CryptoMining:

Energy Use and Local Impact*

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

September 29, 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? Testimonial evidence supports cryptomining as a source of tax revenues and purported local economy spillovers. We assemble a novel panel dataset for cities in China and New York State to take these claims to the data. First, we estimate that in China cryptomining operations lead to 10% higher energy consumption, which is mainly derived from fossil fuels. Second, we study the local effects of cryptomining on the public, household and business sectors. We find that cryptomining substantially increases business tax revenues relative to GDP in Chinese cities, thus providing a strong incentive for local governments to attract this type of business. 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 both households and businesses. 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 and NBER. Email: morse@haas.berkeley.edu.

The functioning of decentralized blockchain-based payment systems, known as cryptocurrencies, requires enormous amounts of world energy. De Vries (2018) estimates that to clear a paltry 81 million transactions in 2018, Bitcoin mining consumed more energy than Ireland. As of the summer of 2019, the website Digiconomist.com estimates that Bitcoin mining has the carbon footprint of Denmark, with each transaction consuming the electricity equivalent of a U.S. househod for 21 days. This 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 uncompetititve due to the organizational structure Cong et al. (2018), an arms race has occurred in mining resulting in a massive buildup and use of cryptomining processing power to validate transactions. Furthermore, this consumption of computing electricity is not mitigated by drops in the trading pricings of the cryptocurrencies. Figure 1 shows the estimated consumption of energy from the beginning of 2017 to July 2019. A sharp increase in electricity consumption in correspondence with the increase in the price of Bitcoin; however, the decline in the price of Bitcoin does not usher in a parallel fall in electricity consumption because of the market and pricing structures in cryptomining.

In this paper, we study implications from cryptomining. We first take up the issue of energy consumption. 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, giving rise to negative local and global externalities. (Even a use of renewables may lead to substitution to fossil fuel consumption by other demanders or electricity, a point we ignore.) Yet, 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," (e.g. the University of Cambridge report by Rauchs et al. (2018), henceforth referred to as Cambridge, 2018). We test this proposition.

During the last decade, China has been the location of 70-83% of cryptomining (Cambridge, 2018). We manually read local newspapers for each of the 164 non-coastal city-seats in China, looking for mention of cryptomining facilities (not trading, but physical property). Using these data mapped to the closest power plants, we find that just short of 60% of Chinese cryptomining is in locations powered by coal (48.2%) or natural gas (11.1%). This implies that even if the rest of the world only uses renewals (a false statement), more than half of cryptomining electricity consumption is derived from fossil fuels, especially coal.

Our second goal is to study the positive and negative implications of cryptomining for local economies. Testimonial evidence suggests that because crypomining is a very profitable use of local electricity supply, local governments would favor the tax benefits from cryptomining. By contrast, however, and taking into account the fact that cryptomining facilities employ negiligible labor, it may be that other stakeholders in the local economy fare worse when cryptomining consumes the local energy supply. Anecdotes suggest that energy crowding out is occurring, whereby local businesses 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). We study these economic spillovers and tax incentives in the political economy of allowing cryptomining.

We start by providing a stylized modelling framework to understand the role of crytominers electricity demand in the local economy. We consider two main cases: an economy where the electricity supply curve is flat, i.e. prices are fixed, as in local energy markets in China; and an economy where the supply curve is upward-sloping, which implies that prices do adjust to changes in demand, as in local energy markets in the US. We discuss the cases when a potential capacity constraint is binding and also an extension with an additional pollution externality. 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, 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 (Tørsløv et al., 2018).

We collect two novel datasets of the local economies in China and New York State to study the fixed price and floating price regimes, respectively. Our empirical design embeds the endogenous choice of locations in a difference-in-differences design. From a production vantage, the key determinants of cryptomining locations are temperature, distance from power plant and electricity prices. A location model provides us with a production-based inverse probability weighting (IPW) that we can use to level cities on the desirability of the location from a cryptomining production viewpoint. The other side of observed location decisions comes from the vantage of local governments. Intuitively, and as supported by testimonies, all else equal on production desirability, the communities which solicit cryptominers most aggressively are those with declining manufacturing bases. Thus, we can sign any bias in our IPW difference-in-difference design.

We find that cryptomining operations lead to 10% higher energy consumption in local China (inland) cities. This is not an obvious result ex ante. 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. This effect is larger in magnitude in provinces which rely heavily on coal for energy. Because of the bias signing, any omitted variable in the IPW-difference in-differences leads us to conclude our estimates are likely to be conservative. We replicate the result on the effect of cryptomining on electricity consumption in New York State. We find a strong correlation of Bitcoin prices and energy consumption at local township levels.

We then study the three stakeholders – the public, household, and business sectors. First, we find strong evidence that Chinese cities engaging in cryptomining generate more business tax revenues. Our estimates are again signed to be conservative and reinforced by 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 suggesting that this elasticity should be large. Local authorities in regions with cheap energy seem to be seeking out and welcoming opportunities to cryptominers. These 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.

Second, in the household sector, we find no support for the idea that locals benefit from cryptomining. Wages appear to decline in cryptomining locations based on fossil fuel powered plants. Consumption, as proxied by value-add taxes, does not increase. This evidence is consistent with a story that the local labor conditions worsen because of the use of electricity by labor-scarce cryptomining rather than in other labor-intensive industries. However, we caveat this interpretation because, although we use multivariate controls for the local economy trends in our difference-in-differences setup, the possibility remains for a bias in the selection decision by declining cities.

Third and likewise, in the business sector, we find evidence that cryptomining leads to negative externalities in terms of local investment, but only in fossil-fuel-based cities. This evidence supports anecdotes that Venezuelan homes and businesses have been experiencing blackouts while electricity consumption by miners has increased. We again caveat these results. Nevertheless, we do not find support for positive spillovers, especially in light of the fact that governments are realizing more tax revenues.

Our final exercise turns to focusing on New York State to understand the local effect of cryptomining in a scenario with floating electricity prices. 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 rose by 16% for business and 6% for households. These crowding out effects constitute an important (possibly unintended) consequence of hosting cryptomining 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 (Nakamoto, 2008; Harvey, 2016). However, the economics literature has focused most proof-of-work attention to the features and stability of the proof-of-work protocol itself (Kroll et al., 2013; Carlsten et al., 2016; Budish, 2018; Pagnotta and Buraschi, 2018; Chiu and Koeppl, 2019). 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 et al., 2018; Dimitri, 2017). Others have studied other aspects of the bitcoin-blockchain supply model including the role of transaction fees (Easley et al., 2018; Ciamac and Moallemi, 2017). 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 et al. (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 et al., 2019; Truby, 2018; De Vries, 2018) and the work that discusses costs, limitations and alternatives to proof-of-work (Prat and Walter, 2018; Kugler, 2018; Saleh, 2019) 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.

Overview. The paper is organized as follows. In Section 1, we outline the conceptual framework. Section 2 describes the novel data sets we collected from China. Section 3 describes the empirical methodology. Section 4 contains the empirical results for China. Section 5 discusses the data and results for NY State. Section 6 concludes.

1 Conceptual Framework

Our key goal is to quantify the effect of cryptomining on local energy markets. To motivate our empirical strategy, here we depict a simple model of energy demand and supply.

In Panel A of Figure 2, we start with the fine dashed (blue) line representing the aggregate local demand (households and businesses) prior to the entry of cryptominers. We refer to this demand as "community demand." The solid (black) line is the supply curve, which is flat, implying that the local utility companies are willing to provide any amount of energy below the capacity Q_{max} at a fixed price. This depiction, which is relaxed in the next figure, reflects the realities of many localities where electricity prices are fixed by governments or utilities at least in the medium run. The initial equilibrium is given by the point E_0, where the community demand intersects the supply curve. Cryptominers enter the locality with the wide dashed (red) demand curve. Note that this curve is flatter than the community demand indicating that cryptominers are more price elastic than the local community. This reflects the fact that one of the key factors driving the cryptominers' location decisions is electricity prices (something we will document empirically in Section 3.2) and that, conversely, community demand includes local consumption for necessities such as heating and lighting. The horizontal sum of community demand and cryptomining demand (the lighter (green) solid line) is total local demand for electricity, and its intersection with the supply curve (denoted E_1) represents the equilibrium after the entry of cryptominers. The new price P_1 is the same as the pre-cryptomining price P_0.

In this setting, although the local community is not affected by cryptomining in prices or quantity consumed, local welfare can be impacted through a few channels. First, to the extent that electricity production involves convex costs, the local utility companies incur increased costs. Second, although we do not model it explicitly, in most locations, each unit of added electricity production leads to a pollution externality. On the other hand, local welfare might increase due to the possibility of added tax revenues. Given that most cryptomining requires minimal human intervention and is carried out by a few large companies, we abstract away from the possibility that cryptomining creates new jobs or that cryptominer profits are reinvested in the local economy.

In Panel B, we model the setting in which the sum of community and cryptominer demand exceeds the supply capacity at the fixed price. Some of the total demand remains unfulfilled corresponding to the difference $Q_{unconstrained} - Q_1$. While the model is silent about who will be left out, the anecdotes in the Appendix suggest that it is often local businesses or even households that bear the brunt. This is consistent with the fact that cryptomining is a highly profitable business and is thus likely to be prioritized by tax revenues-maximizing local governments. The resulting blackouts imply another negative externality.

So far, we have focused on the scenario where the supply curve is flat, and thus prices are fixed, as is the case in China. This is not true of all energy markets. For example, small businesses in the United States typically face an upward-sloping supply curve (even if prices are managed in a dirty float), which implies that prices to a certain extent adjust to changes in demand. Figure 3 considers this scenario. Again, Panels A and B correspond to the case where the capacity constraint is not binding and is binding, respectively. E_0 and E_1 denote the pre- and post-cryptomining market equilibrium. Since supply slopes upward, the increase in total demand now translates into higher prices ($P_1 > P_0$).

In the floating price regime, the welfare implications are slightly different. The local community benefits in tax revenues, although perhaps less so due to the moderating effect of the upward-sloping supply. Offsetting this is again the negative externality of pollution. In addition, the local community is directly impacted via steeper energy bills. In Panel B, electricity capacity binds, which again implies the additional negative externalities incurred with energy shortages.

Thus the local consequences in both settings involve a monetary tradeoff between taxes and costs borne by utility provision (in Figure 2) or borne by local businesses and households in terms of higher prices and quantity blackouts (in 3).

We add to this tradeoff a pecuniary representation of the pollution externalty in Figure 4 for the floating price regime. We plot the marginal social cost curve (labeled $Supply^{Social}$) above the direct cost supply curve. The social marginal cost is higher than the private marginal cost due to the pollution externality. In Panel A, when the capacity constraint is not binding, the market equilibrium is characterized by higher quantity and lower price relative to the social optimum. This holds true both before the entry of cryptominers ($Q_0 > Q_0^{Social}$ and $P_0 < P_0^{Social}$) and after that ($Q_1 > Q_1^{Social}$ and $P_1 < P_1^{Social}$). On the other hand, when the capacity constraint binds (Panel B), the post-cryptomining equilibrium quantity might be the same as the socially optimal one ($Q_1 = Q_1^{Social} = Q_{max}$), but the equilibrium price is still too low ($P_1 < P_1^{Social}$) since it does not internalize the negative externality.

Because pollution has global consequences such as climate change, the negative externalities are not confined to the local markets. In order to formalize this, we adapt the model of Ma et al. (2018) (MGT, henceforth) to allow for externalities. MGT show that, assuming entry into the cryptomining market is free and miners are symmetric, the following relationship hold in the worldwide equilibrium

$$Nc\left(x^{*}\right) = P \tag{1}$$

where N is the total number of cryptominers, $c\left(x^{*}\right)$ is each miner's private cost associated with their chosen level of energy consumption x^{*}, and P is the reward from cryptomining (e.g., the price of a newly minted bitcoin and possibly additional fees). In words, the sum of the private costs of mining equals the reward in equilibrium, so that there are zero aggregate private profits. If energy consumption involves negative externalities $\phi\left(x^{*}\right)$, then the socially optimal equilibrium is characterized by

$$N\left[c\left(x^{*}\right) + \phi\left(x^{*}\right)\right] = P \tag{2}$$

Comparing (1) to (2) yields the following comparative statics: *In the socially optimal equilibrium, either N is lower or x^{*} is lower (or both) relative to the market equilibrium.* In order to correct this market failure, the regulator could decide to impose a tax on consumption of x devoted to cryptomining. However, note that, since anyone in the world is able to participate in cryptomining, 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)).

2 Data

Our goal is to analyze the local consequences of cryptomining, 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 reflecting the intended governmental motives in attracting cryptominers 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, in Section 5 we also study a second location with a more flexible price regime, that of New York State (NY).

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 5 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).[1] 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 fuel-powered if the closest power plant generates electricity from coal, oil, or natural gas. Matching the locations of power plants to the location of cryptomines will be important to assess the environmental impact of cryptomining, which we do in Section 4.1.

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 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 location 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

[1]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.

and Reform Commission.[2] The average (median) price of electricity is about 539 (533) yuan per kilowatt/hour.

Figure 6 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 5); while dash lines represent three regions where we have no (less) evidence of cryptomining activity (light yellow areas in the map in Figure 5). 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 making. 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 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.

3 Empirical Methodology

3.1 Identification Strategy

Our empirical strategy is based on the following model:

[2] See `ndrc.gov.cn`

$$Y_{ct} = \alpha\ mining_c \times Post_t + \beta_1 X_{ct}^{(1)} + \beta_2 X_{ct}^{(2)} + \gamma_c + \gamma_t + \epsilon_{ct} \tag{3}$$

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 (electricity prices and population) that also enter the cryptominers' location decisions modeled in the next section, and $X_{c,t}^{(2)}$ are controls (the percentage changes in population and electricity prices, as well as the percentage change in GDP) that do *not* enter the location model. The dependent variables Y_{ct} measure several outcomes of interest: energy consumption, business tax revenues, wages, value added tax revenues and fixed asset investments. We normalize each of these outcome variables by dividing by city-level GDP and then taking logs.[3]

Notice that, since we interact $mining_c$ with the $Post_t$ indicator in (3), 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 (3) 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 3.2. Specifically, we employ an inverse probability weighting (IPW) strategy where the weights are the propensity scores obtained from the location model

$$mining_c = f\left(Z_{ct}, X_{ct}^{(1)}, \eta_{ct}\right) \tag{4}$$

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

$$Y_{ct}^{(1)}, Y_{ct}^{(0)} \perp mining_c | X^{(1)}, X^{(2)}, Z, \tag{5}$$

an IPW regression based on (3) will yield consistent estimates of the effect of cryptomining

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

on the outcomes even in the presence of time-varying unobservables. In words, the "selection on observables" assumption (5) requires that the observables included in the location and 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 (3) and (4) (see, e.g., Wooldridge (2015)). Specifically, denoting by $\hat{r}_{ct}$ the generalized residuals from the location model (4), we estimate the following regression

$$Y_{ct} = \alpha \ mining_c \times Post_t + \beta_1 X_{ct}^{(1)} + \beta_2 X_{ct}^{(2)} + \gamma_c + \gamma_t + \hat{r}_{ct} + \epsilon_{ct} \tag{6}$$

with IPW. This allows for the fact that unobservable factors affecting the location decisions — η_{ct} in (4) — might also enter the outcome equations and thus provides estimates that are robust to violations of "selection on observables."

3.2 Selection Model

"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 the following location choice model:

$$mining_c = f\left(Z_{ct}, X_{ct}^{(1)}, \eta_{ct}\right) \tag{7}$$

In order to flexibly model the impact of the right-hand side variables on the location decisions, we estimate a logit specification with piecewise linear splines. 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.

The results are shown in Table 2. Column (1) corresponds to a specification with bin-specific constants, but no bin-specific slopes. The results 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 7. 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.

4 Results for a fixed-price regime

4.1 Energy

First, we investigate the energy mix used by cryptomines in China. 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.

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 cryptomining cities being powered by coal (48.2%) and gas (11.1%). It could be that because we do not see capacity at each cryptomine, we are overestimating the importance of 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 world's cryptomining was coal-based or 47.4% was fossil-fuel-based if we add 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. This is in stark contrast to the claim sometimes made by advocates that cryptomining is mostly powered by renewable energy.

Next, we look 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 cryptomines crowd out energy usage by other economic activities.[4] Thus, the net effect is a priori ambiguous, implying that this is ultimately an empirical question. As shown in Table 3, we find robust evidence of an increase in energy consumption per unit of GDP in Chinese cities hosting crypto operations

[4] Indeed, anecdotal evidence from several countries suggest that cryptomining does lead to increased prices and even blackouts (see Appendix).

powered by fossil fuels. The magnitude of the effect varies across the different specifications; a conservative estimate is that cryptomining increases energy consumption per unit of GDP by around 10%.

4.2 The Public Sector

Given the results in the previous section, it is natural to ask why local governments in China might be willing to allow or even encourage an activity as energy-consuming and polluting as cryptomining. The anecdotes in the Appendix suggest that one reason is that cryptomines provide a substantial source of tax revenues for local governments in areas with declining economies. For example, the government in Inner Mongolia has partnered with Bitmain, owner of two of the largest mining pools in the world, and even granted the company access to subsidized electricity.

We use our data to test whether this pattern holds more broadly. The results in Table 4 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) by at least 10%. This is consistent with the fact that cryptomining is a highly profitable activity[5] and, thus, one that tends to yield more tax dollars per unit of output.

Note that even the OLS regression in column (1) of Table 4 yields a positive and significant effect of cryptomining on local taxes, in spite of the fact that cryptomining tends to locate in cities with declining economies. Indeed, the pattern in Table 4 is consistent with this type of selection: as we control for the endogenous location decisions better (i.e. moving from left to right in Table 4), the estimated effect on taxes increases.

4.3 The Household Sector

In addition to increased tax revenues, advocates argue that cryptomining might induce positive spillovers in local economies. Local governments from Inner Mongolia to Alberta in Canada to Washington state have cited this among the motives behind their decision to allow cryptomines. In order to test this claim, we look at the impact of cryptomining on wages as well as value-added tax revenues. Interestingly, Table 5 shows that wages tend to *decrease* as a result of crypto operations, with a more statistically and economically significant effect

[5] See, e.g., *digiconomist.com*.

for cities located near fossil fuel power plants. Tables 5 also points to a negative effect on value-added taxes revenues, although not statistically significant.

4.4 The Business Sector

Finally, we consider whether cryptomining has any positive spillover effects on local business activity. The results in Table 6 indicate a negative impact on fixed asset investments. 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.

5 Results for a floating-price regime

"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. 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 cryptomining in the mid-2010s. In NY, electricity prices float to some degree, especially for businesses, with pressures of supply and demand.

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.

5.1 Data and empirical methodology

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.[6] Panel A of Figure 8 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 7 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 8 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 7 shows the data at the provider-user type-county level. The mean

[6]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 7 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.

Our empirical strategy is based on the following model, which we estimate separately for each user type:

$$Y_{put} = \alpha BTC\ price_t + \beta X_{tu} + \gamma_p + \epsilon_{put}, \tag{8}$$

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 8). However, we leverage the different geographical distribution of the operations of different utility providers (Panel B of Figure 8) 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:

$$Y_{put} = \alpha BTC\ price_t \times Treated\ provider_p + \beta X_{tu} + \gamma_p + \gamma_t + \epsilon_{put}, \tag{9}$$

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 (9), 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]

5.2 Results

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 9 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

[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.

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 9 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 10 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. [8] 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.

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 (8). 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

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

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 11 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 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 11 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 (9). 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.

6 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.

Carlsten, M., H. Kalodner, S. Weinberg, and A. Narayanan (2016). On the instability of bitcoin without the block reward. In *2016 ACM SIGSAC Conference on Computer and Communications Security*.

Chiu, J. and T. V. Koeppl (2019). Blockchain-based settlement for asset trading. *The Review of Financial Studies 32*(5), 1716–1753.

Ciamac, G. H. J. D. L. and C. Moallemi (2017). Monopoly without a monopolist: An economic analysis of the bitcoin payment system.

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

De Vries, A. (2018). Bitcoin's growing energy problem. *Joule 2*(5), 801–805.

Dimitri, N. (2017). Bitcoin mining as a contest. *Ledger 2*, 31–37.

Easley, D., M. O'Hara, and S. Basu (2018). From mining to markets: The evolution of bitcoin transaction fees. Working Paper.

Harvey, C. R. (2016). Cryptofinance. *Available at SSRN 2438299*.

Kroll, J. A., I. C. Davey, and E. W. Felten (2013). The economics of bitcoin mining, or bitcoin in the presence of adversaries. In *Proceedings of WEIS*, Volume 2013, pp. 11.

Kugler, L. (2018). Why cryptocurrencies use so much energy: and what to do about it. *Communications of the ACM 61*(7), 15–17.

Li, J., N. Li, J. Peng, H. Cui, and Z. Wu (2019). Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies. *Energy 168*.

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

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Available: https://bitcoin.org/bitcoin.pdf.

Pagnotta, E. and A. Buraschi (2018). An equilibrium valuation of bitcoin and decentralized network assets. *Available at SSRN 3142022*.

Prat, J. and B. Walter (2018). An equilibrium model of the market for bitcoin mining.

Rauchs, M., A. Blandin, K. Klein, G. Pieters, M. Recanatini, and B. Zhang (2018). 2nd global cryptoasset benchmarking study.

Saleh, F. (2019). Blockchain without waste: Proof-of-stake. *Available at SSRN 3183935*.

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

Truby, J. (2018). Decarbonizing bitcoin: Law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies. *Energy Research and Social Science 44*.

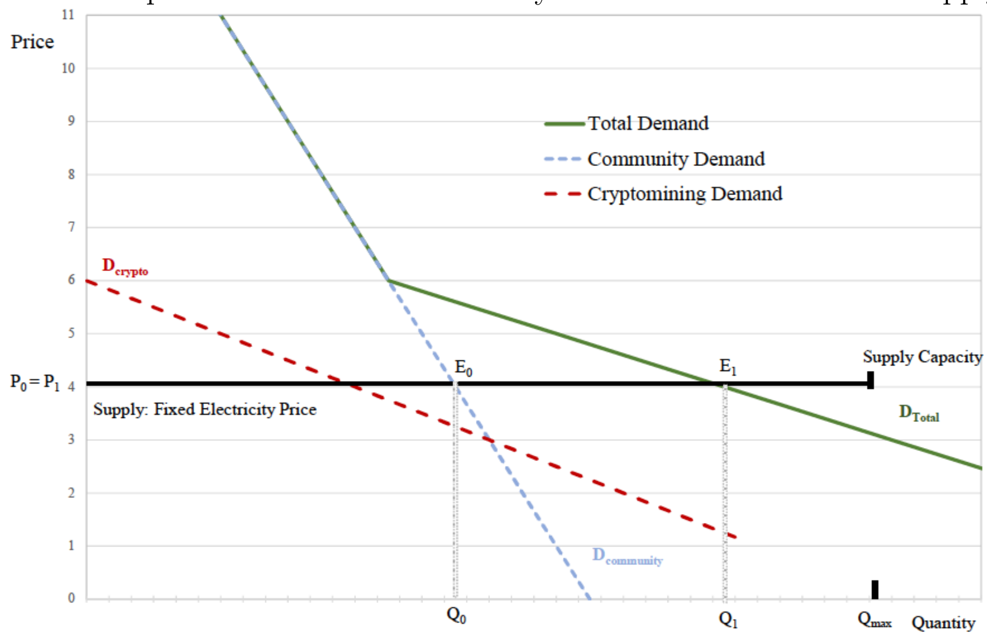
Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*.

Figure 1: Bitcoin price and world-wide electricity consumption

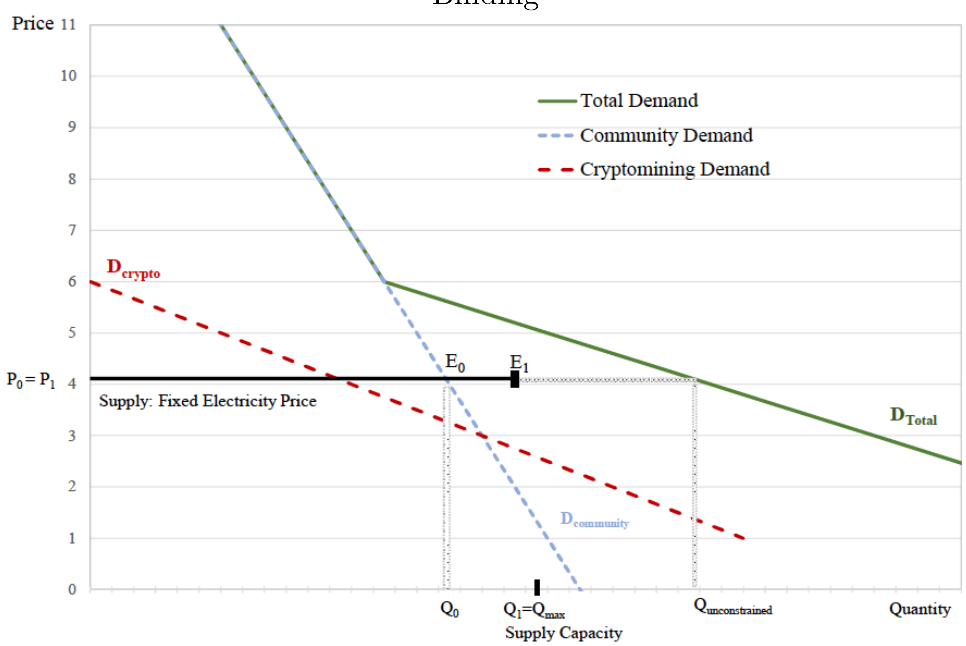
Note: The chart shows the price of Bitcoin and the minimum and estimated energy consumption per year for Bitcoin mining. Bitcoin prices comes from Coinmarketcap. Bitcoin minimum and estimated energy consumption comes from `https://digiconomist.net/bitcoin-energy-consumption`.

Figure 2: Cryptomining with fixed electricity prices

Panel A: Equilibrium in Local Electricity Market with Fixed-Price Supply



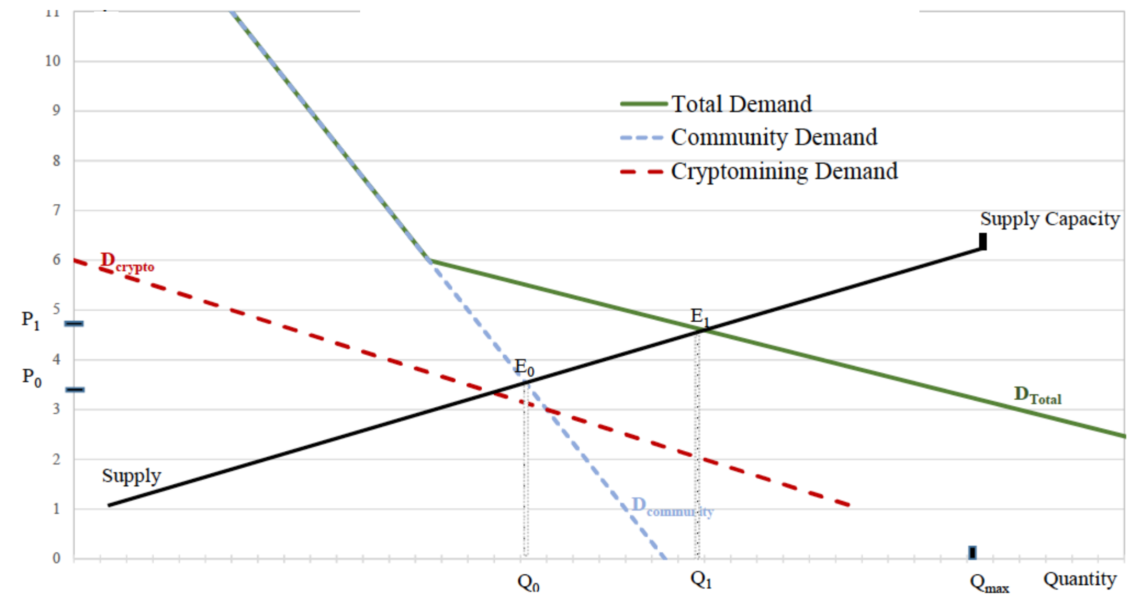
Panel B: Equilibrium in Local Electricity Market with Fixed-Price Supply & Capacity Binding



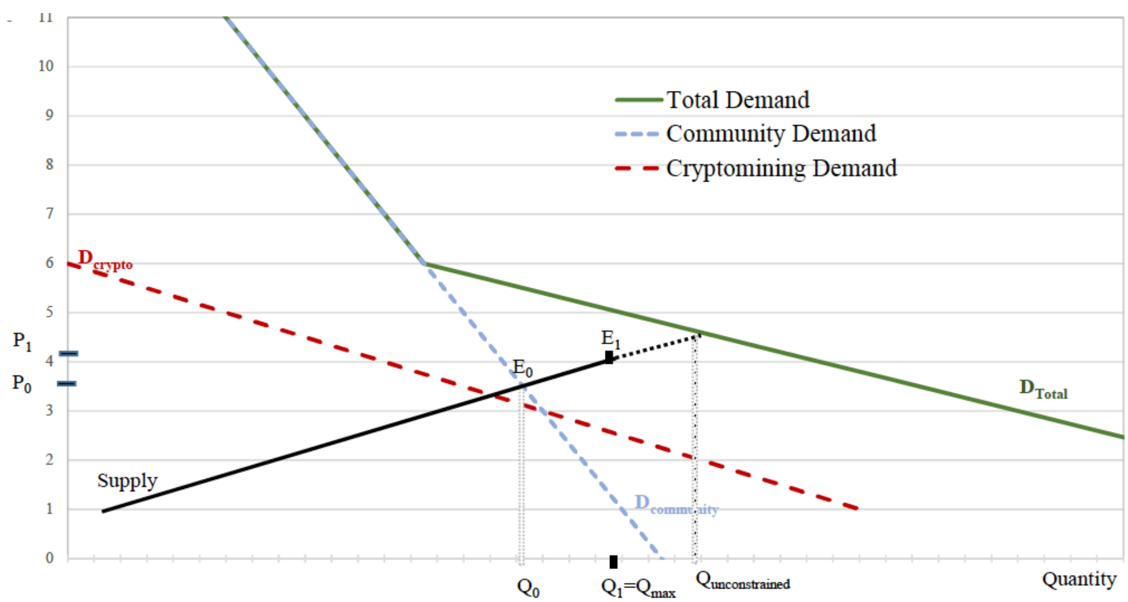
Note: The chart shows illustrations of supply and demand in markets with (Panel B) and without (Panel A) supply capacity binding. The figures depict the setting in which the local electricity supplier provides electricity up to capacity at a fixed price.

Figure 3: Cryptomining with floating electricity prices

Panel A: Equilibrium in Local Electricity Market with Upward-Sloping Supply



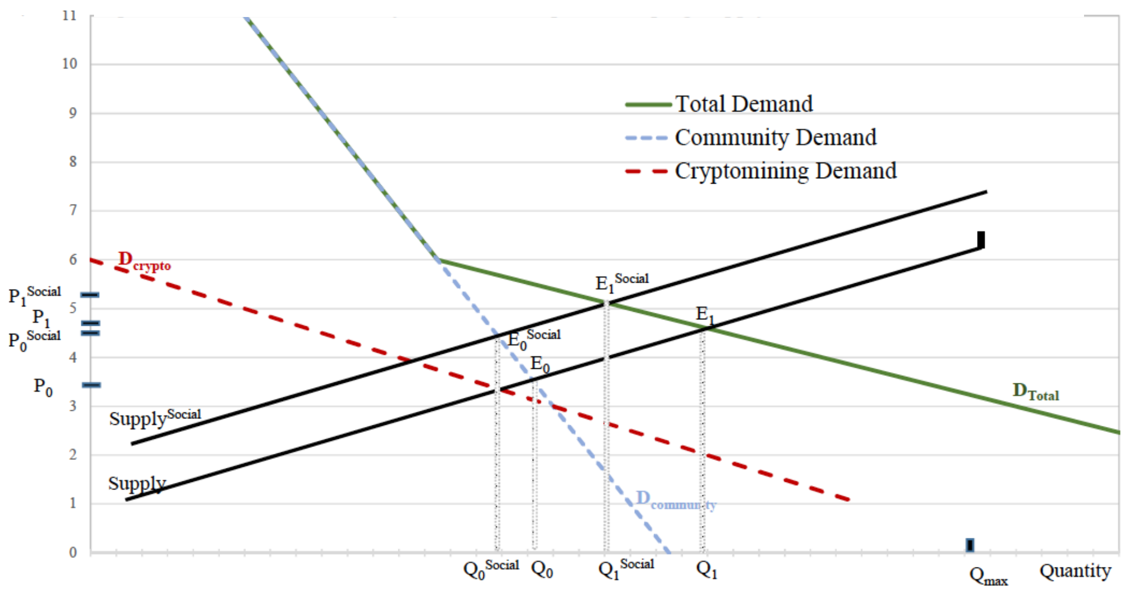
Panel B: Equilibrium in Local Electricity Market with Upward-Sloping Supply & Capacity Binding



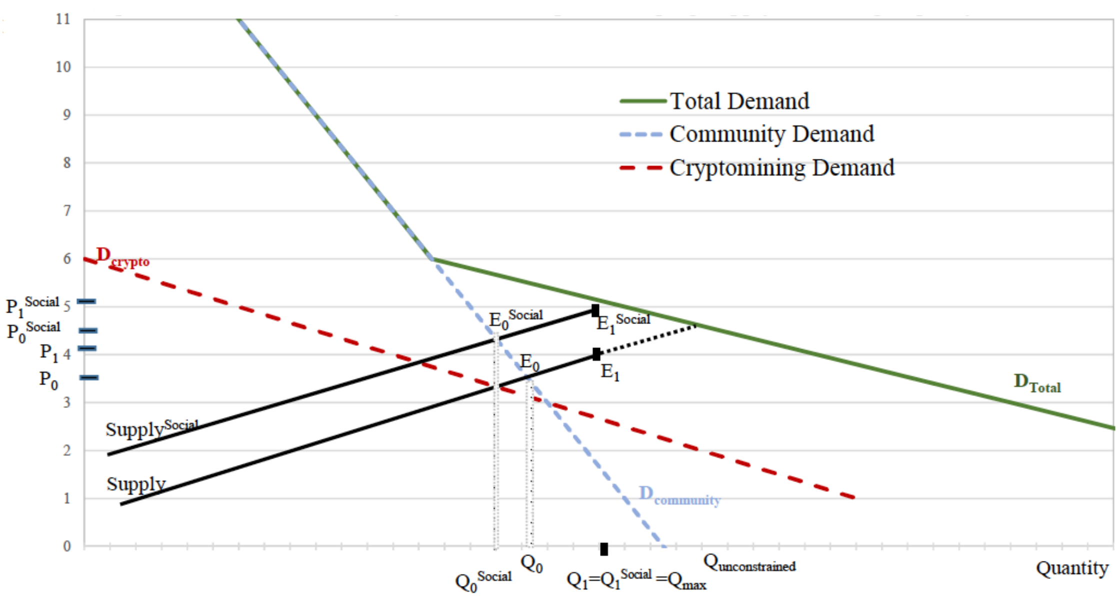
Note: The chart shows illustrations of supply and demand in markets with (Panel B) and without (Panel A) supply capacity binding. The figures depict the setting in which the local electricity supplier provides electricity up to capacity with a standard upward-sloping supply curve.

Figure 4: CRYPTOMINING WITH FLOATING ELECTRICITY PRICES AND POLLUTION EXTERNALITY

Panel A: Equilibrium in Local Electricity Market with Fixed-Price Supply



Panel B: Equilibrium in Local Electricity Market with Fixed-Price Supply & Capacity Binding

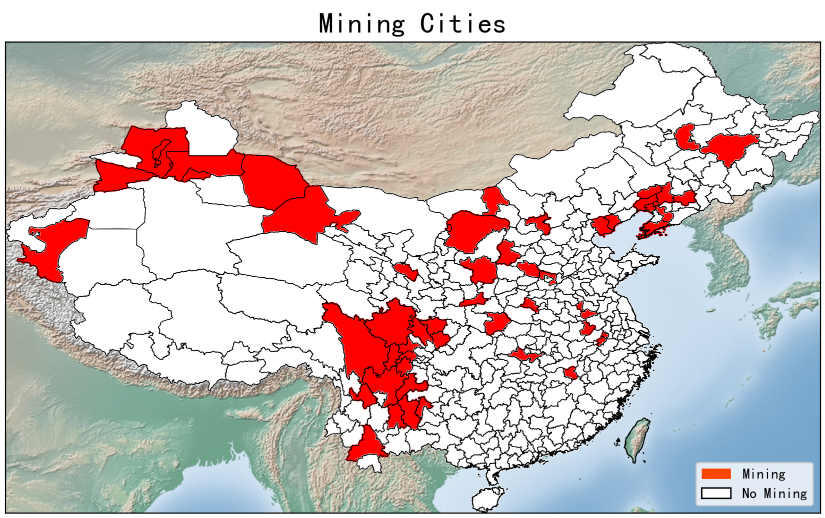


Note: Plotted are illustrations of supply and demand in markets with (Panel B) and without (Panel A) supply capacity binding. Two supply curves are depicted, both with the local electricity supplier provides electricity up to capacity with a standard upward-sloping supply curve. One supply curve, however, embeds the societal cost of pollution externality.

Figure 5: Mining cities

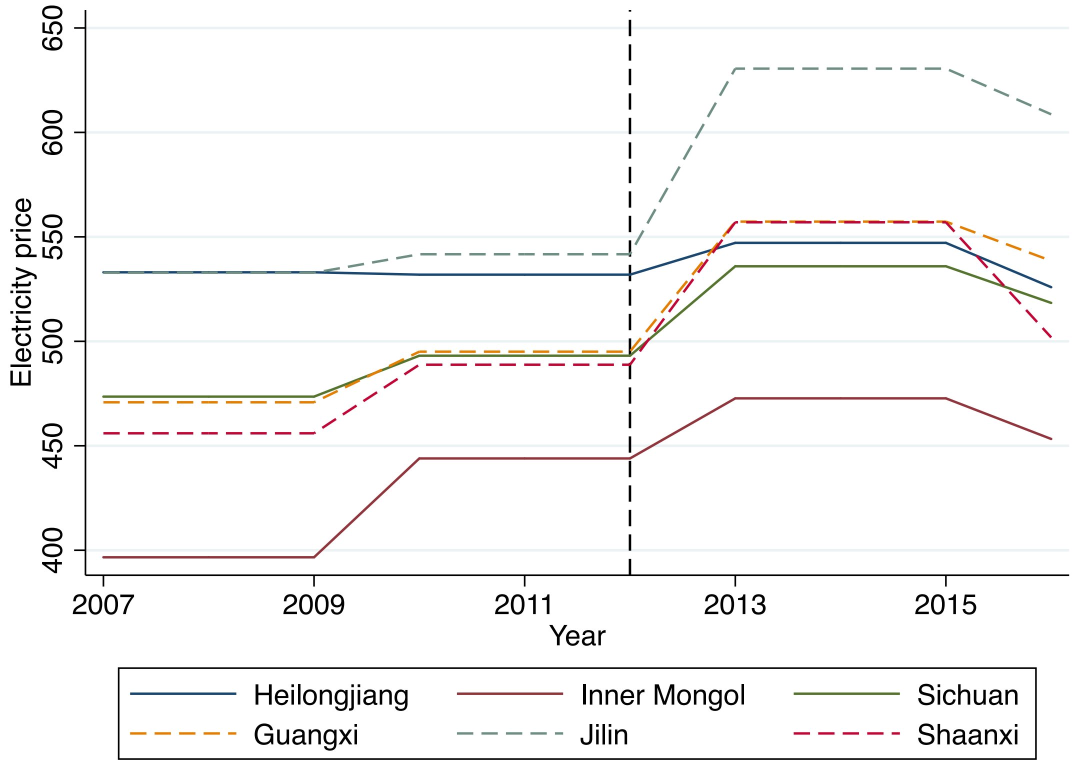
Panel A: Province-level locations of crytomining

Panel B: City-Seat-level locations of cryptomining



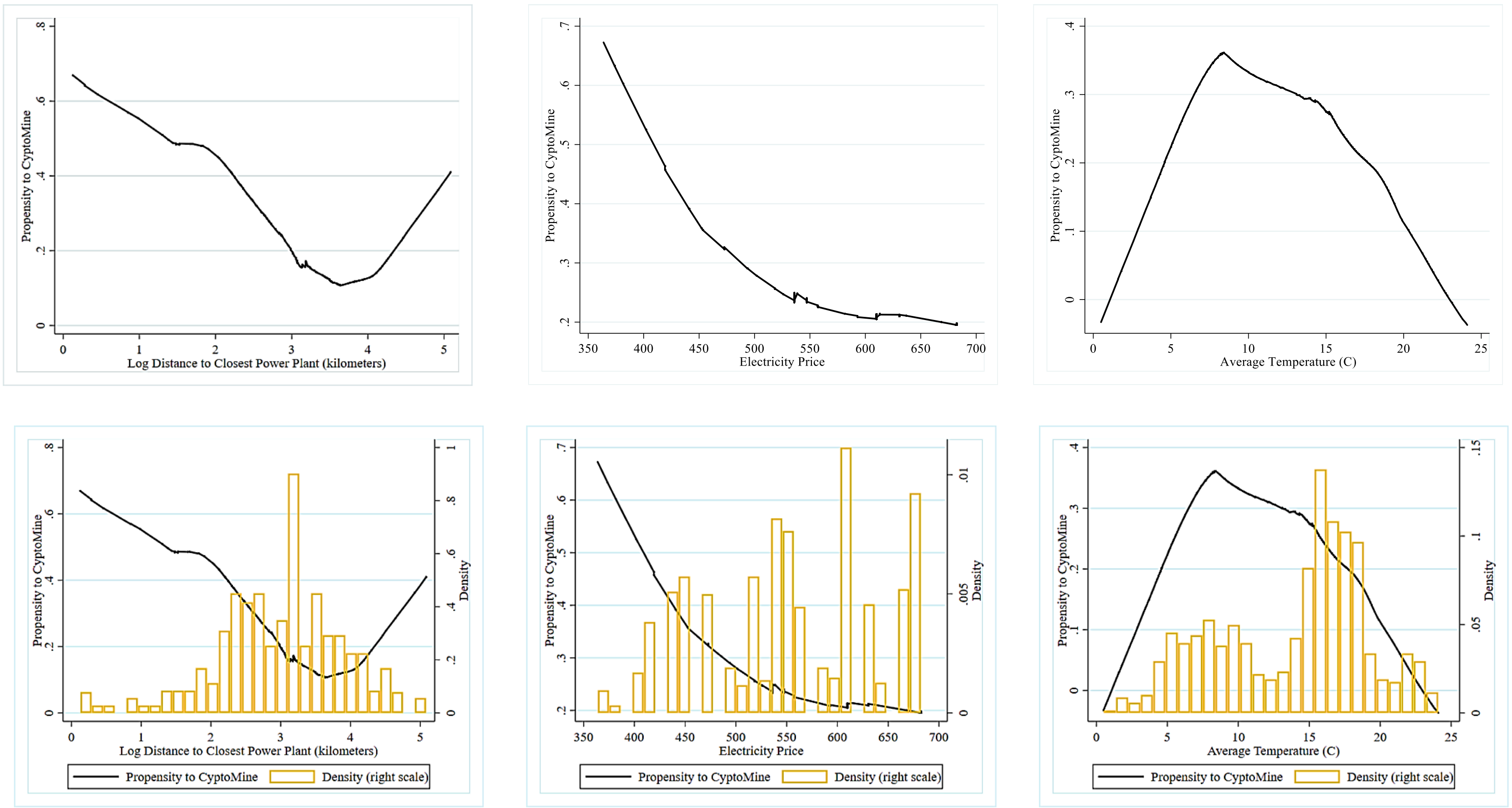
Note: Data on mining locations come from manual searches in local newspapers and newsources in Mandarin through Baidu and in English through Google. In panel A, we depict a heat map of China Province-level cryptomining counts. In panel B, we present locations at our finer level of cities-seat, where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

Figure 6: 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 5.

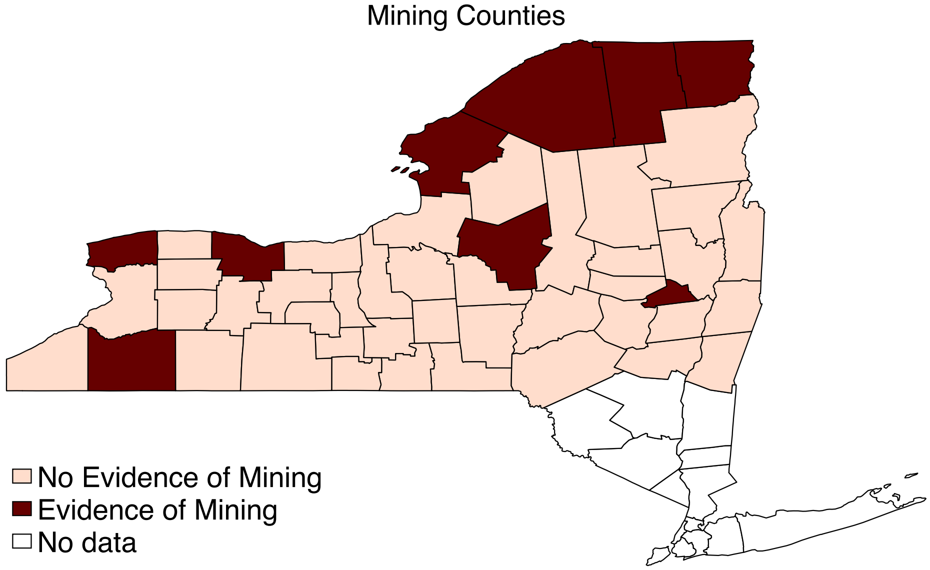
Figure 7: Predicted Propensity of a City to Host CrytoMining by Distance to Power Plant, Electricity Price & Temperature



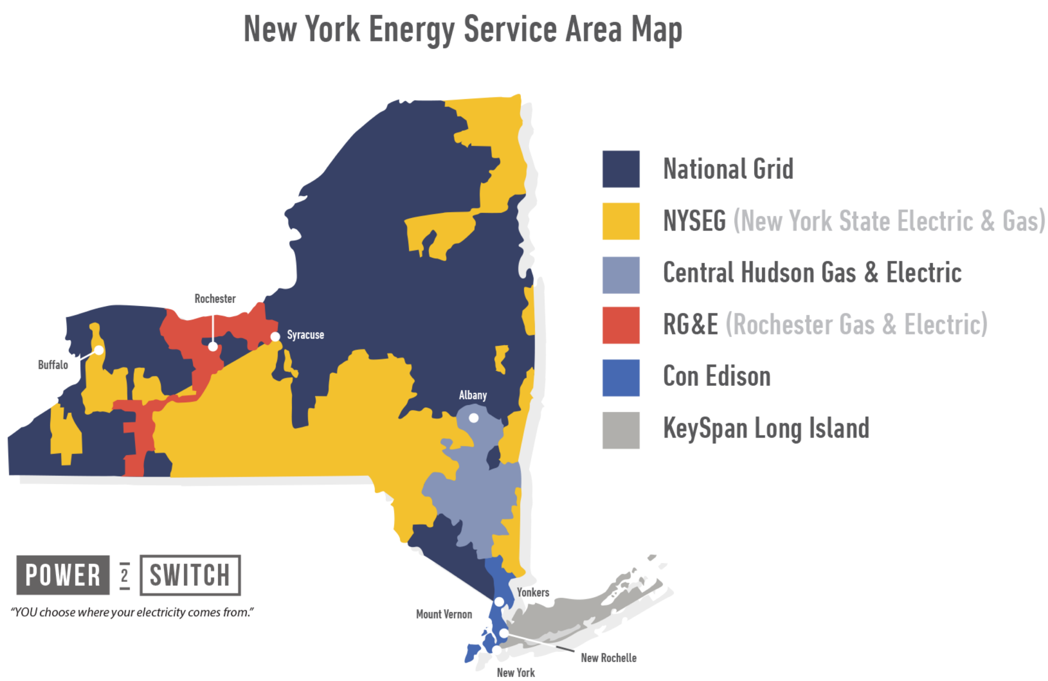
Note: Presented are graphics emerging from the predicted values of the location decision of the logit model column (2) of Table 2. The model includes the full spline specification of knot constants and interval slopes for each of the three variables depicted above - log distance to closest power plant, 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 8: Mining counties and electricity providers in New York state

Panel A: County-level locations of crytomining

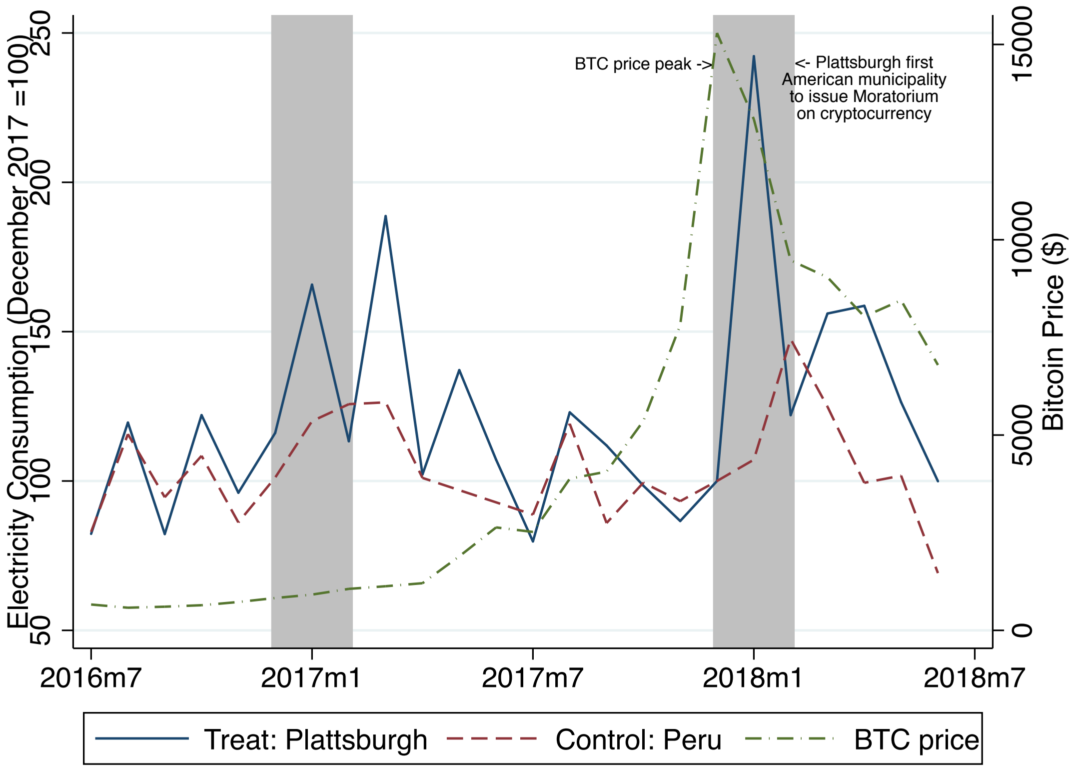


Panel B: Map of electricity providers



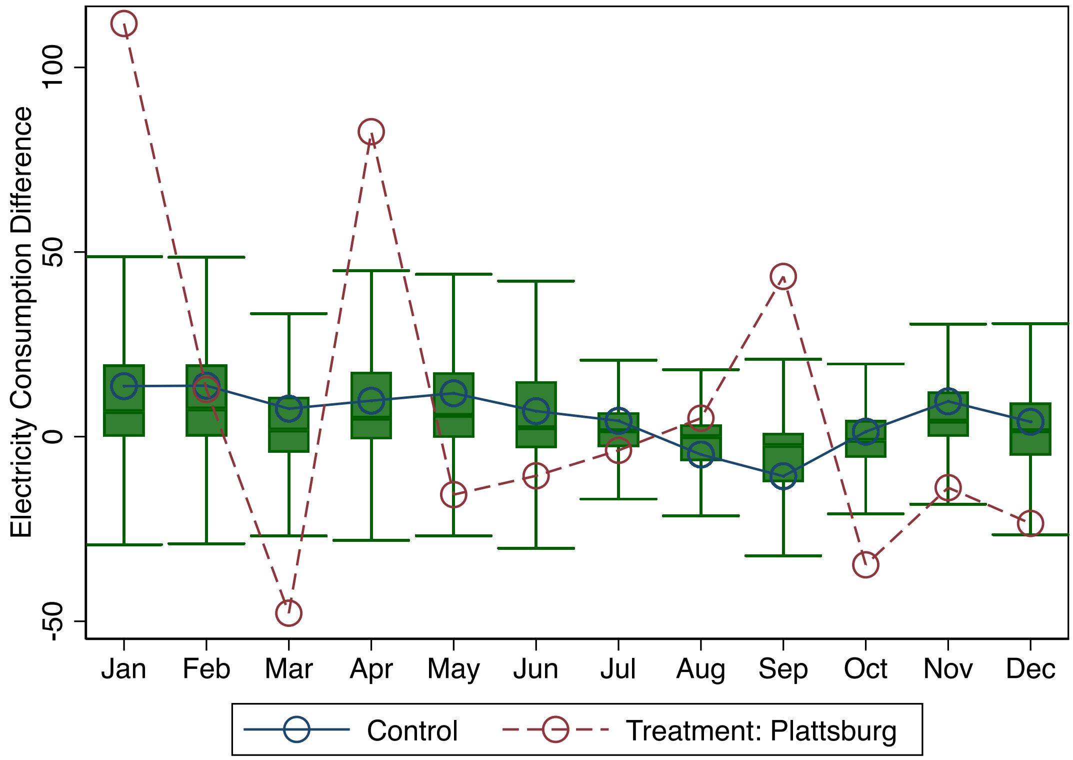
Note: In panel A, we present a map with mining counties identified from manual searches in local newspapers and newsources through Google. Panel B shows the map of electricity providers in New York State (URL: `https://power2switch.com/NY/utility_territory_map/`).

Figure 9: Bitcoin prices and electricity consumption



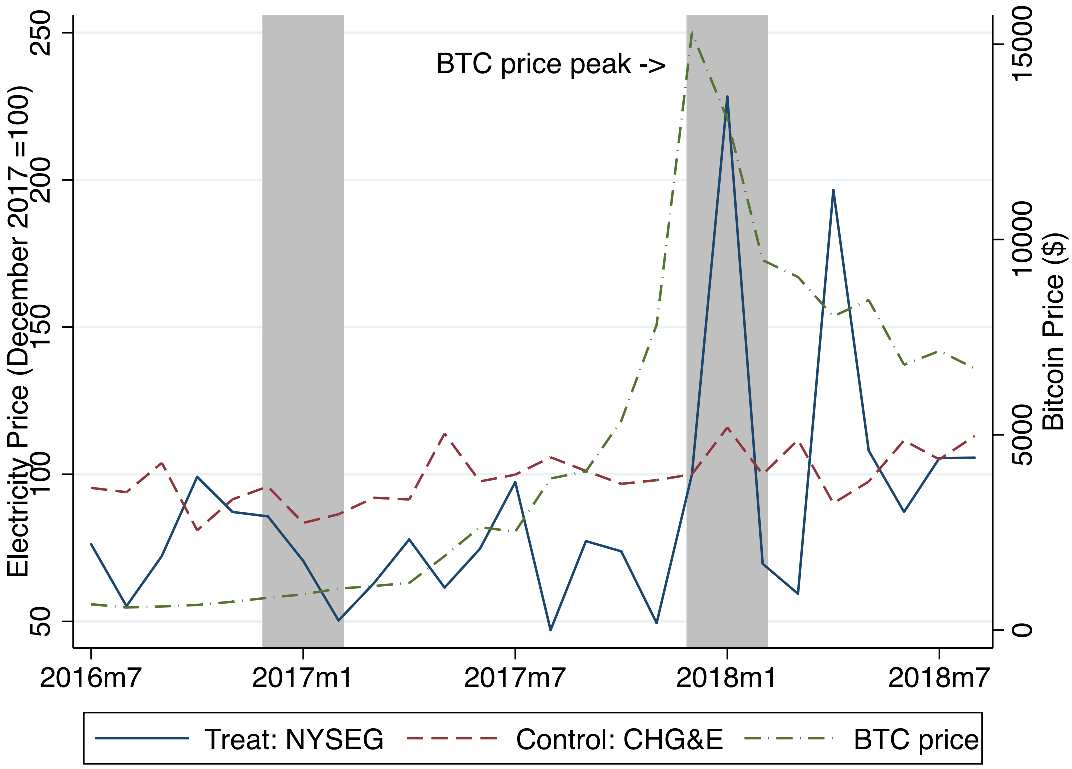
Note: Electricity consumption data comes from NYSERDA. The blue sold line and the red dash line shows total electricity consumption by small businesses in Plattsburgh and Peru, respectively. We normalize electricity consumption in each town to 100 in December 2017, which is the month is which Bitcoin 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 10: 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 × IQR of the upper/lower quartiles.

Figure 11: 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 for China**

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.

	Unique Cities	Mean	St.Dev	Min	Median	Max
Panel A: Inland Cities without Cryptomining						
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	65.9	89.3	195.2	390.3
Wages (CNY / year)	154	46,171	8,248	28,594	45,752	83,742
Value-Add Taxes (million CNY)	54	148.7	76.7	22.1	140.2	373.8
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						
Population (1,000s)	52	375.6	251.5	55.3	326.7	1,319.4
GDP (million CNY)	52	18,770**	18,026	1,904	12,698	89,726
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
Wages (CNY / year)	52	51,337***	12,845	32,570	50,109	114,759
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: **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 3: **Effect of Cryptomining on Energy**

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. All columns have control variables log GDP, GDP growth, log population, population growth, electricity price, electricity price growth, and year dummies. 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)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	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			0.0429			
			[0.0506]			
Post * Predicted MiningCity * Clean				0.0506	0.0752	
				[0.122]	[0.122]	
Post * Predicted MiningCity * Fossil				0.227*	0.246*	
				[0.130]	[0.129]	
Post * ControlFunction * Clean					-0.115**	
					[0.0556]	
Post * ControlFunction * Fossil					0.00461	
					[0.0563]	
Post * Predicted MiningCity						0.192
						[0.123]
Post * ControlFunction						-0.0238
						[0.0481]
Control Variables	Y	Y	Y	Y	Y	Y
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	0.954	0.947	0.946	0.947	0.948	0.947

Table 4: **Effect of Cryptomining on the Public Sector**
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 cityseat 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. All columns have control variables GDP growth, log population, population growth, electricity price, electricity price growth, and year dummies. 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	0.0576				
	[0.0468]	[0.0427]				
Post * MiningCity * Fossil	0.117*	0.124*				
	[0.0628]	[0.0644]				
Post * MiningCity			0.101*			
			[0.0538]			
Post * Predicted MiningCity * Clean				0.220*	0.242**	
				[0.125]	[0.115]	
Post * Predicted MiningCity * Fossil				0.252**	0.281**	
				[0.120]	[0.130]	
Post * ControlFunction * Clean					-0.0952**	
					[0.0458]	
Post * ControlFunction * Fossil					-0.0496	
					[0.0590]	
Post * Predicted MiningCity						0.272**
						[0.119]
Post * ControlFunction						-0.0665
						[0.0452]
Control Variables	Y	Y	Y	Y	Y	Y
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	0.891	0.89	0.892	0.893	0.893

Table 5: **Effect of Cryptomining on the Household Sector**

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. All columns have control variables: GDP growth, log population, population growth, electricity price, electricity price growth, and year dummies. 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	-0.0113	-0.00331					0.0452	0.0341				
	[0.0369]	[0.0461]					[0.119]	[0.139]				
Post * MiningCity * Fossil	-0.0768**	-0.0608*					-0.108	-0.145				
	[0.0335]	[0.0341]					[0.106]	[0.0906]				
Post * MiningCity			-0.0444						-0.0918			
			[0.0288]						[0.0954]			
Post * Predicted MiningCity * Clean				-0.015	-0.0104					0.387	0.375	
				[0.0605]	[0.0619]					[0.477]	[0.359]	
Post * Predicted MiningCity * Fossil				-0.113***	-0.112**					-0.205	-0.127	
				[0.0429]	[0.0439]					[0.176]	[0.213]	
Post * ControlFunction * Clean					-0.00461						-0.426	
					[0.0316]						[0.346]	
Post * ControlFunction * Fossil					0.00247						-0.0258	
					[0.0175]						[0.0980]	
Post * Predicted MiningCity						-0.0931**						0.0504
						[0.0405]						[0.261]
Post * ControlFunction						0.00251						-0.144
						[0.0157]						[0.174]
City & Year Fixed Effects, Controls	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	0.871	0.891	0.891	0.893	0.893	0.892	0.761	0.742	0.742	0.745	0.751	0.743

Table 6: **Effect of Cryptomining on the Business Sector**

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. All columns have control variables: log GDP, GDP growth, log population, population growth, electricity price, electricity price growth, and year dummies. 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)					
Difference-in-differences Model:	OLS	IPW	IPW	IPW-IV	IPW-CF	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			-0.134			
			[0.0887]			
Post * Predicted MiningCity * Clean				-0.163	-0.179	
				[0.283]	[0.285]	
Post * Predicted MiningCity * Fossil				-0.233*	-0.241*	
				[0.135]	[0.135]	
Post * ControlFunction * Clean					0.0648	
					[0.173]	
Post * ControlFunction * Fossil					0.0181	
					[0.0619]	
Post * Predicted MiningCity						-0.224
						[0.136]
Post * ControlFunction						0.0293
						[0.0622]
Control Variables	Y	Y	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	704	704	704	704	699	699
R-squared	0.897	0.886	0.886	0.887	0.887	0.887

Table 7: **Summary statistics for New York State**

Data are from the economic statistics website of New York State and from each electricity provider's required reporting of the electricity regulator. 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 shows the data at the provider-user type-county level. Panel C shows the price of BTC whic is available online (see among other sources `https://coinmarketcap.com`).

	Obsevations	Mean	St.Dev	Min	Median	Max
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 8: **Effect of Cryptomining 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 timevarying 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

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					