alberta, Canada, western Australia, and many other places in the media with cryptomining. Thus, we conservatively conclude that one-half to two-thirds of cryptomining involved fossil fuels during this time period.

2.2 Chinese Local Economy Variables

We gather data on Chinese local economies from the province-level Yearbooks directly from each province's statistical website. We supplement with data from aggregators, whose coverage is often incomplete. Included in the data are annual local economic indicators, as

[2]The data on location of power plants comes from the Global Power Plant Database, which is comprehensive, global, open source database of power plants. We complemented this source with a manual search for additional plants not included in the database.

well as energy consumption, at the city level. Our data cover years 2011-2017 across 206 cities.

Table 1 reports the summary statistics for 154 cities without cryptomining and 52 cities with evidence of cryptomining. The average city has a population of about 360 thousands with no large differences between cities with or without cryptomining. The average GDP of cities without cryptomining is about 13 billion Yuan, while cryptomining cities have a lower average GDP around 2 billion Yuan. Despite the lower GDP cryptomining cities consume on average more energy than cities without cryptomining, collect higher business and value added taxes and have higher fixed assets investments.

Table 1 also reports the variables used in the selection model. The average (median) temperature in the sample is about 13.5 (15.6) degrees celsius. The average (median) distance of the city from the closest power plant is about 31 (23) kilometers. Finally, we gather the price of electricity at the province level from the government agency National Development and Reform Commission.[3] The average (median) price of electricity is about 539 (533) yuan per kilowatt/hour.

Figure 3 shows the evolution of electricity prices over time for six selected regions in China. Solid lines represent three regions where we have evidence of intense cryptomining activity (dark red areas in the map in Figure 2); while dash lines represent three regions where we have no (less) evidence of cryptomining activity (light yellow areas in the map in Figure 2). Over time electricity prices trend upward in all regions, but with some interesting differences across regions with higher vs lower mining intensity. Regions where there is less evidence of cryptomining activity experiences the largest increase in electricity prices, while we find lower increases in regions with intense cryptomining activity. As a result, by the end of the period all regions with cryptomining activity have lower electricity prices than region with no cryptomining activity.

Several reasons can explain this differential trends, but two remarks are worth. First, some high cryptomining regions may experience lower increases in electricity prices because the local economy is overall declining, thus lowering the demand for (and possibly the price of) electricity. This may indeed be the case of Inner Mongolia, which is always an "outlier" along the price electricity dimension. However, Jilin and Heilongjiang have almost identical electricity prices during the first half of the sample, while in the second half prices in Jilin increase significantly, while prices Heilongjiang are almost unchanged, despite the high

[3]See `ndrc.gov.cn`

electricity usage by cryptominers in the area. Second, the dynamics of electricity prices in China is an interesting comparison with our result for the US, where we find increase in electricity prices associated with increases in mining of Bitcoin. The different responses of electricity prices in China and the US following increase in demand coming from cryptomining are important to understand how market forces and regulation may shape the future of cryptocurrencies.

2.3 Cryptomines, electricity prices and consumption in New York State

We follow a similar procedure to the one in China to uncover the location of cryptomines in NY state. In this case we focus on counties as the relevant geographical unit, but present also some evidence at the city/town level. For each county, we do manual searches in Google and Google news in English. Our search terms include cryptomining (and any variation of it, such as crypto mining, crypto-mining, etc.), the names of the top crypto currencies (Bitcoin, Ethereum, Ripple), and the names of the top mining pools (BTC.com, AntPool). We coded a mining variable equal to 1 only if an article or webpage explicitly mentioning crypto operations in the county. We find 9 unique counties with cryptomining, and 52 unique counties without cryptomining.[4] Panel A of Figure 4 shows the location of cryptomining counties. Not surprisingly, cryptomining has more intensity in the northern regions with cooler temperatures and excess supply of electricity.

NY State regulators mandate counties to report monthly of data on electricity information from the utilities and data on a uniform set of economic statistics from governments. Table 2 reports the summary statistics for the main variable in the analysis. Panel A shows the data at the provider-user type level. The list of providers includes the six major utility companies in NY State. Panel B of Figure 4 shows the main provider of electricity in different areas of NY State. User types are corporate, business and household. The mean (median) monthly revenues are $42 (26) million coming from selling 360 (248) thousands megawatts per hour to 440 (225) thousands customers. The average (median) electricity price is 0.11 (0.11) $ per kilowatts per hour.

Panel B of Table 2 shows the data at the provider-user type-county level. The mean

[4]For one of the cryptomining county and five of the counties without cryptomining we do not have data on electricity price and consumption and therefore we drop them analysis.

(median) sales are 27 (8) thousands megawatts per hour to 17 (4) thousands customers. We also report average temperature at the county level It is worth nothing that we do not observe variation in electricity prices at the county level, but only the the aggregate NY State level by provider and user type.

Finally, panel C of Table 2 shows the price of BTC, which varies only over time (we have 32 months in our analysis from January 2016 to August 2018). The price of BTC is easily available online (see among other sources `https://coinmarketcap.com`). During our sample, the price of BTC is on average \$3.7 thousands, but it ranges from \$400 to more than \$15 thousands. In the empirical analysis we exploit this large swings in the price of BTC to identify the impact of electricity prices and consumption in NY State.

3 Empirical Analysis

3.1 Location of Cryptominers in China

"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

As the above quote makes clear, the location decision for cryptominers incorporates temperature (because the machines become hot and malfunction without cooling), the price of electricity, proximity to a power plant, and a friendly local government. We use the first three of these in a location choice specification.

In particular, Table 3 presents the results of a logit model for whether or not a city has cryptomining as a function of distance to closest power plant, electricity price (at the province level), and temperature (at the city level). In order to flexibly model the dependence on these variables, we use a piecewise linear spline specification. Specifically, for each variable, we partition the support into five bins based on the quintiles of the distribution, and we include an intercept and a linear slope term for each of the bins. Because our analysis on outcomes uses predictions from this estimation, we limit the sample period to 2013 and 2014, the earliest years with a full panel of data yet prior to the cryptomining period. We cluster standard errors by city to adjust for the short panel.

Column (1) shows the results based on the specification with bin-specific constants, but no bin-specific slopes. The patterns in column (1) are easy to interpret. We find that cities which are not within the first two quintiles of being the closest to a power plant are much less likely to host cryptomining. As for temperature, the pattern is non-monotonic at first. The lowest quintile locations are less likely to host cryptomining, perhaps due to the lack of power supply. Afterwards, there is a decreasing monotone pattern that colder locations are more likely to host. In pricing, the pattern becomes much more clear when we include the bin-specific slopes. Column (2) reports the results for the full specification with both intercepts and slopes varying across bins of the explanatory variables. The full specification is best interpreted by plotting the predicted probability resulting functions, which we do in Figure 5. Note that in the lower panels, we provide the histogram of the distribution of the explanatory variables in order to elucidate which regions on the graphs are economically of trivial relevance. We see clearly that distance from power plants is very important, with the closest locations having a predicted probability of nearly 0.6 on average as compared to 0.15 for those farthest away. Turning to pricing, the specification with the full set of splines in column (2) reveals a monotonically-declining relationship between between electricity prices and probability of hosting cryptomining activities. Finally, regarding temperature, we again obtain a non-monotonic pattern, but the histogram suggests that that there are few cities accounting for the increasing portion of the function.

What is perhaps most important is the very good fit of the models in columns (1) and (2) as revealed by the high pseudo R-squared coefficients. Clearly, the variables we are using to model the location decisions of cryptominers play an essential role consistent with the testimonial evidence reported at the beginning of the section.

3.2 Local Economy Outcomes in China

3.2.1 Empirical Strategy

Our empirical strategy is based on the following model:

$$Y_{ct} = \alpha \ mining_c \times Post_t + \beta_1 X_{ct}^{(1)} + \beta_2 X_{ct}^{(2)} + \gamma_c + \gamma_t + \epsilon_{ct} \tag{7}$$

where $mining_c$ is a dummy equal to one if there is evidence of cryptomining operations in city c and $Post_t$ is a dummy equal to one if $t \geq 2015$; γ_c and γ_t are city and year fixed effects; $X_{c,t}^{(1)}$ are time-varying city level controls that also enter the location model in Section 3.1 (electricity prices and population), and $X_{c,t}^{(2)}$ are controls that do *not* enter the location model (the percentage changes in population and electricity prices, as well as the percentage change in GDP). The dependent variables Y_{ct} measure the outcomes of interest corresponding to the different channels: energy consumption (the energy channel), business tax revenues (the tax revenue channel), wages, value added tax revenues and fixed asset investments (the crowding out channel). We normalize each of these outcome variables by dividing by city-level GDP and then taking logs.[5]

Notice that, since we interact $mining_c$ with the $Post_t$ indicator in (7), this is a diff-in-diff specification. In other words, the coefficient α measures how hosting cryptomining activities affects *changes* in the outcome variables over time. Any time-invariant unobservables are captured by the city fixed-effects γ_c. Thus, if miners' location decisions were only based on time-invariant unobserved factors, we could consistently recover α by estimating (7) by OLS.

However, one might be worried that time-*varying* factors might also influence the miners' location decisions. For example, our testimonial evidence suggests that cryptomining tends to locate in declining cities. In order to account for this possibility, we rely on the location decision model estimated in Section 3.1. Specifically, we employ an inverse probability weighting (IPW) strategy where the weights are the propensity scores obtained from the location model

$$mining_c = f\left(Z_{ct}, X_{ct}^{(1)}, \eta_{ct}\right) \tag{8}$$

In order to make this formal, we define $Y_{ct}^{(1)}, Y_{ct}^{(0)}$ as the potential outcomes for city c in year t with and without cryptomining, respectively. Then, under the "selection on observables" assumption

$$Y_{ct}^{(1)}, Y_{ct}^{(0)} \perp mining_c | X^{(1)}, X^{(2)}, Z, \tag{9}$$

an IPW regression based on (7) will yield consistent estimates of the effect of cryptomining on the outcomes even in the presence of time-varying unobservables. In words, the "selection on observables" assumption (9) requires that the observables included in the location and

[5]We do not normalize wages by GDP since they are already measured on a per-capita basis.

outcome models be rich enough that all the remaining variation in the location decisions is independent of the potential outcomes. The high pseudo-R^2 of the location logit model lends support to this assumption.

Still, in order to tackle potential violations of "selection on observables," we apply a control function approach to (7) and (8) (see, e.g., Wooldridge (2015)). Specifically, denoting by $\hat{r}_{ct}$ the generalized residuals from the location model (8), we estimate the following regression

$$Y_{ct} = \alpha \; mining_c \times Post_t + \beta_1 X_{ct}^{(1)} + \beta_2 X_{ct}^{(2)} + \gamma_c + \gamma_t + \hat{r}_{ct} + \epsilon_{ct} \tag{10}$$

with IPW. This allows for the fact that unobservable factors affecting the location decisions — η_{ct} in (8) — might also enter the outcome equations and thus provides estimates that are robust to violations of "selection on observables."

3.2.2 Results

Tables 4 to 7 show the results of our main regressions. The different columns correspond to different approaches to deal with the endogeneity of cryptominers' location decisions, as detailed in Section 3.2.1.

We start by looking at whether crypto operations lead to higher energy consumption. On the one hand, one would expect energy consumption to increase due to the nature of cryptomining, all else equal; on the other, it could be that crypto operations crowd out energy usage by other economic activities. Thus, the net effect is a priori ambiguous, implying that this is ultimately an empirical question. As shown in Table 4, we find some evidence of an increase in energy consumption per unit of GDP in Chinese cities hosting crypto operations.

Next, we investigate the reasons why local governments in China might be willing to allow or even encourage cryptomining. The results in Table 5 strongly support the thesis that governments have an incentive to attract cryptomining due to the fact that it tends to increase business tax revenues (relative to GDP).

Given this, an interesting question is whether local governments are able to fully predict the ramifications of hosting cryptomines. To this end, we consider the effect of cryptomining on economic measures other than business tax revenues. Interestingly, Table 6 shows that wages tend to *decrease* as a result of crypto operations, with a more statistically and economically significant effect for cities located near fossil fuel power plants. Tables 6 and 7 also point to a negative effect on value-added taxes revenues and fixed asset investments, although not statistically significant. Taken together, these findings suggest that, while governments benefit from cryptomining via a substantial increase in business tax revenues, large swaths of the local economies suffer as a result. This crowding out effect constitutes an important (possibly unintended) consequence of hosting crypto operations that local governments should weigh against the benefits in terms of increased business tax revenues.

3.3 Electricity Consumption and Prices in New York State

"In recent months, NYMPA members have experienced a dramatic increase in requests for new service for disproportionately large amounts of power. Most such requests come from similar types of potential customers: server farms, generally devoted to data processing for cryptocurrencies. ... These applicants tend to require high quantities of power and have extremely high load density and load factors. In addition, these customers do not bring with them the economic development traditionally associated with similar load sizes. These customers have few to no associated jobs, and little if any capital investment into the local community. ... The potential for sudden relocations results in unpredictable electrical use fluctuations in the affected areas. In sum, HDL customers negatively affect existing customers."

— Read AND Laniado, LLP, February 15, 2018

The above quote summarizes the heated debate taking places in some areas of New York State, where cryptominers exploited the cold climate and cheap electricity to set up some of their largerst facilities. In this section, we turn to New York State to consider another consequence of cryptomining at the local level — the incidence of price impact on local actors. The electricity market in NY is divided (and uniformly reported) into three markets — household, small commercial, and business. In the small commercial market, pricing is often bound by contracts. Thus, electricity prices do not react in the short-term to pressures or shocks in supply and demand. Likewise, household utility prices are often fixed, except when a utility implements a well-publicized change through a process of negotiation with the local government. However, in the business market, prices are much more variable.

3.3.1 An Event Study

We begin our analysis of the impact of Bitcoin prices on electricity consumption and prices in NY State by focusing on the dynamics around a clear event. Most notably, we focus on the city of Plattsburgh in New York state, which has been the first municipality in the US to issue a moratorium on cryptocurrency. Plattsburgh attracted a lot of mining activities due to its cold climate and cheap electricity. Residents pay about 4.5 cents per kilowatt-hour, compared to 10 cents which is what the rest of the country pays on average, and the price of electricity for industrial activity is even lower at 2 cents per kilowatt-hour.

Figure 6 shows monthly electricity consumption in the town of Plattsburgh and the neighboring town of Peru. Before the end of 2017 both Plattsburgh and Peru experience a similar pattern in electricity consumption. However, in January 2018 just after the peak of the Bitcoin price we observe an increase in electricity consumption of almost 150% relative to December in Plattsburgh, while almost no change in Peru. Interestingly, after Plattsburgh issues the moratorium on cryptocurrencies the energy consumption returns to a pattern which resembles the one of the neighboring town Peru. Preliminary evidence from articles suggests that residents in Plattsburgh experienced increases in electricty bills by $100-200 during January and February 2018.

In Figure 6 we also look at the pattern of electricity consumption in Plattsburgh and Peru exactly one year before the Bitcoin price peaked. We emphasize the month of the Bitcoin price peak and the same month the previous year in grey. We do not find large differences in consumption between Plattsburgh and Peru as the price of Bitcoin fluctuates mildly around an average of $1.000.

To reinforce our story of a causal effect of cryptomining on local electricity consumption we perform an additional test. In Figure 7 we compute for the each city-town and each month in 2018 the difference in electricity consumption relative to the same months the previous year. [6] We then compare changes in Plattsburgh relative to the changes in all other towns in NY state, for which we show different moments of the distribution. Plattsburgh displays absolute differences in electricity consumption across years that are significantly larger than other towns in NY state. The large local presence of cryptomining companies increase the volatility of electricity demand which respond to sudden changes in the price of Bitcoin.

[6] Note that for September to December we are computing 2017 relative to 2016, as our data ends in August 2018.

3.3.2 Empirical Strategy

In this section we sketch our empirical strategy to understand the impact of Bitcoin prices on the price of electricity. Our empirical strategy is based on the following model, which we estimate separately for each user type:

$$Y_{put} = \alpha BTC\ price_t + \beta X_{tu} + \gamma_p + \epsilon_{put}, \tag{11}$$

where $BTC\ price_t$ is the logarithm of Bitcoin prices; γ_p are provider fixed effects; X_{tu} are additional controls (month fixed effects and temperature). The dependent variable Y_{put} measure the main outcomes of interest, the logarithm of electricity prices by provider p to user type u at time t. In the appendix we also report estimates for the same model on some closely related variables that we also observe at the same level of aggregation: revenues, sales and number of customers. Our parameter of interest is α which measures the elasticity of electricity price to Bitcoin price. Notice that with months fixed effects we are controlling for variation in prices due to seasonality and with temperature we are controlling for year-on-year differences due to exceptional weather circumstances which can affect the price of electricity.

Given that electricity prices do not vary across counties we cannot fully exploit cross-sectional variation in mining activities (Panel A in Figure 4). However, we leverage the different geographical distribution of the operations of different utility providers (Panel B of Figure 4) to create a measure of exposure of utility providers to variation in Bitcoin prices. More precisely, we focus on New York State Electricity and Gas (NYSEG) and Central Hudson Gas and Electricity (CHG&E). The former operates in several counties in the north-east of NY State, where we found evidence of cryptomining. The latter operates instead in counties in the south (Albany and below), where we founds no evidence of cryptomining. Using electricity prices from these two providers, we estimate the following empirical model:

$$Y_{put} = \alpha BTC\ price_t \times Treated\ provider_p + \beta X_{tu} + \gamma_p + \gamma_t + \epsilon_{put}, \tag{12}$$

where $BTC\ price_t$ is the now a dummy equal to one if the price of Bitcoin is above \$10 thousands; $Treated\ provider_p$ is a dummy equal to one if the provider is located in areas with evidence of cryptomining; γ_p and γ_t are provider and time fixed effects; X_t are additional controls (temperature). The dependent variables Y_{put} measure the main outcomes of interest, the logarithm of electricity prices by provider p to user type u at time t. Our parameter of interest if α which in this case measures the differential effect of extremely high Bitcoin prices on the price of electricity for providers in areas where cryptomining is likely to take place. Notice that, since we interact *Treated provider*$_p$ with the *BTC price*$_t$ indicator in (12), this is a diff-in-diff specification. In other words, the coefficient α measures how hosting cryptomining activities affects *changes* in the electricity prices over time when the price of Bitcoin is extremely high. Any time-invariant unobservables are captured by the provider fixed-effects γ_p and all macro-level time-varying factors are now absorbed by the time fixed-effects γ_t.[7]

3.3.3 Results

We now present the results on the effect of Bitcoin prices on electricity prices for NY State. Table 8 collects the main results.

Columns (1) to (3) shows the estimates from equation (11). We find an average positive and significant association between Bitcoin price and price of electricity for all user types in NY State. Looking at magnitudes, the effects are largest for business with an elasticity of almost 0.08. A 100% increase in Bitcoin price generates a 8 percent increase in electricity prices for businesses. The elasticities for commercial and households are smaller, but still not negligible in magnitude. A 100% increase in Bitcoin price generates a 2 (3) percent increase in electricity prices for commercials (households). To put these numbers in context, when the price of Bitcoin went from about \$5 thousands to more than \$15 thousands at the end of 2017 (a threefold increase) electricity prices raised on average by 16 percent for business, 4 percent for commercials and 6 percent for households.

One possible concern with our estimates of the elasticities of electricity prices to the price of Bitcoin is that they are biased by unobservable time-varying factors correlated with the price of Bitcoin. To address this concern we exploit cross-sectional variation in "exposure" to fluctuations in the price of Bitcoin among providers of electricity in NY State. Figure 8 provides the graphical representation of our difference in differences exercise. We focus on the price of electricity for Businesses by New York State Electricity and Gas (NYSEG) and Central Hudson Gas and Electricity (CHG&E) and normalized the price to 100 in December 2017. Before the end of 2017 both NYSEG and CHG&E experience a similar pattern in

[7]Note that the time fixed-effects fully absorb the average effect of Bitcoin prices, while we can still estimate the effect of temperature because the latter varies over time but also across providers due to their different geographical location.

the price of electricity. It is interesting to note that NYSEG has more volatility on average than CHG&E. However, in January 2018 just after the peak of the Bitcoin price the price electricity more than double for NYSEG, while CHG&E only displays a small increase.

In Figure 8 we also look at the price of electricity by NYSEG and CHG&E exactly one year before the Bitcoin price peaked. We emphasize the month of the Bitcoin price peak and the same month the previous year in grey. We do not find large differences in the price of electricity between NYSEG and CHG&E as the price of Bitcoin fluctuates mildly around an average of $1.000.

Columns (4) to (6) of Table 8 shows the estimates from equation (12). We find an average positive and significant association between high Bitcoin price and the price of electricity by NYSEG for businesses and commercials. The magnitude of the effects are large too. In the periods in which the Bitcoin price is above $15 thousands businesses (commercial companies) in affected areas in NY state pay about a 54 (27) percent higher prices for electricity than business (commercial companies) in unaffected areas. The estimates are positive, but not significant for the case of households, consistent with the higher stickiness of electricity prices for households.

4 Conclusion

In this paper, we have presented testimonial and empirical evidence of the effects of cryptomining on local economies. Using data from Chinese cities, we find that crypto operations tend to substantially increase business taxes, which provides a strong incentive for local governments to attract cryptominers. At the same time, we find negative impacts on local wages and value added taxes, suggesting that cryptomining results in crowding-out of other economic activities. The evidence from New York State points to an upward pressure on electricty prices for business and commercial operations, with potential spillovers to electricity prices for households as well. Overall, our findings suggest that local governments in their decisions to allow cryptomining should weigh against the benefits in terms of increased taxes the potentially large costs in terms of crowding-out of other economic activities. A fully-fledged welfare analysis of cryptomining must balance global pollution externalities and local crowding out against oligopolistic cryptomining profits and local government revenue gains.

References

Alsabah, H. and A. Capponi (2018). Bitcoin mining arms race: R&d with spillovers. Working Paper.

Budish, E. (2018). The economic limits of bitcoin and the blockchain. Working Paper.

Cong, L. W., Z. He, and J. Li (2018). Decentralized mining in centralized pools. Working Paper.

Ma, J., J. Gans, and R. Tourky (2018). Market structure in bitcoin mining. NBER Working Paper 24242.

Tørsløv, T. R., L. S. Wier, and G. Zucman (2018). The missing profits of nations. NBER Working Paper 24701.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*.

Figure 1: Bitcoin price and world-wide electricity consumption

Note: The chart shows the price of Bitcoin and the minimum and estimated energy consumption per year for Bitcoin mining. Bitcoin prices comes from Coinmarketcap. Bitcoin minimum and estimated energy consumption comes from `https://digiconomist.net/bitcoin-energy-consumption`.

Panel A: Province-level locations of crytomining

Panel B: City-Seat-level locations of cryptomining

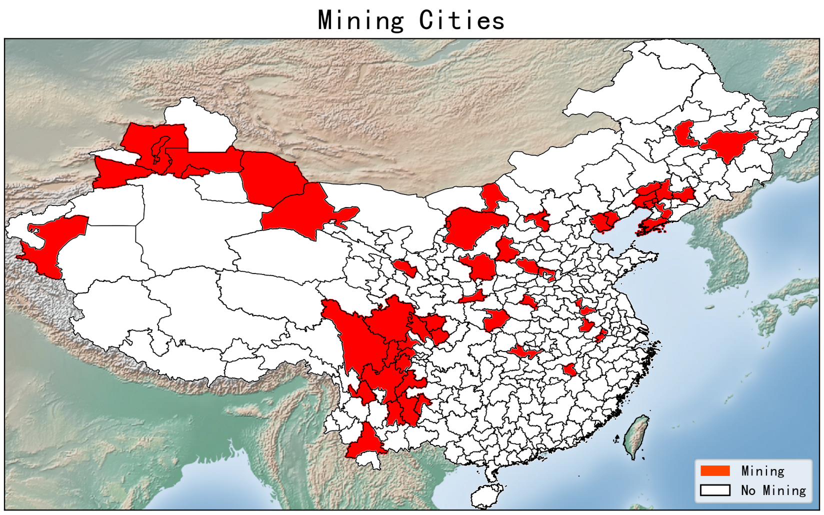


Figure 2: Mining cities

Note: Data on mining locations come from manual searches in local newspapers and newsources in Mandarin through Baidu and in English through Google. In panel A, we depict a heat map of China Province-level cryptomining counts. In panel B, we present locations at our finer level of cities-seat, where a city-seat is the main city with its controlling surrounding areas (akin to counties).

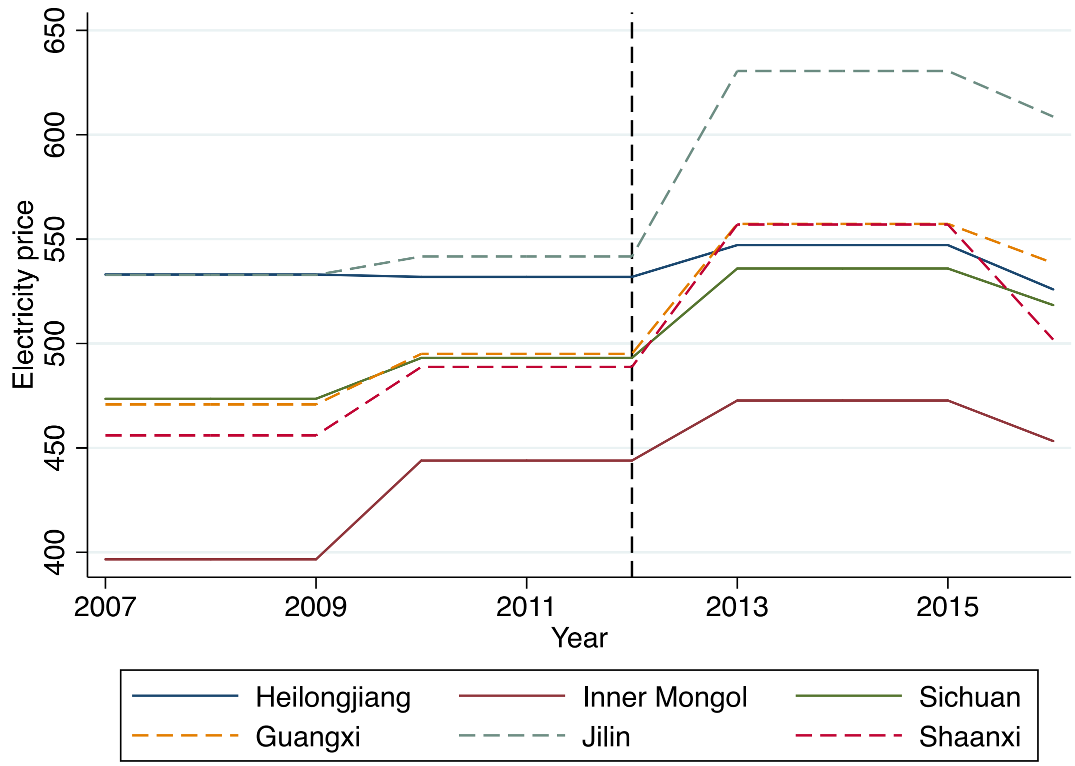
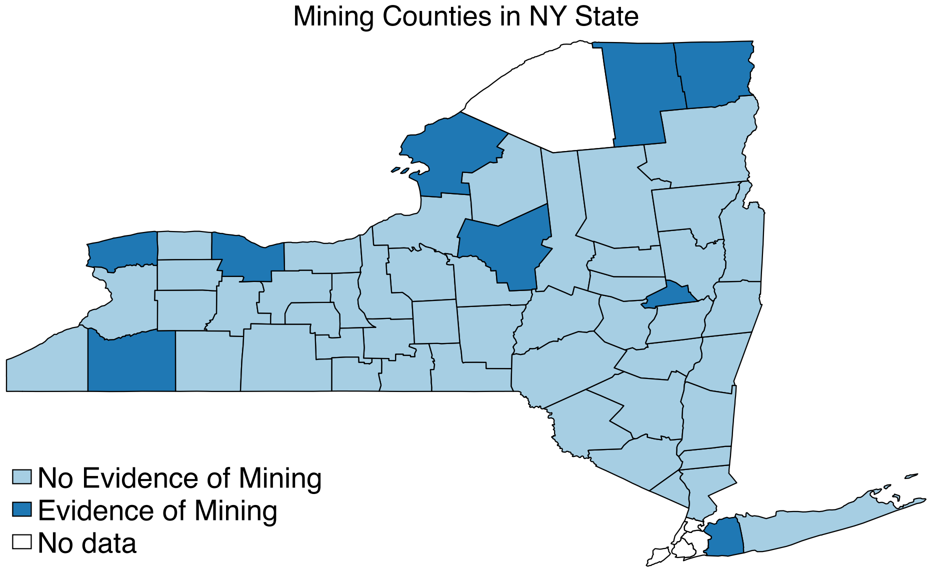


Figure 3: Electricity prices over time in China

Note: Data on electricity prices in China from from the government agency National Development and Reform Commission (URL: `ndrc.gov.cn`). We collected data for all provinces in China for 2009-2010 and 2015-2016. We fill the missing years in the following way. We attribute 2009 prices for all years up to 2009, 2010 prices for years between 2010 and 2012, 2015 prices for years between 2013 and 2015, and 2016 prices for years from 2016 onward. The chart reports electricity prices for three regions with high cryptomining activity (Heilongjiang, Inner Mongolia and Sichuan) and three regions with low cryptomining activity (Guangxi, Jilin and Shaanxi) based on the data reported in Figure 2.

Panel A: County-level locations of crytomining



Panel B: Map of electricity providers

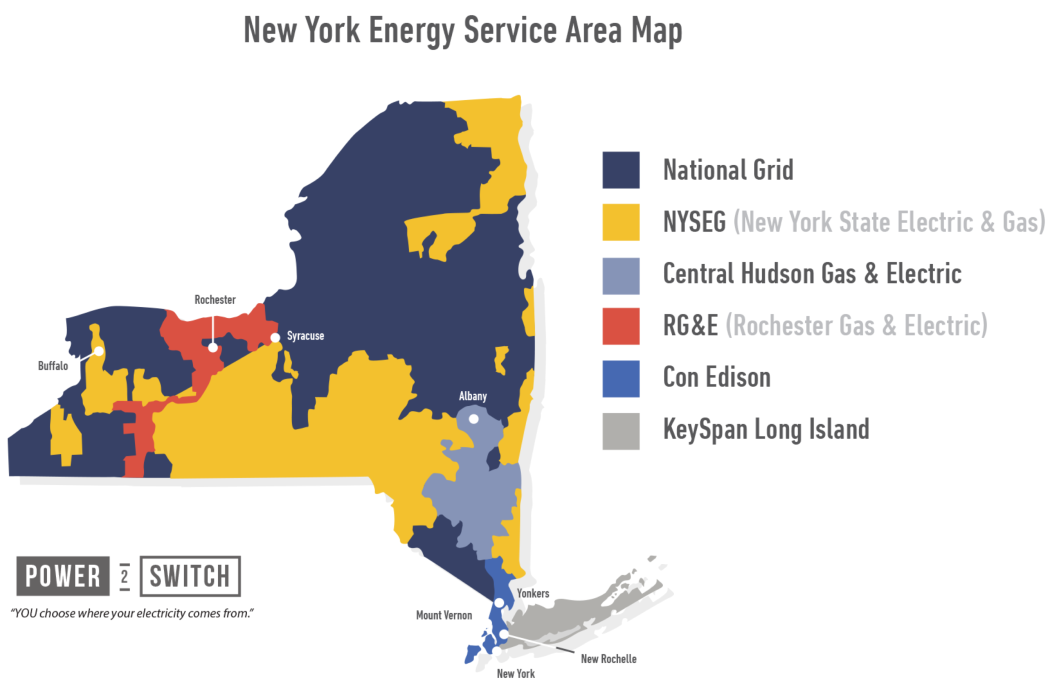


Figure 4: Mining counties and electricity providers in New York state

Note: In panel A, we present a map with mining counties identified from manual searches in local newspapers and newsources through Google. Panel B shows the map of electricity providers in New York State (URL: `https://power2switch.com/NY/utility_territory_map/`).

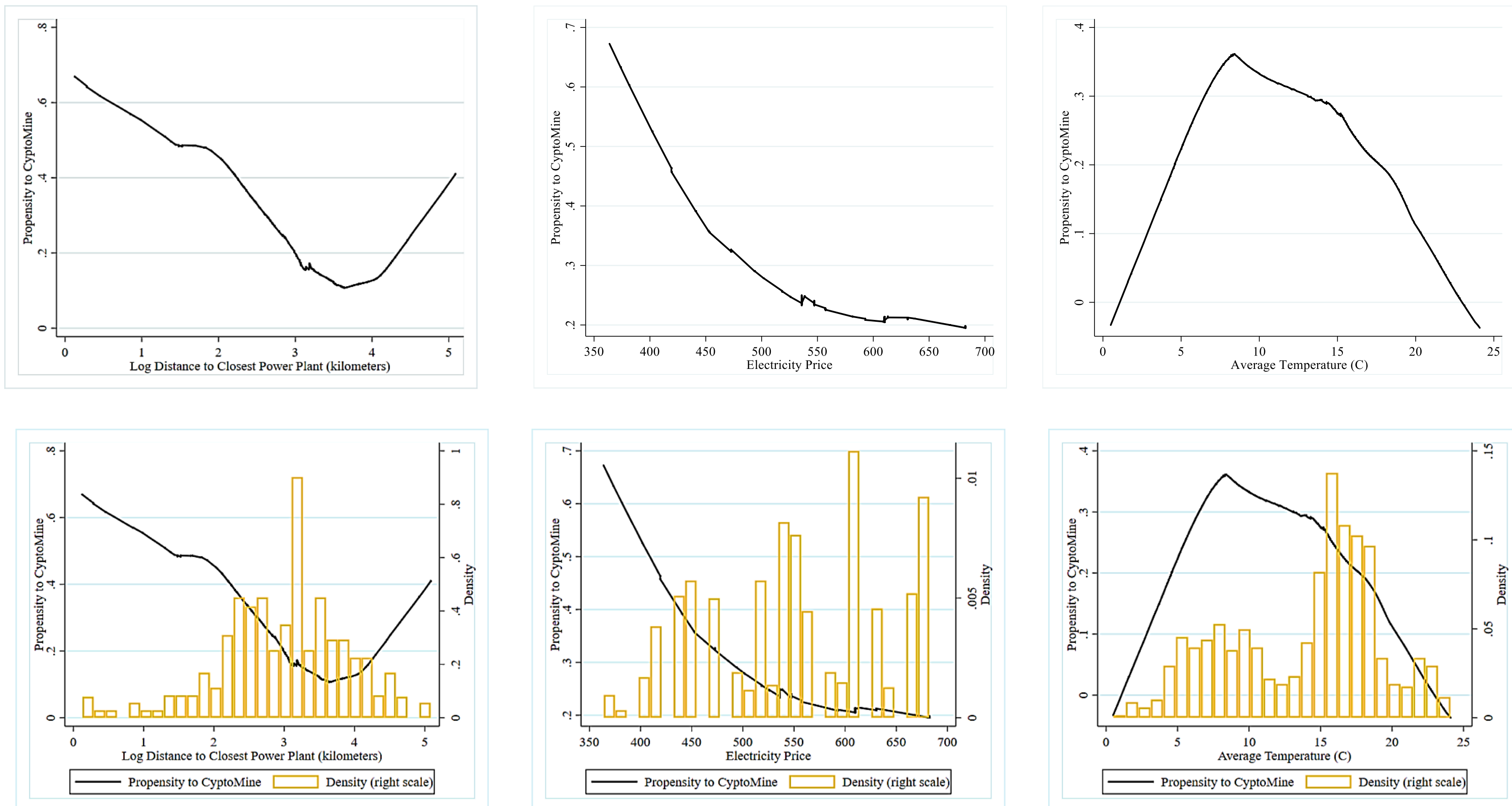


Figure 5: Predicted Propensity of a City to Host CrytoMining by Distance to Power Plant, Electricity Price & Temperature

Note: Presented are graphics emerging from the predicted values of the location decision of the logit model column (2) of Table 2. The model includes the full spline specification of knot constants and interval slopes for each of the three variables depicted above - log distance to closest power plant, electricity price, and average city temperature (Celsius). The top row of figure are the predict location propensity score plotted against the continuous variable. The bottom figures add in the underlying density (a simple histogram) of the x-axis variable to show which regions of the plots are relevant.

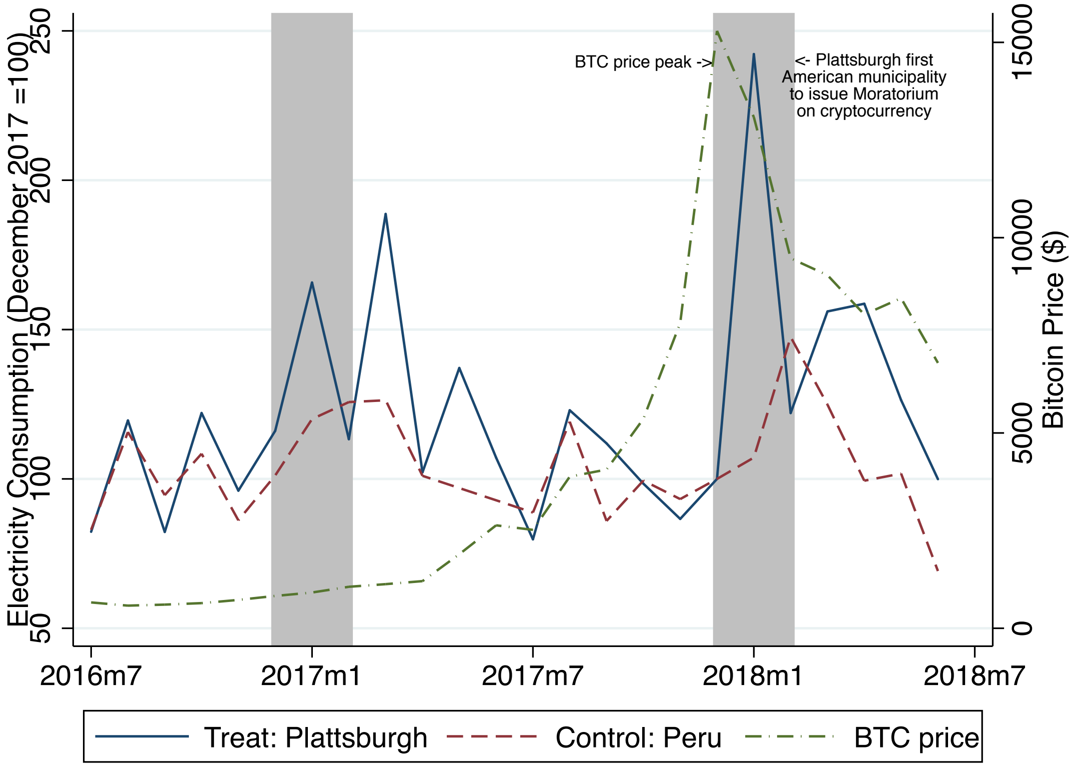


Figure 6: Bitcoin prices and electricity consumption

Note: Electricity consumption data comes from NYSERDA. The blue sold line and the red dash line shows total electricity consumption by small businesses in Plattsburgh and Peru, respectively. We normalize electricity consumption in each town to 100 in December 2017, which is the month is which Bitcoin prices reach their maximum at around $15.000. Bitcoin price data comes from Coinmarketcap. Grey areas denote december, january and february of 2016-2017 and 2017-2018.

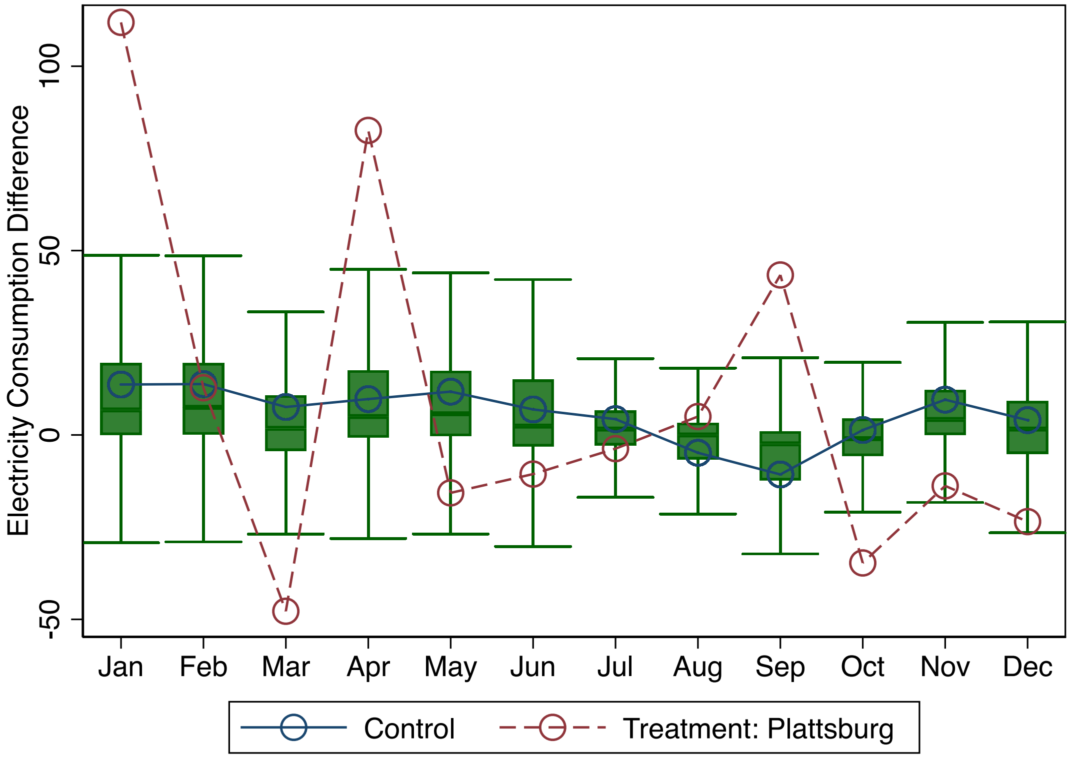


Figure 7: Bitcoin prices and electricity consumption within town across years

Note: Energy consumption data comes from NYSERDA. For each town we compute for the each month in 2018 the difference in electricity consumption relative to the same months the previous year. For September to December we compute the difference between the month in 2017 relative to the same month in 2016, as our data ends in August 2018. The dash red line shows the case of Plattsburgh. The differences for all other cities and towns represented by Tukey boxplots, where the box represents the interquartile range (IQR) and the whiskers represent the most extreme observations still within 1.5 $\times$ IQR of the upper/lower quartiles.

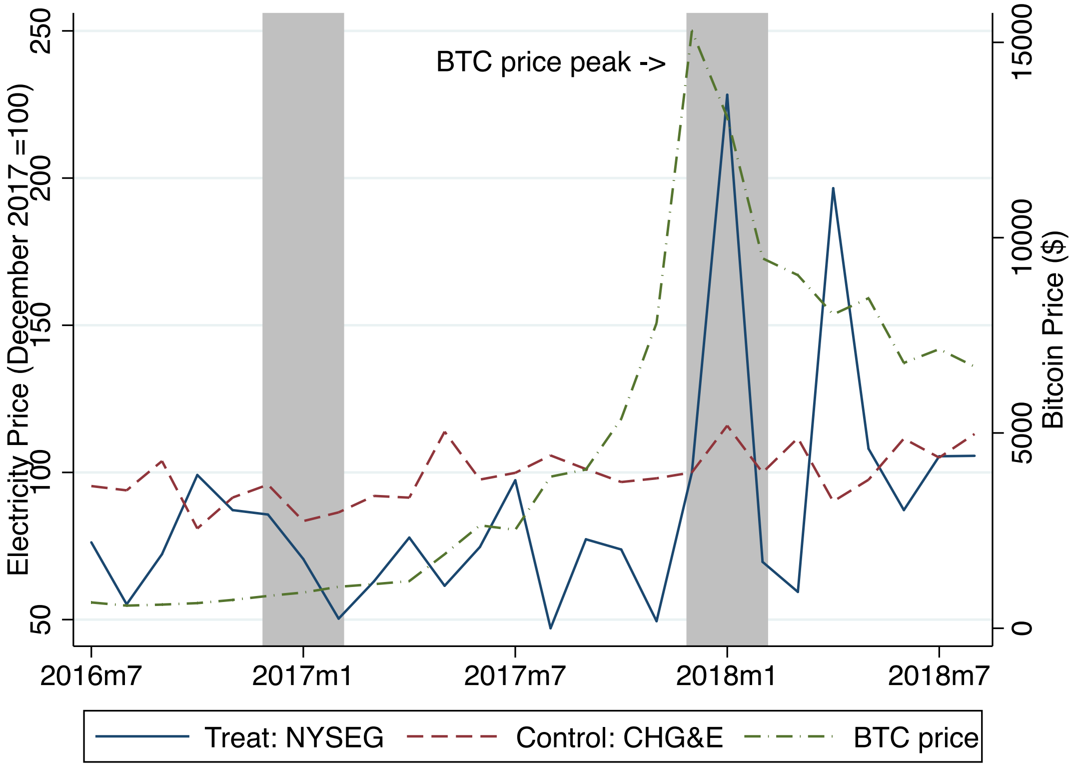


Figure 8: Bitcoin prices and electricity prices

Note: Price of electricity data comes from NYSERDA. The blue sold line and the red dash line shows the electricity price for corporate in NYSEG and CHG&E (Central Hudson Gas & Electric), respectively. We normalize electricity prices for each utility provider to 100 in December 2017, which is the month is which Bitcoin prices reach their maximum at around $15.000. Bitcoin price data comes from Coinmarketcap. Grey areas denote december, january and february of 2016-2017 and 2017-2018.

Table 1: Summary Statistics

Summary statistics are presented at the city-seat level for all of the cities within the inland provinces of China, with the exception of three export-oriented, large metropolitian areas. The city data is the average over the time period 2010-2017 for each city, unbalanced in the early years. Panel A reports statistics for cities not hosting cryptomining, and Panel B, with cryptomining. Economic variable data are from Province Yearbooks. The location of cryptomines are from manual news searches in Baidu using each city name and keywords for cryptomining.

Panel A: Inland Cities without Cryptomining

	Unique Cities	Mean		St. Dev	Minimum	Median	Maximum
Population (1,000s)	154	355.7		237.2	20.6	298.5	1,194.2
GDP (million CNY)	154	13,550		126,523	8,394	99,155	843,242
Energy (10,000 Kwh)	148	513,162		579,782	18,763	333,605	3,730,726
Business Taxes (million CNY)	43	214.1		0.7	0.9	2.0	3.9
Value-Add Taxes (million CNY)	54	148.7		0.8	-0.2	1.4	3.7
Fixed Asset Invest. (million CNY)	163	111,974		1,014	59	852	6,392
Location Prediction Variables							
Temperature (Celsius)	123	13.8		5.6	-1.0	15.6	23.2
Electricity Price (yuan /KwH)	155	539		71	362	533	638
Closest Distance to Power (Km)	164	31.8		33.7	1.2	23.2	324.2
Closest Power Plant Type:	Coal	61.0%					
	Gas	7.9%					
	Hydro	19.5%					
	Oil	0.6%					
	Solar	1.8%					
	Wind	9.2%					

Panel B: Inland Cities with Cryptomining

	Unique Cities	Mean		St. Dev	Minimum	Median	Maximum
Population (1,000s)	52	375.6		251.5	55.3	326.7	1,319.4
GDP (million CNY)	52	1,877	**	1,803	190	1,270	8,973
Energy (10,000 Kwh)	44	956,075	***	958,055	53,061	512,366	4,878,905
Business Taxes (million CNY)	10	282.5	**	107.2	163.8	259.2	515.6
Value-Add Taxes (million CNY)	12	239.3	**	116.5	87.6	200.7	438.8
Fixed Asset Invest. (million CNY)	54	154,877	**	147,673	23,719	100,727	696,984
Location Prediction Variables							
Temperature (Celsius)	40	13.1		4.2	5.0	14.7	19.7
Electricity Price (yuan /KwH)	52	519	*	75	407	519	638
Closest Distance to Power (Km)	54	21.8	**	24.4	1.1	13.3	137.5
Closest Power Plant Type:	Coal	48.2%					
	Gas	11.1%					
	Hydro	27.8%					
	Oil	0.0%					
	Solar	0.0%					
	Wind	13.0%					

Table 2: New York State Data

Data are from the economic statistics website of New York State and from each electricity provider's required reporting ot the electricity regulator

	Obsevations	Mean	St. Dev	Minimum	Median	Maximum
Panel A: Provider-user type level						
Revenues (1.000$)	502	42,327	41,386	282	26,425	173,524
Sales (MWH)	502	364,422	348,739	2,698	248,439	1,383,197
Customers (Count)	502	443,750	481,623	285	225,763	1,377,314
Price ($/kWh)	502	0.11	0.03	0.04	0.11	0.21
Panel B: County level						
Sales (MWH)	10,880	27,740	59,857	0	8,713	634,171
Customers (Count)	10,880	17,439	37,159	0	4,661	298,589
Temperature (Degrees Fahrenheit)	10,880	47.50	17.01	13.50	49.70	76.80
Panel C: Other						
BTC price ($)	32	3,779	4,072	404	1,207	15,294

Table 3: CryptoMining Location Decision

Presented are logit coefficients from the choice of cryptomining city location. Economic variable data are from Province Yearbooks. The location of cryptomines are from manual news searches in Baidu using each city name and keywords for cryptomining. The data are from 2013-2014. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable:	Logit (City has CryptoMining)	
	(1)	(2)
Distance to Closest Power Plant		
Quintile 2	-0.432	-16.39*
	[0.600]	[9.156]
Quintile 3	-2.779***	-64.19*
	[0.833]	[34.98]
Quintile 4	-1.646**	9.848
	[0.813]	[14.52]
Quintile 5	-1.637**	-13.55**
	[0.751]	[6.136]
Slope Quintile 1 to 2		-0.022
		[0.703]
Slope Quintile 2 to 3		5.763*
		[3.488]
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]
Temperature		
Quintile 2	1.833**	14.39***
	[0.733]	[5.233]
Quintile 3	1.297	14.73***
	[0.888]	[4.133]
Quintile 4	1.215*	13.83***
	[0.700]	[3.897]
Quintile 5	-0.316	12.61***
	[0.898]	[3.837]
Slope Quintile 1 to 2		2.195***
		[0.631]
Slope Quintile 2 to 3		0.132
		[0.265]
Electricity Price		
Quintile 2	-1.288	-48.6
	[0.935]	[47.01]
Quintile 3	-0.259	-25.47
	[0.910]	[15.64]
Quintile 4	-1.988*	-28.85*
	[1.136]	[15.97]
Quintile 5	-0.855	-27.67*
	[0.845]	[16.00]
Slope Quintile 1 to 2		-0.0640*
		[0.0375]
Slope Quintile 2 to 3		0.0426
		[0.0831]
Log Population	0.405	0.303
	[0.373]	[0.419]
Observations	276	276
Pseudo R-squared	0.25	0.387

Table 4: Effect of Cryptomining on Energy Consumption

All models are difference-in-differences specifications, with varying methods to account for location selection. The dependent variable is an annual observation of kilowatt hours of energy consumption per city GDP at the city-seat level for all of the cities within the inland provinces of China. Economic variables data are from Province Yearbooks. MiningCity is an indicator that the city-seat hosts cryptomines, manually collected from news searches in Baidu and other sources using each city name and keywords for cryptomining. Post indicates post-2015. Clean indicates that the city's clostest power plant is hydropower, wind or solar. Fossil indicates that the power plant is coal, oil, or gas. The Predicted MiningCity and ControlFunction variables are respectively the predicted probability of cryptomining (propensity score) and the residual from Table 3, column (2). Column (1) is OLS. Columns (2) and (3) are IPW, weighting observations by the inverse probability weight, normalized, to level the estimated weights to make the treatment and control have the same probability of hosting cryptomining. Column (4) is an IV-specification where the variables temperature and distance to power plant from Table 3, column (2) serve as the instruments, still within the IPW difference-in-differences framework. Columns (5) and (6) are control function IPW difference-in-differences specifications. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Log (Energy Consumption per GDP)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	IPW-CF
Post * MiningCity * Clean	-0.108	-0.0381				
	[0.109]	[0.101]				
Post * MiningCity * Fossil	0.227***	0.234***				
	[0.0635]	[0.0701]				
Post * MiningCity			0.151**			
			[0.0719]			
Post * Predicted MiningCity * Clean				0.0474	0.0528	
				[0.150]	[0.151]	
Post * Predicted MiningCity * Fossil				0.202	0.228	
				[0.152]	[0.151]	
Post * ControlFunction * Clean					-0.0824	
					[0.0585]	
Post * ControlFunction * Fossil					0.118	
					[0.0970]	
Post * Predicted MiningCity						0.161
						[0.145]
Post * ControlFunction						0.0714
						[0.0802]
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	595	595	595	595	590	590
R-squared	0.923	0.919	0.919	0.919	0.92	0.919

Table 5: Effect of Cryptomining on Local Business Taxes

All models are difference-in-differences specifications, with varying methods to account for location selection. The dependent variable is an annual observation of the log of business taxes collected per city GDP at the city-seat level for all of the cities within the inland provinces of China. Economic variables data are from Province Yearbooks. MiningCity is an indicator that the city-seat hosts cryptomines, manually collected from news searches in Baidu and other sources using each city name and keywords for cryptomining. Post indicates post-2015. Clean indicates that the city's clostest power plant is hydropower, wind or solar. Fossil indicates that the power plant is coal, oil, or gas. The Predicted MiningCity and ControlFunction variables are respectively the predicted probability of cryptomining (propensity score) and the residual from Table 3, column (2). Column (1) is OLS. Columns (2) and (3) are IPW, weighting observations by the inverse probability weight, normalized, to level the estimated weights to make the treatment and control have the same probability of hosting cryptomining. Column (4) is an IV-specification where the variables temperature and distance to power plant from Table 3, column (2) serve as the instruments, still within the IPW difference-in-differences framework. Columns (5) and (6) are control function IPW difference-in-differences specifications. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Log (Business Taxes per GDP)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	IPW-CF
Post * MiningCity * Clean	0.0566	0.0569				
	[0.0468]	[0.0425]				
Post * MiningCity * Fossil	0.117*	0.127*				
	[0.0628]	[0.0645]				
Post * MiningCity			0.104*			
			[0.0544]			
Post * Predicted MiningCity * Clean				0.235*	0.260**	
				[0.134]	[0.123]	
Post * Predicted MiningCity * Fossil				0.262**	0.292**	
				[0.118]	[0.126]	
Post * ControlFunction * Clean					-0.106**	
					[0.0483]	
Post * ControlFunction * Fossil					-0.0492	
					[0.0553]	
Post * Predicted MiningCity						0.285**
						[0.121]
Post * ControlFunction						-0.0681
						[0.0449]
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	255	255	255	255	255	255
R-squared	0.904	0.889	0.891	0.906	0.892	0.892

Table 6: Effect of Cryptomining on Households

All models are difference-in-differences specifications, with varying methods to account for location selection. The dependent variable in columns (1) to (6) is an annual observation of the log of hourly wages at the city-seat level for all of the cities within the inland provinces of China. The dependent variable in columns (7) to (12) is an annual observation of the log of value-added taxes paid (as a proxy for consumption) per GDP. Economic variables data are from Province Yearbooks. MiningCity is an indicator that the city-seat hosts cryptomines, manually collected from news searches in Baidu and other sources using each city name and keywords for cryptomining. Post indicates post-2015. Clean indicates that the city's clostest power plant is hydropower, wind or solar. Fossil indicates that the power is coal, oil, or gas. The Predicted MiningCity and ControlFunction variables are respectively the predicted probability of cryptomining (propensity score) and the residual from Table 3, column (2). Column (1) is OLS. Columns (2) and (3) are IPW, weighting observations by the inverse probability weight, normalized, to level the estimated weights to make the treatment and control have the same probability of hosting cryptomining. Column (4) is an IV-specification where the variables temperature and distance to power plant from Table 3, column (2) serve as the instruments, still within the IPW difference-in-differences framework. Columns (5) and (6) are control function IPW difference-in-differences specifications. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable: Log (Wages)						Dependent Variable: Log (VA Tax per GDP)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	IPW-CF	OLS	IPW	IPW	IPW-IV	IPW-CF	IPW-CF
Post * MiningCity * Clean	-0.0139	-0.0105					0.0452	0.0308				
	[0.0379]	[0.0467]					[0.119]	[0.140]				
Post * MiningCity * Fossil	-0.0843**	-0.0665*					-0.108	-0.147				
	[0.0341]	[0.0349]					[0.106]	[0.0901]				
Post * MiningCity			-0.0506*						-0.0963			
			[0.0294]						[0.0949]			
Post * Predicted MiningCity * Clean				-0.0405	-0.0341					0.382	0.369	
				[0.0624]	[0.0641]					[0.504]	[0.392]	
Post * Predicted MiningCity * Fossil				-0.115***	-0.115**					-0.228	-0.146	
				[0.0437]	[0.0449]					[0.173]	[0.205]	
Post * ControlFunction * Clean					-0.00495						-0.463	
					[0.0340]						[0.366]	
Post * ControlFunction * Fossil					-0.00359						-0.0198	
					[0.0179]						[0.0921]	
Post * Predicted MiningCity						-0.0995**						0.00763
						[0.0410]						[0.254]
Post * ControlFunction						-0.0024						-0.136
						[0.0161]						[0.171]
City Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	698	698	698	698	693	693	301	301	301	301	301	301
R-squared	0.969	0.934	0.933	0.935	0.935	0.935	0.761	0.740	0.740	0.743	0.750	0.741

Table 7: Effect of Cryptomining on Local Investment

All models are difference-in-differences specifications, with varying methods to account for location selection. The dependent variable is an annual observation of the log of fixed asset investment per city GDP at the city-seat level for all of the cities within the inland provinces of China. Economic variables data are from Province Yearbooks. MiningCity is an indicator that the city-seat hosts cryptomines, manually collected from news searches in Baidu and other sources using each city name and keywords for cryptomining. Post indicates post-2015. Clean indicates that the city's clostest power plant is hydropower, wind or solar. Fossil indicates that the power is coal, oil, or gas. The Predicted MiningCity and ControlFunction variables are respectively the predicted probability of cryptomining (propensity score) and the residual from Table 3, column (2). Column (1) is OLS. Columns (2) and (3) are IPW, weighting observations by the inverse probability weight, normalized, to level the estimated weights to make the treatment and control have the same probability of hosting cryptomining. Column (4) is an IV-specification where the variables temperature and distance to power plant from Table 3, column (2) serve as the instruments, still within the IPW difference-in-differences framework. Columns (5) and (6) are control function IPW difference-in-differences specifications. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Log (Fixed Asset Investment per GDP)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	IPW-CF
Post * MiningCity * Clean	-0.101	-0.124				
	[0.126]	[0.175]				
Post * MiningCity * Fossil	-0.170**	-0.117				
	[0.0825]	[0.0771]				
Post * MiningCity			-0.119			
			[0.0790]			
Post * Predicted MiningCity * Clean				-0.324	-0.335	
				[0.287]	[0.290]	
Post * Predicted MiningCity * Fossil				-0.161	-0.173	
				[0.120]	[0.122]	
Post * ControlFunction * Clean					0.0514	
					[0.144]	
Post * ControlFunction * Fossil					-0.0272	
					[0.0565]	
Post * Predicted MiningCity						-0.196
						[0.128]
Post * ControlFunction						-0.0132
						[0.0549]
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	704	704	704	699	699	699
R-squared	0.63	0.616	0.616	0.618	0.619	0.618

Table 8: Effect of Bitcoin Price on Electricity Prices

Columns (1) to (3) report the estimates of the fixed effect model. Columns (4) to (6) report the estimates of the difference-in-differecens model. The dependent variable is an the log of the monthly price of electricity per provider per user type. Electricity data are from NYSERDA. Bitcoin price data are from Coinmarketcap. Temperature data are from the National Center for Environmental Information. In columns (4) to (6) we focus on two providers: NYSEG and Central Hudson Gas and Electric. Treated provider is an indicator for NYSEG, a provider operating in areas in which we manually collected evidence on crypomining from news searches in google and other using each county name and keywords for cryptomining. Month fixed effects are dummies for the months capturing seasonality. Provider fixed effects are dummies for each provider capturing time-invariant differences in electricity prices. Time fixed effects are dummy for the year-month capturing aggregate time-varying trends in electricity prices. Errors are clustered at the time level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Log (Electricity Price)					
	Fixed effect model			Difference-in-differences		
	Business	Commercial	Household	Business	Commercial	Household
BTC price (log)	0.077***	0.019***	0.028***			
	[0.014]	[0.006]	[0.004]			
BTC price above $10K X Treated Provider				0.538*	0.277*	0.045
				[0.276]	[0.083]	[0.092]
Temperature (log)	-0.337	-0.204	0.067	-0.793	1.864*	1.127
	[0.26]	[0.161]	[0.062]	[2.469]	[0.938]	[0.872]
Month Fixed Effects	Y	Y	Y			
Provider Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects				Y	Y	Y
SD Y	0.34	0.16	0.16	0.31	0.16	0.2
Obs.	126	126	126	64	64	64
R2adj	0.67	0.65	0.85	0.44	0.53	0.88

Table A1: Effect of Bitcoin Price on Sales, Customers and Revenues

All columns report the estimates of the fixed effect model. In columns (1) to (3) the dependent variable is an the log of the monthly sales of electricity per provider per user type.In columns (4) to (5) the dependent variable is an the log of the monthly customers per provider per user type. In columns (7) to (9) the dependent variable is an the log of the monthly revenues from electricity per provider per user type. Electricity data are from NYSERDA. Bitcoin price data are from Coinmarketcap. Temperature data are from the National Center for Environmental Information. Month fixed effects are dummies for the months capturing seasonality. Provider fixed effects are dummies for each provider capturing time-invariant differences in electricity prices. Errors are clustered at the time level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: Log(Sales)			Dependent Variable: Log(Customers)			Dependent Variable: Log(Revenues)		
	Business	Commercial	Household	Business	Commercial	Household	Business	Commercial	Household
BTC price (log)	-0.077***	0.025***	0.012**	-0.008***	0.015***	0.013***	0	0.044***	0.041***
	[0.01]	[0.004]	[0.006]	[0.002]	[0.002]	[0.002]	[0.012]	[0.009]	[0.006]
Temperature (log)	-0.086	0.023	-0.182***	-0.050*	0.012	0.006	-0.423*	-0.181	-0.116
	[0.104]	[0.054]	[0.062]	[0.028]	[0.027]	[0.025]	[0.241]	[0.19]	[0.092]
Month Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Provider Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	9.33	11.49	12.62	6.29	10.8	13.04	6.86	9.31	10.62
SD Y	1.14	0.67	0.68	0.37	0.61	0.68	0.91	0.58	0.58
Obs.	126	126	126	126	126	126	126	126	126
R2adj	0.98	0.99	0.99	0.99	0.995	0.995	0.96	0.97	0.97

Appendix Table 1: Testimonial Evidence on Local Government Motives for CryptoMining

	Country	Province	Government Motive	Source	Author	Date
1	China	Inner Mongolia	Tax Revenue	*Tech In Asia*	Eva Xiao	11/22/2016
	"China's bitcoin mining scene is catching the eye of the government": In Inner Mongolia, for instance, Bitmain is partnering with the local government to access electricity from the State Grid for about four cents per kilowatt hour. In exchange, the profit from Bitmain's Ordos mine is taxed.					
2	China	Inner Mongolia	Employment, Tax Revenues, GDP	*Quartz*		11/22/2016
	"How bitcoin miners work": A decade ago, after a speculative coal boom fizzled, the once-thriving desert city of Ordos, in Inner Mongolia, became China's largest ghost town, littered with unfinished or empty buildings and desperate for another way to make money... The bitcoin mine and the industrial firms have one thing in common: They use a lot of electricity. The local government has attracted Bitmain...to the park by offering them a 30% discount on the electricity price, said Su Jiahai, who deals with local governments to build mining farms for Bitmain. The mining farm uses 40 megawatts of electricity per hour, about equivalent to the amount used by 12,000 homes during the same period. It pays roughly $39,000 a day for its electricity bill, even with the discount. The electricity in Ordos mostly comes from nearby coal-fired power plants, which provide a stable and constant source of electricity—although at a price to the environment.					
3	China	Inner Mongolia	Jobs, Economic Spillovers	*New York Times*	Cao Li, Giulia Marchi	9/13/2017
	In China's Hinterlands, Workers Mine Bitcoin for a Digital Fortune: ... On the other hand, the digital currency may represent an opportunity for China to push into new technologies. Now the mine has about 50 employees," said Wang Wei, the manager of Bitmain China's Dalad Banner facility. "I feel in the future it might bring hundreds or even thousands of jobs, like the big factories."...The county of about 370,000 people on the edge of the vast Kubuqi Desert boasts coal reserves and coal-powered heavy industries like steel. But it lags behind much of the rest of the country in broadly developing its economy.					
4	Canada	Alberta	Jobs, Investment, Diversification	*Medicine Hat News*	Collin Gallant	3/20/2018
	It's a major economic win for the city, said Mayor Ted Clugston, who hailed it as a strong move toward diversification, and the city gaining a high-tech industry and another industrial-sized power user in need of a massive 42-megawatt power supply. "It's an exciting day," he told reporters following the meeting. "It's 42 jobs, an investment of $100 million, and it's just what we need right now.					
5	U.S.	Washington	Taxes, Economic Spillovers	*CNBC*		1/11/2018
	Interview with Ron Cridlebaugh, the Port of Douglas County economic development manager. "It's good for the economy. We're seeing [bitcoing mining] really diversifying our economy. There are millions of dollars being invested in the economy. It's going to help our tax base.... Our infrastructure is actually being put to the test. We're full"					
6	Georgia / Abhazia		Economic Spillovers	*BitCoin News*		10/20/2018
	"Cryptocurrency Mining Could Crash The Entire Power Grid Of Abkhazia": The tiny Republic of Abkhazia has high hopes that cryptocurrency mining and operations could be its solution to economic woes. But the rickety ex-Soviet electricity network is already at capacity, leaving risks of blackouts if a cold snap hits.					
7	Australia		Economic Spillovers	*CoinTelegraph*	William Suberg	5/7/2018
	"Australia: Disused Coal Plant To Become 'Blockchain Applications Complex'": Two blockchain companies have partnered to launch a $190 mln Bitcoin mining operation in a disused coal plant in Australia....Similar attempts in New York State and across the border in Canada drew criticism from authorities, who considered such projects did not generate sufficient value for the local economy.					

Appendix Table 2: Testimonial Evidence on Non-Motive Outcomes from CryptoMining

	Country	Province	Local Outcome Expressed	Source	Author	Date
1	Georgia / Abhazia		Blackouts	*BitCoin News*		10/20/2018
	"Cryptocurrency Mining Could Crash The Entire Power Grid Of Abkhazia": ...But the rickety ex-Soviet electricity network is already at capacity, leaving risks of blackouts if a cold snap hits.					
2	Australia		More Fossil Fuels	*CoinTelegraph*	William Suberg	5/7/2018
	"Australia: Disused Coal Plant To Become 'Blockchain Applications Complex'": Two blockchain companies have partnered to launch a $190 mln Bitcoin mining operation in a disused coal plant in Australia.					
3	U.S.	Oregon	More Fossil Fuels	*Willamette Week*	Katie Shepherd	2/21/2018
	"Bitcoin Miners Are Flocking to Oregon for Cheap Electricity. Should We Give Them a Boost?": The Bitcoin boom poses a challenge to small towns like The Dalles. Electricity here may be cheap, but it isn't endless. Dams kill endangered salmon. And the more hydropower is used by Bitcoin miners, the more the rest of the state must rely on electricity generated by fossil fuels, including coal.					
4	U.S.	Oregon	Rising Energy Costs	*Politico*	Paul Roberts	3/9/2018
	"This Is What Happens When Bitcoin Miners Take Over Your Town": Many also fear that the new mines will suck up so much of the power surplus that is currently exported that local rates will have to rise. In fact, miners' appetite for power is growing so rapidly that the three counties have instituted surcharges for extra infrastructure, and there is talk of moratoriums on new mines. There is also talk of something that would have been inconceivable just a few years ago: buying power from outside suppliers.					
5	Venezuela		Blackouts	*Daily Mail*	Scot Campbell	1/19/2019
	"Bitcoin mining 'is causing electricity blackouts": In Venezuela, Bitcoin mining has caused blackouts while experts say the mass amounts of energy consumed could instead be used to power homes and businesses.					
6	U.S.	New York	Rising Energy Costs	*CoinTelegraph*	Aaron Wood	3/16/2018
	"US: Plattsburgh NY Introduces Temporary Ban On New Crypto Mining Operations": The city council unanimously approved an 18 month moratorium on crypto mining activities in Plattsburgh. The moratorium only affects new Bitcoin mining operations and does not affect ones already existing in the city. The idea of a moratorium was first introduced by mayor Colin Read in January after residents reported inflated electricity bills					