When cryptomining comes to town: High electricity-use spillovers to the local economy*

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Abstract

Cryptomining, the clearing of cryptocurrency transactions, uses large quantities of electricity. We document that cryptominers' use of local electricity implies higher prices for existing small businesses and households. Studying the electricity market in Upstate NY and using the Bitcoin price as an exogenous shifter of the supply curve faced by the community, we estimate the electricity demand functions for small businesses and households, and find price elasticities of -0.17 and -0.07 respectively. Based on our estimates, we calculate counterfactual electricity bills, finding that small businesses and households paid \$79 million and \$165 million extra annually in Upstate NY because of increased electricity consumption from cryptominers. Using data on China, where prices are fixed, we find that rationing of electricity in cities with cryptomining entrants deteriorates wages and investments, consistent with crowding-out effects on the local economy. Local governments in both Upstate NY and China, however, realize more business taxes, but only offsetting a small portion of the costs from higher community electricity bills. Our results point to a yet-unstudied negative spillover from technology processing to local communities, which would need to be considered against welfare benefits.

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"One-third of the county's residential energy [is] used in one factory that employs 19 people."

City Commissioner, Missoula, Montana (CrowdfundInsider, 3/19/2019)

"There is no job commitment and they have a huge powerload that destroys the [purchase power adjustment], it forces all the ratepayers to pay a higher rate."

Mayor of Village of Westerfield, NY (Village Board Minutes, 3/19/2018)

1 Introduction

High energy use is no longer confined to sectors of the economy such as metals, pulp, and oil, but it is increasingly a feature of many technology processing industries, including quantum computing, artificial intelligence, natural language processing, and cryptocurrency mining ("cryptomining"). Estimates suggest that technology processing passed the milestone of consuming 1% of world energy in 2010 and is on trajectory to increase to 6% by 2030 (Masanet et al. (2020); Andrae and Edler (2015)). Data centers and Bitcoin mining alone now consume 0.9% and 0.5% of global electricity, respectively (Andrae (2017); Cambridge Center for Alternative Finance.).[1] Technology firms prefer to avoid this topic; Google, for example, was recently accused of firing a top ethics researcher because her study highlighted the vast electricity use in language processing (*MIT Technology Review*, 2020).[2] The reason is that intensive electricity use can cause externalities. The obvious first externality is the carbon emission resulting from electricity production. The website *Digiconomist* estimates that the global pollution damage from Bitcoin mining alone is equivalent to that of Pakistan (also see De Vries (2018) and Blandin et al. (2020)). This paper concerns a second, unstudied externality — the effect of technology processing on local economies. In particular, we study the spillovers from cryptomining on households and small businesses, happening through the interaction of supply and demand in the electricity market.

Cryptomining is the clearing of payment transactions for certain decentralized blockchain-based payment systems called (proof-of-work) cryptocurrencies.[3] Cryptomining involves a race to solve complex mathematical problems, which in turn requires huge amounts of computational power. The idea behind this process is to avoid designating a central agent for validating 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

[1] `https://cbeci.org/cbeci/comparisons`.

[2] `https://www.technologyreview.com/2020/12/04/1013294/google-ai-ethics-research-paper-\ forced-out-timnit-gebru/`

[3] Not all cryptocurrencies use proof-of-work cryptomining to clear transactions; our study does not pertain to other forms of blockchain technologies, distributed ledgers, and private party-cleared stablecoins.

the validity of the transactions (see Ciamac and Moallemi (2020) and Chen et al. (2019)). This has led to an arms race among firms who run large cryptomines — essentially warehouses full of specialized computers crunching numbers — across the world.

The story we tell is a simple one. When a large technology processor enters a town, the new entrant shifts out the total demand curve for electricity. If the supply curve is upward-sloping, those on the original community demand curve face a different, higher-price portion of the supply curve. If instead the supply of electricity operates in a fixed-price regime, the new demand may instead induce shortfalls in the availability of electricity for the community.

We begin our analysis in New York State, specifically Upstate NY, excluding New York City and Long Island. NY has a typical grid electricity system. The grid operator, NYISO, employs a marginal supply pricing scheme, whereby upward pressure on prices from demand gets passed onto households and small businesses through a component of the electricity bill called electricity supply charge or purchase price adjustment. This pricing is location-specific in that it is affected by congestion as well as distance from the marginal power plant (i.e., that which can provide the next increment of needed supply at the cheapest rate). We analyze whether the use of electricity by cryptominers affects the location-specific marginal price of electricity that small businesses and households pay.

Using town-month level data, we estimate the local demand for electricity from NY households and small businesses. We address the well-known problem of quantities and prices being endogenous by instrumenting the price of electricity paid by small businesses and households with the price of Bitcoin. When Bitcoin prices are high, the returns from cryptomining are higher in expectation, since the reward to miners is paid in Bitcoins. Thus, the Bitcoin price shifts the demand for electricity by cryptominers. In a first stage regression, we find that the F-statistic is approximately 700, indicating that the instrument is strong. Further, we argue that the exclusion restriction required of the instrument is reasonable, as it is unlikely that the Bitcoin price would affect the demand for electricity by small businesses and households in NY. In the second stage, we find a statistically significant, negative price elasticity of demand for electricity by the local communities. In particular, the price elasticity of demand for households and small business are respectively -0.17 and -0.07, consistent with the literature on electricity demand. For example, Ito (2014) estimates medium-long run elasticities to be between -0.071 and -0.088 for California households.

Next, we apply the instrumental variable (IV) estimates in a community welfare calculation.[4] We use the first stage regression to compute a counterfactual price for the equilibrium under no cryptomining and then simply integrate the demand curves estimated in the second

[4]Cryptominers, like other high electricity-use technology processors, are somewhat unique in the very narrow path whereby their production can promote local welfare. Cryptomining facilities are usually remote from the corporate owner, implying that producer surplus is realized in other physical locations. Cryptocurrency production is immediately transferred remotely via technology; thus, any positive upstream or downstream externalities from the production of cryptocurrencies are not realized locally. Likewise, cryptomining facilities create very few jobs. Together these unique features allow us to hone in on how spillovers from cryptomining directly affect local households and small businesses by focusing on the electricity market channel.

stage between the counterfactual price and the higher price with cryptomining. This integral corresponds to the reduction in household or small business welfare due to the cryptomining-driven increase in electricity prices.

We find that cryptomining leads to the representative household and small business in NY paying $71 and $144 more in their electricity bills per year, respectively. In aggregate, NY households and small businesses pay $165 million and $79 million more annually (excluding any spillovers to New York City). These results are just the tip of the iceberg. If Upstate NY represents a quarter of U.S. cryptomining[5] and other states have similar price effects, our results imply that cryptomining itself induces a cost of $1 billion annually to U.S. households and small businesses, with the caveats of a back-of-the-envelope aggregation to national scale. The implications of our cryptomining price results likely extend to data centers; if so, these aggregations would be a substantial underestimate.

The U.S. represented only 7.24% of global cryptomining in 2020.[6] In other countries, local externalities may occur through quantity rationing rather than increases in prices. This possibility might be particularly important in China, which hosted 65-82% of world cryptomining during the last decade.[7] In China, the pricing mechanism is shut down because provinces set fixed electricity prices, updated only infrequently. Further, electricity grids are regional and cover long distances. Hence, when total demand increases, the electricity supply may need to be rationed in some locations until the physical infrastructure can be adjusted.

To explore possible externalities associated with the rationing of electricity in local economies, we exploit an annual panel of statistics at the city level for China (cities in the data include the surrounding areas). Our empirical design embeds the endogenous choice of cryptomining locations in a difference-in-difference identification strategy. From a production vantage point, the key determinants of cryptomining location choice are temperature (since the computers used for cryptomining require cooling), distance from a power plant, and the price of electricity. We first use data on each of these determinants to estimate a location model; the estimated propensity scores are then used in an inverse probability weighting (IPW) model to identify the effect of cryptomining on a range of local economy outcomes. Our location model produces an area under the ROC curve (a measure of predictive accuracy) of over 0.90. This suggests that our IPW strategy controls for the vast majority of the selection in the location decision.

We find that after cryptomining enters a city, the local business sector declines. In particular, local fixed asset investments decline annually by 0.36%, and the labor market wage level declines by 0.68%. These results suggest that cryptomining tends to crowd out other business uses of electricity.

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[5]Other locations of cryptomining in the United States include Washington, Texas, Nebraska, Georgia, North Carolina, Kentucky, Oregon, and Montana.

[6]CCAF, 2020, January, 2021, from `https://cbeci.org/mining_map`.

[7]This range is derived from Hileman and Rauchs (2017) and current information on `https://digiconomist.net`.

The discussion thus far suggests only negative welfare effects on the local community. However, it is possible that local governments allowing cryptomining in their jurisdictions may benefit from a more lucrative source of taxes. Testimonial evidence suggests that cryptomining is a very profitable (and thus very taxable) use of the local electricity supply. Therefore, our final exercise tests whether the entrance of cryptomining in a community results in a change in tax revenues. We conduct this test both in NY and in China, using the same location choice IPW model discussed above. We find that Upstate NY communities hosting cryptomining experience an increase in taxes per capita by $29.5 dollars. Given that average per capita community taxes are $508, the effect represents an increase of about 6%. In China, we find that cryptomining generates 0.15% more business tax revenues.

We conclude by combining our cost and benefit estimates for local communities in Upstate NY. On the one hand, we estimated a local welfare cost of over $240 million per year via higher electricity prices. On the other, we found that cryptomining is associated with an increase in annual tax revenues by almost $40 million. Hence, higher tax revenues recover approximately 15% of the losses for households and small businesses. Overall, we estimate a local net cost of about $200 million per year in Upstate NY only.

Our analysis abstracts from a number of advantages of proof-of-work cryptocurrencies for users worldwide, including the democratic nature of the process whereby transactions are validated, anonymity, and lower transaction fees. A full assessment of proof-of-work cryptocurrencies requires trading off these advantages against the local economy spillovers studied in this paper as well as the global externalities from energy consumption inherent in cryptomining (Li et al. (2019); Truby (2018); De Vries (2018); Goodkind et al. (2020)).[8] While this comparison is beyond the scope of this paper, we contribute to the discussion by highlighting and quantifying the effects on local economies.

To the best of our knowledge, our paper is the first to study local externalities from energy-intensive technology processing, and in particular cryptomining. We believe that this may have been overlooked in the literature due to three reasons. First, one might assume that electricity supply is insulated from demand pressures because of the transmission grids in electricity supply. Yet, the very local nature of supply of and demand for electricity can matter. Second, those who are negatively impacted are atomistic users of electricity (households and small businesses) and are thus more likely to be overlooked relative to larger entities. Third, it is possible that because energy consumption is a small fraction of expenditure for local community, the externality is not deemed first order. For example, in the UK, electricity consumption is only 4% to 6% of monthly household expenditures and 3% of monthly small business expenditures (Department of Energy and Climate Change (2014)). We find that the effects aggregate to substantial costs for local communities, and the magnitudes would be much larger if we were to extrapolate from cryptomining to all other high electricity-use technology processes. It is also useful to note, as a comparison,

[8] 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.

that Baker Institute for Public Policy (2014) estimates an effect of energy carbon taxes on GDP per capita in the US of the same order of magnitude as our estimates.

In addition to the references cited above, our paper is related to a literature discussing the potential for instability in the blockchains associated with proof-of-work cryptocurrencies due to attacks (Budish (2018), Biais et al. (2018)), cheating (Chiu and Koeppl (2019)), mechanisms in the fee system (Easley et al. (2018)), or fraud in the holding of assets (Twomey and Mann (2019)).[9] Critics also question proof-of-work blockchains as a useful store of value and an integral component of the financial system architecture (Liu and Tsyvinski (2018); Li et al. (2019); Makarov and Schoar (2020)). Finally, our paper contributes to the literature on the impact of large economic players on local economies (e.g., Basker (2005), Jia (2008), Ellickson and Grieco (2013)). This literature has focused on the effect that large entrants — e.g. Wal-Mart — have on local competitors and the labor market. Our paper sheds light on a different channel, the equilibrium in the electricity market, which is likely to play an increasing role given the rise of high energy-use technologies.

2 Conceptual Framework

"The city council unanimously approved an 18 month moratorium on crypto mining activities in Plattsburgh.... The idea of a moratorium was first introduced by mayor Colin Read in January after residents reported inflated electricity bills."

Coin Telegraph, March 16, 2018

"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."

Daily Mail, January 19, 2019

In this section, we introduce an electricity supply and demand framework to illustrate how the entry of a cryptominer can impact the local economy, specifically by increasing the price and potentially hindering the availability of electricity for local businesses and households. Cryptomining requires minimal human intervention and is carried out by a few large companies; thus, we can realistically abstract away from the possibility that cryptomining creates new jobs where the cryptomine is located or that cryptominer profits are reinvested in the local economy. We also abstract from negative pollution externalities, both locally (e.g.,

[9] Additional references on cryptocurrencies and the limitations of proof-of-work protocols include Kroll et al. (2013); Yermack (2015); Halaburda et al. (2016); Dimitri (2017); Alsabah and Capponi (2018); Budish (2018); Kugler (2018); Ma et al. (2018); Prat and Walter (2018); Carlsten et al. (2016); Saleh (2019), Chiu and Koeppl (2019); Pagnotta and Buraschi (2018).

air quality could deteriorate due to increased activity of a local power plant) and globally (notably, climate change).

In our simple model of energy demand and supply, we focus on the case in which the electricity supply curve is upward sloping, and thus electricity prices vary with market conditions, as is the case in the U.S.[10] In Panel A of Figure 1, the fine dashed blue line represents the aggregate local demand (households and businesses) prior to the entry of cryptominers. We refer to this as "community demand" and denote it by $D_{community}(P)$. The solid (black) line is the supply curve so that the initial equilibrium is given by the point E_0, where the community demand intersects the supply curve.

Cryptominers enter the locality with the dotted red demand curve, denoted $D_{crypto}(P)$. 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 a cryptominers' location decision is electricity prices (something we will document empirically) 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

$$D_{total} = D_{community} + D_{crypto},$$

and its intersection with the supply curve (denoted E_1) represents the equilibrium after the entry of cryptominers. Since supply slopes upward, the increase in total demand due to the entry of a cryptominer translates into higher prices ($P_1 > P_0$) for the community.

In Panel B of Figure 1, we consider the case in which the total demand after the entry of cryptominers exceeds the available capacity. Some of the total demand remains unfulfilled corresponding to the difference $Q_{unc} - Q_1$. While the model is silent about who will be left out, 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 revenue-maximizing local governments, who may have binding contracts with cryptominers. The resulting potential blackouts imply another negative externality.

For the purposes of our empirical analysis, we specify the community demand as a standard constant elasticity demand function:

$$D_{community} = \exp\left(\alpha + \gamma X\right) P^{-\beta}, \tag{1}$$

which, taking logs, leads to the log-linear form

$$\log D_{community} = \alpha + \gamma X - \beta \log P. \tag{2}$$

We will take equation (2) to the data. Integrating (1), we can compute the change in

[10] In other markets, prices are set by regulators for extended periods of time, so that the supply curve is flat. We consider this variation in our empirical analysis of cryptomining effects on communities in China.

community surplus due to an increase in P from p_0 to p_1 as

$$\Delta\text{Welfare Community} = -\int_{p_0}^{p_1} D_{community}(p)dp = -\frac{\exp(\alpha+\gamma X)}{1-\beta}\left(p_1^{1-\beta} - p_0^{1-\beta}\right). \quad (3)$$

Community welfare decreases if electricity prices increase due to the entry of cryptominers. Figure 2 provides a visual representation of the welfare loss that mirrors the expression in (3): the welfare loss is obtained by integrating the community demand function between the initial price and the new higher price.

However, a countervailing effect could be that the local tax revenues might increase if local governments are able to tax the cryptomining taking place in their jurisdictions in a way that offsets potential concurrent decreases in tax revenues. We denote this by

$$\Delta\text{Welfare Government} = \tau \times \pi\left(D_{crypto}\right), \quad (4)$$

where τ is the local tax rate on cryptomining profits and π denotes the mapping from energy used as an input to cryptomining into profits.

To summarize, the total social welfare change for the local community will be the sum of the increase in government welfare due to possibly higher tax revenues and the decrease in community welfare due to higher electricity prices:

$$\begin{aligned}\Delta\text{Social Welfare} = \quad & \underbrace{\Delta\text{Welfare Government}(D_{crypto}, \tau)}_{(+)} + \\ & \underbrace{\Delta\text{Welfare Community}(P(D_{crypto}), D_{community})}_{(-)}.\end{aligned} \quad (5)$$

The goal of our empirical analysis will be to quantify each of the two effects in (5), thus providing a measure of the overall impact of cryptomining on local welfare.

3 Data and Summary Statistics

Our primary analysis focuses on the electricity use and local economies in New York State. New York (NY) is an attractive market to study local economy effects because of large cryptomining energy use, rich local economy data, and a large number of rural communities and small cities. In manual searches from online sources — mostly, local news and local government documents — we find that 12 of 52 counties have at least one cryptomining facility in Upstate NY. (We exclude New York City and Long Island given their unique local economy setting relative to the rest of the State.) Given that electricity pricing transmits through the NY electricity grid, cryptomining in any of these twelve counties could affect pricing throughout the State.

We complement this analysis with evidence from China. As mentioned, China is the country hosting the most cryptomining in the world, and thus an important market to study. In addition, the vast number of cryptomining facilities across China allow us to estimate a cross-sectional location choice model which we then use to identify the causal impact of cryptomining on economic outcomes at the city level. Further, in China, the price of electricity does not vary within a province and only adjusts every few years.[11] Therefore, the price channel is shut down in China, and quantity of electricity available is the main mechanism through which cryptomining may affect local communities.

3.1 New York State Data

"Bitcoin mining companies were attracted to the abundant and cheap electricity, with two cryptocurrency mining businesses reportedly operating in Plattsburgh in 2017... During a particularly cold winter... electric power had to be purchased from other sources at higher rates... The two cryptocurrency companies operating in Plattsburgh at the time contributed to an increase of nearly $10 to monthly electricity bills in January 2018 for residential customers."

Congressional Research Service (2019)

3.1.1 Overview of NY Electricity Pricing Grid

At over 19 million people, NY is the fourth most populous state in the country, and alone would be the eleventh largest economy in the world. Moreover, NY emits one out of every 200 tons of energy-related carbon dioxide in the world.[12] Electricity providers divide consumption of electricity in NY into three local sectors – residential, commercial (small business), and industrial. The average NY monthly electricity bill is $107 for residential customers, $919 for small business, and $9,390 per month for industrial customers, with residential, small business, and industrial customers paying 17.6 cent/kWh, 15.06 cent/kWh, and 6.7 cent/kWh, respectively.[13] While the residential and small business rates are among the five most expensive in the country, the industrial rate is much lower, ranking right in the middle among the states. According to a report by the Congressional Research Service,

[11]Figure 3 shows average electricity prices for selected provinces in China. We find limited variation across years, which is likely to reflect political decisions rather than economic forces, such as cryptocurrencies entry in specific markets. If anything in the provinces where we find more evidence of cryptomining presence (Heilongjiang, Inner Mongolia and Sichuan) electricity prices increase by less than in provinces without cryptomining activity (Guangxi, Jilin and Shaanxi).

[12]Forbes, February 20, 2020, "New York Power Grid Proposes Adding Carbon Costs to Market Price of Electricity".

[13]`https://www.electricitylocal.com/states/new-york/`.

favorable electricity rates in Upstate New York may have encouraged cryptominers to relocate their operations to the area.[14]

The electricity price faced by end users is the combination of a number of line items appearing on the monthly statement. A statement will have a fixed monthly service charge, a delivery charge per kilowatt, a number of adjustment and legacy charges, and a component called electricity supply charge.[15] For our purposes, the key aspect of this pricing system is the electricity supply charge, which varies over time and by location as we discuss next.

Electricity is generated at various plants and is transmitted via a grid, with the New York Independent System Operator (NYISO) managing the wholesale electricity market.[16] The grid revolves around a pricing mechanism called the location-based marginal pricing (LBMP). Power generating plants inform the grid IT system as to their supply schedules (prices and quantities) on an ongoing basis. The system then decides which generator is the next marginal supplier, based on demand and supply. The generators have projections for these calculations, so that they can plan ahead to bring supply online or offline as demand warrants. The marginal price is then adjusted for each demand location according to transmission distance and congestion on the lines, thus ending with a location-based marginal price.[17]

Putting these mechanics together, we see that electricity prices fluctuate by location and by sector within the economy and that the LBMP — which affects the electricity supply charge and is thus passed onto end users — would be affected by an increase in demand relative to the usual level. In our context, cryptominers increase total demand, which affects what portion of the supply curve the community faces and may drive up the electricity price for all community users (residential and small business) at all locations through the LBMP grid mechanism.

3.1.2 Local NY Consumption of Electricity

New York State regulators mandate the reporting of monthly data on electricity utilization and prices from utility providers. Upstate New York has four major investor-owned utility companies and several smaller community providers. Our main empirical analysis is based on highly detailed data on electricity consumption for the largest investor-owned utility companies collected by the New York State Energy Research and Development Authority

[14] The report can be found at `https://crsreports.congress.gov/product/pdf/R/R45863`.

[15] See, for example, `https://www.nationalgridus.com/Upstate-NY-Home/Rates/Service-Rates`.

[16] Further explanation of the electricity grid is available at NYISO's webpage: `https://www.nyiso.com`.

[17] Some power plants have independent contracts with municipalities and industrial users, including cryptominers. For example, Tim Rainey, the CFO of cryptomining company Atlas, who bought the Greenidge Generation power plant, discusses the role of the grid: "As both the cryptocurrency markets and the power markets are constantly fluctuating, we do whichever is more profitable at any given time—either sell the generated power or mine crypto with that power." "Bitcoin Mining Can Be Profitable, If You Generate The Power," Forbes, Aug 13, 2020.

(NYSERDA), and high-frequency data on location-based marginal prices at the generator level collected by the New York Independent System Operator (NYISO).[18]

Panel A of Table 1 reports summary statistics from our combined dataset. First, we report electricity consumption by user type at the community, electricity provider and year-month level. The average community consumption by households is about 1,500 MWh, while the median is about half at 0.7 thousands MWh. The average number of residents per community-provider is about 2,300, while the median is almost 900. The average consumption of electricity by small businesses is lower than for households, while other businesses consume about seven times as much as small businesses (500 and 3,500 MWh, respectively). The difference between small and other businesses is even starker if we look at per capita consumption. The average (median) number of small business customers is about 250 (90), while the average (median) number of other businesses is about 100 (40).

Second, panel A of Table 1 reports the average LBMP after merging the data on the location-based marginal price (LBMP) with the electricity consumption dataset. To combine the data on electricity consumption with information on the LBMP, we first construct a daily time series at the generator level by averaging real time LBMP data from NYISO. Then we assign each generator to its community based on geographical coordinates. Finally, we compute the average LBMP at the year-month and community level by averaging across days of the month and across generators in the community. The average LBMP is about $27/MWh and it ranges from $2.5/MWh to more than 100$/MWh across communities/providers and over time.

3.1.3 Cryptomines and Other Local Economy Variables

We gather additional data on communities in Upstate NY from several sources which we report in Panel B of Table 1. First, we report average temperatures in Fahrenheit. The mean temperature is about 47, ranging from a minimum of about 13 to a maximum of 75. Second, we show the average monthly price of Bitcoin (obtained from `https://coinmarketcap.com`). In our sample period, the price of Bitcoin is on average $4,000, but it ranges from $400 to more than $15,000. In the empirical analysis, we exploit these large swings in the Bitcoin price to identify the electricity demand in Upstate NY.

Panel B of Table 1 also shows additional town-level variables that we use in our analysis of the effect of cryptomining on local government finances. Taxes per capita are on average $520, ranging from a minimum of $66 to a maximum of $9,000. Total local government expenditures per capita are higher on average than taxes and exhibit more variability. Expenditures per capita are on average $820, ranging from a minimum of $43 to a maximum of about $15,000.

Finally, we since no public registries exist as to the location of cryptomines, we hand

[18] The two dataset can be downloaded at `https://www.nyserda.ny.gov/All-Programs/Programs/Clean-Energy-Communities/Community-Energy-Use-Data` and `https://www.nyiso.com/energy-market-operational-data`, respectively.

collected data on their likely location, starting from the list of all communities in Upstate NY from the electricity consumption dataset. For each community, we do manual searches in Google and Google News to look for local news articles or other web references to any crypto-mining facilities. Our search terms include cryptomining (and variations of it, such as crypto mining and crypto-mining), the names of the top cryptocurrencies (Bitcoin, Ethereum, Ripple), and the names of the top mining pools (BTC.com, AntPool). We do multiple concurrent (blind) coding rounds so as to verify the information with different manual reads. We code a mining variable equal to 1 only if an article or webpage explicitly mentioning crypto operations in the community. We find evidence of cryptomining in 13 communities which are located in 12 different counties. Figure 4 shows a map that summarizes our hand-collected data on local evidence of cryptomining in Upstate NY. The majority of cryptomining activity in Upstate NY is concentrated in the colder and less-populated North, close to large hydropower sources. This pattern is consistent with anecdotal evidence that cryptomining companies prefer location with colder weather (because the machines become hot and malfunction without cooling), and with affordable and reliable energy supply.

3.2 China Data

3.2.1 Cryptomines and Power Plant Locations in China

Turning to China, we follow an approach similar to the one discussed in Section 3.1 for Upstate NY to identify location of cryptomines. We start with all the cities reported in each Province's economic statistics Yearbook. City designations are more akin to a county with a city seat and a surrounding area under the same jurisdiction; all of the land mass is covered by city divisions. We exclude all coastal provinces and three major urban centers (Beijing, Chongqing, and Tianjin) as their economies are not similar to the inland areas where cryptomining operations occur (Blandin et al. (2020)), and cryptomining is not a feature of these outward-facing economies. Further, we exclude the autonomous regions of Tibet and Qinghai, due to sparse data on economic outcomes.

For each city, we do manual searches in Google and Google News (in English), but also in Baidu and Baidu News (in Mandarin) to look for local news articles or other web references to any cryptomining facilities. As for Upstate NY, we have multiple concurrent (blind) coding rounds so as to verify the information with different manual reads. We code 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). In China, we find 54 cities with cryptomining and 164 cities without cryptomining. Figure 5 shows a map that summarizes our collected data on local evidence of cryptomining in China. Panel A shows the number of cities with cryptomining activities across provinces, while Panel B shows the cities where we find evidence of cryptomining.

Testimonial evidence suggests that cryptominers tend to view a location as desirable if it exhibits colder temperature, low electricity price, proximity to a power plant, and a friendly local government. This motivates us to 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 power source (hydro, coal, solar, gas, wind, or oil). The data on location of power plants comes from the Global Power Plant Database, which is a comprehensive, global, open source database of power plants.[19] We use temperature, proximity to a power plant and electricity price in the location model. As our subsequent analysis will show, our location model reaches an area under the ROC curve of over 0.90, indicating that the included variables capture most of the drivers of cryptominers' location decisions.

3.2.2 Energy Mix

Anecdotally, the media often mention two Chinese provinces as hosting many cryptomining facilities. One province, including the cities of Erdos and Baotou, is Inner Mongolia, largely powered by coal plants. The other is Sichuan, which has hosted a large volume of cryptomining during its high-river season close to the city of Mianyang. The disparity of cryptomining being supported by fossil fuels as opposed to hydropower may be important for our business activity tests, but also is important in and of itself.

We find that 27.8% of cryptomining cities are powered by hydropower and that an additional 13% are powered by wind. This leaves just short of 60% of cryptomining cities being powered by coal (48.2%) and gas (11.1%). Since we do not observe capacity at each cryptomine, we are not able to translate this into a breakdown of the energy mix used to power the overall cryptomining taking place in China. However, given that some of the largest cryptomines are known to be located in Inner Mongolia, it is likely that 48.2% is an underestimate of the importance of coal.

If 48.2% of Chinese cryptomining is powered by coal, and 80% (in 2020, 60%) of the world's cryptomining happened in China during our sample period, this implies that at least 39% (in 2020, 29%) of the world's cryptomining was coal-based or 47.4% (36% now) was fossil-fuel-based if we also include 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 where the media have documented cryptomining takes place. Thus, we conservatively conclude that one-half to two-thirds of cryptomining involved fossil fuels during this time period.

3.2.3 Local Economy Variables

We gather data on the local economies of Chinese cities from the province-level Yearbooks, published directly on each province's websites. Our Chinese city data cover the years 2011-2017. Table 2 reports the summary statistics for 154 Chinese cities without cryptomining and 52 cities with evidence of cryptomining. The average city has a population of 356,000 with no large differences between cities with or without cryptomining. The average GDP of

[19]The dataset can be downloaded at `http://datasets.wri.org/dataset/globalpowerplantdatabase`.

cities with cryptomining (19 billion yuan) is higher than that of cities without cryptomining (14 billion yuan). Further, cryptomining cities consume on average more energy than cities without cryptomining, collect higher business and value added taxes and have higher fixed assets investments. Finally, we gather data on electricity prices at the province level from the government agency National Development and Reform Commission.[20] Consistent with anecdotal evidence and the selection model we will discuss later, cryptomining cities tend to be located closer to power plants, face lower electricity prices and experience lower temperatures.

4 Empirical Analysis: New York State

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

— Read and Laniado, LLP, February 15, 2018

Our main empirical analysis considers the impact of increasing electricity demand from cryptominers on community small businesses and households through the equilibrium in the electricity market. We study this effect in New York State. We first present a case study as suggestive evidence. We then lay out our main empirical strategy and present our estimation results. Finally, we report a welfare calculation from our estimates.

4.1 Descriptive Evidence

We begin our analysis by considering a case study, which shows the impact of Bitcoin prices on electricity consumption in NY State. Specifically, we focus on the city of Plattsburgh, which attracted cryptomining operations — even before the large increase in cryptocurrency prices between 2017 and 2018 — due to its cold climate and cheap electricity.

Figure 6 shows monthly electricity consumption — for small and industrial businesses — in the town of Plattsburgh and the neighboring town of Peru. Before the end of 2017, both Plattsburgh and Peru experienced a similar pattern in electricity consumption for businesses.

[20]See `ndrc.gov.cn`

However, in January 2018 — when the Bitcoin price peaked — electricity consumption by Plattsburgh businesses increased by almost 150%, whereas almost no change occurred in Peru. While we do not directly observe the electricity consumption by cryptomining firms, suggestive evidence indicates that cryptomining accounted for about 10% of the local demand in Plattsburgh in January and February 2018 and contributed to an increase of about $10 in monthly electricity bills.[21] Soon after this spike, Plattsburgh issued a moratorium on cryptomining, and energy consumption returned to a pattern similar to that of neighboring Peru.

4.2 Estimating Equations

Our identification strategy leverages an increase in cryptominer electricity demand as an exogenous shock that drives up the price faced by the local community. We exploit the role of the price of Bitcoin. When the Bitcoin price is high, cryptomining production has a higher expected payoff since the reward from cryptomining is paid in the cryptocurrency. Thus, the Bitcoin price shifts out the demand of electricity by cryptominers — and therefore total demand — which in turn affects which portion of the supply curve is faced by the local community.

For each user type u, our first stage equation is as follows:

$$\log p_{ct} = \alpha^u \log p_t^{BTC} + \gamma_1^u X_{ct} + \mu_{1,p}^u + \mu_{1,c}^u + \varepsilon_{pct}^u, \tag{6}$$

where p_{ct} is the location-based marginal price in community c at time (month-year) t; X_{ct} includes other determinants of electricity consumption (e.g., local temperatures); $\mu_{1,p}^u$ and $\mu_{1,c}^u$ are provider and community fixed effects. Provider fixed effects control for differences in fixed costs or pricing structures across providers. The key parameter is α which captures the elasticity of the location-based marginal price to the price of Bitcoin.

We now present our main outcome equations which follows directly from the framework presented in Section 2. First, for each user type u, we estimate the following model:

$$\log q_{pct}^u = \beta^u \log p_{ct} + \gamma^u X_{ct} + \mu_p^u + \mu_c^u + \epsilon_{pct}^u, \tag{7}$$

where q_{pct}^u is the electricity consumption by user type u (household or small business) in community c for provider p at time t. The key parameter is β, which captures the elasticity of electricity consumption to the marginal price. When we use the price of Bitcoin as an instrument for electricity prices to address the well-known endogeneity of prices and quantities, our IV equation is given by:

$$\log q_{pct}^u = \beta^u \widehat{\log p_{ct}} + \gamma^u X_{ct} + \mu_p^u + \mu_c^u + \epsilon_{pct}^u \tag{8}$$

[21]See Ana Alexandre, "New York State Regulators Approve New Power Rate Structure for Crypto Miners," Cointelegraph, July 13, 2018.

where $\widehat{p_{ct}}$ is instrumented using the Bitcoin price and all other variables are as in equation (7).

4.3 Results

Table 3 reports the results for small business (Panel A) and residential (Panel B) electricity consumption at the community level. Focusing first on column (1), which reports the results of our first stage regression, we find an elasticity of the location-based marginal electricity price to the price of Bitcoin of about 0.14. In other words, a 10% increase in the price of Bitcoin is associated to a 1.4% increase in the location-based marginal price. The regression includes year fixed effects and controls for temperature. Importantly, the $F-$statistic is approximately 700, suggesting that demand by cryptominers does put upward pressure on electricity prices and, thus, that are our instrument is relevant.

Column (2) of Table 3 shows the results from the non-instrumented OLS regression of electricity quantity demanded on the location-based marginal price; Panel A shows the results for small businesses, while Panel B considers residential customers. The estimation includes temperature as a control, community fixed effects, and utility provider and year fixed effects. The positive coefficient on the LBMP reflects the well-known endogeneity issue in estimating demand functions from data generated by the equilibrium interaction of demand and supply. In the data, price increases could be driven by increases in demand (as opposed to reductions in supply), thus complicating the task of recovering the true — i.e., all else equal — effect of a price change on quantity demanded.

Column (3) Table 3 show the IV results, the main results of the paper, following from equation (8). The instrumental variable strategy allows us to interpret the coefficient on the LBMP as the true elasticity of community demand to price changes. The coefficient is now negative and significant. As prices increase exogenously, quantity of electricity demanded declines. In particular, small businesses have an elasticity of demand of -0.179, while residential customers have a lower elasticity of -0.074. For comparison, Ito (2014) estimates medium-long run elasticities to be between -0.071 and -0.088 for California households. These findings lead to two implications. Households and small businesses choose to consume less electricity in response to prices, and the price they pay is higher.

4.4 Local Welfare Calculation

Using our framework in Section 2 and our empirical results, we estimate the local welfare effects of cryptomining on small businesses and consumers.

For each location, we use the estimates from the first stage regression (6) to compute the predicted marginal price before and after the entry of cryptominers. Specifically, for each community c and month-year t, we calculate

$$\widehat{\log p}_{ct,nocrypto} = \hat{\alpha}^u \log p_{2016}^{BTC} + \hat{\gamma}_1^u X_{ct} + \hat{\mu}_{1,p}^u + \hat{\mu}_{1,c}^u, \tag{9}$$

where the coefficients are the estimates from the first stage regression (column (1) of Table 3) and p^{BTC}_{2016} is the average price of Bitcoin in 2016. Since the price of Bitcoin spiked in 2017 and early 2018 (spurring an increase in cryptomining worldwide), we take 2016 as our "pre-cryptomining" benchmark. Thus, we interpret $\widehat{\log p}_{ct,nocrypto}$ as the (log) counterfactual electricity price that would have emerged in the community had cryptominers not entered. Similarly, we compute

$$\widehat{\log p}_{ct,crypto} = \hat{\alpha}^u \log p^{BTC}_{2018} + \hat{\gamma}^u_1 X_{ct} + \hat{\mu}^u_{1,p} + \hat{\mu}^u_{1,c}, \tag{10}$$

and interpret this as a measure of the electricity price after the entry of cryptominers.

Given $\widehat{p}_{ct,nocrypto}$ and $\widehat{p}_{ct,crypto}$ (the non-logged versions of (9) and (10)), we calculate the total welfare change at the community level using the integral in equation (3) as follows

$$\Delta \text{Welfare Community}_{ct} = -\int_{\widehat{p}_{ct,nocrypto}}^{\widehat{p}_{ct,crypto}} D_{community}(p)dp = -\frac{\exp\left(\hat{\alpha} + \hat{\gamma} X_{ct}\right)}{1-\hat{\beta}} \left(\widehat{p}^{1-\hat{\beta}}_{ct,crypto} - \widehat{p}^{1-\hat{\beta}}_{ct,nocrypto}\right),$$

where the coefficients $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ are given in the IV column of Table 3. In words, the decrease in welfare is simply the integral of the community demand function between $\widehat{p}_{ct,nocrypto}$ and $\widehat{p}_{ct,crypto}$. Finally, for each location, we divide the total welfare changes by the number of accounts to obtain per-capita (or per-business) welfare changes.

We find that households experience an extra cost of \$6 per month, or \$71 per year. While the amount might seem small, we doubt that any residents would be indifferent if they realized that they were paying higher prices because of cryptomining. The average monthly electricity bill in NY is \$106 for residents;[22] thus, the welfare cost in percentage terms is +6%. Further, note that our result is similar to our previously highlighted quote from Plattsburgh that cryptomining had driven up the electricity prices for households by \$10 per month.

Small business losses are higher at \$12 per month on average, adding up to \$144 per year. The average monthly electricity bill in NY for businesses is \$919,[23] implying a +1.3% cost on average. However, since the distribution of electricity bills has a long right tail, the percentage increase in costs is substantially higher for many businesses. Further, as the Covid-19 pandemic has made very transparent, small businesses often operate with thin margins.[24]

The aggregate implication is the households in Upstate New York pay \$80 million extra annually in electricity costs. Small businesses in Upstate New York pay \$165 million more

[22] See `https://www.electricitylocal.com/states/new-york/`.

[23] See `https://www.electricitylocal.com/states/new-york/`.

[24] See, for example, Davis et al. (1996); Davis et al. (2007); Haltiwanger et al. (2013); Decker et al. (2014).

in aggregate because of cryptomining.[25] We represent these effects in Figure 7. Following the discussion in Section 2, we show the market equilibrium before and after the entry of cryptominers. Increased demand due to cryptominers' entry leads to higher equilibrium prices. The shaded areas represent the welfare losses for households (Panel A) and small businesses (Panel B). Note that, consistent with our findings and the existing literature, we plot both household and small business demand as very inelastic. Further, as in our data, we depict household demand as being larger and less elastic relative to small business demand.

5 Empirical Analysis: China

We now turn to the case of China, which is the country hosting the most cryptomining in the world. Unlike in NY State, electricity prices are fixed at the province level in China. Therefore, in this section we do not focus on price effects, but rather consider the impact of cryptomining on local economy activity happening through quantity channels. In particular, the entry of highly energy-intensive players could crowd out other electricity uses and have a negative impact non-cryptomining economic activity. On the other hand, cryptomining could in principle boost local economies, e.g., by creating new jobs and pushing up wages, although this seems unlikely given the nature of the business as we discussed above. To study these possibilities, we estimate a difference-in-difference model with an embedded location choice model to address endogenous selection.

5.1 Estimating Equations

We consider several outcome variables, denoted Y_{ct}, for each city c and year t. Specifically, we look at: (i) energy consumption (corresponding to $D_{community}+D_{cryptomining}$ in the framework of Section 2), and (ii) labor market indicators and fixed asset investments (a proxy for the commercial and industrial side of $D_{community}$). In the next section, we will use the same design to study (iii) business tax revenues (for the government side of local welfare). Our estimating equation is given by:

$$\log Y_{ct} = \alpha \ cryptomining_c \times Post_t + \gamma X_{ct} + \mu_c + \mu_t + \epsilon_{ct}, \tag{11}$$

where $cryptomining_c$ is a dummy equal to one if there is evidence of cryptomining operations in city c; $Post_t$ is a dummy equal to one if $t \geq 2015$; μ_c and μ_t are city and year fixed effects; and X_{ct} is a vector of time-varying city level controls.[26] The interaction between $cryptomining_c$ and $Post_t$ yields a standard difference-in-difference specification, with the coefficient α measuring how hosting cryptomining activities affects the outcome variables over time.

[25]We discuss and revisit this aggregate calculation in Section 6 and in reference to Table 9 after including the effect of cryptomining on local government finances.

[26]Cryptomining entered China in earnest a few years earlier than it entered NY.

In this specification, if miners' location decisions were only based on time-invariant factors, we could consistently recover α. However, one might be worried that time-varying factors might also influence the cryptominers' location decisions. Hence, we employ inverse probability weighting (IPW) where the weights are the propensity scores obtained from a location model:

$$cryptomining_c = f\left(X_c, Z_c, \eta_c\right). \tag{12}$$

This location model analyzes location characteristics that are desirable for cryptominers, using pre-2015 data. To formalize this, we define $Y_{ct}^{(1)}, Y_{ct}^{(0)}$ as the potential outcomes for city c in year t with and without cryptomining, respectively. The value $Y_{ct}^{(0)}$ is the outcome in city c had cryptomining never happened. By definition, it is not observed if city c hosts cryptomining in the data. Conversely, $Y_{ct}^{(1)}$ is the outcome for a city had cryptomining taken place there. Then, under the "selection on observables" assumption

$$Y_{ct}^{(1)}, Y_{ct}^{(0)} \perp cryptomining_c | X_c, Z_c, \tag{13}$$

an IPW regression based on (11) will yield consistent estimates of the effect of cryptomining on the outcomes even in the presence of time-varying unobservables. In words, the "selection on observables" assumption (13) requires that the observables included in the location and outcome models be rich enough that all remaining variation in the location choice is independent of potential outcomes. We cannot prove this claim, but are reassured by the fact that the location model has very high predictive accuracy, as discussed next.

5.2 Results

5.2.1 Location Selection

"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

We model the location choice of cryptominers as a function of the city proximity (log distance) to the closest power plant, the price of electricity, and the average annual temperature in the city. 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 three bins based on the terciles of the distribution, and we include an intercept and a linear slope term for each of the bins. We also include the natural logarithms of population, the city government budget, and GDP.

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 period in which cryptomining took off.

The results are shown in Table 4. Because the spline coefficients and node shifters are not easily interpretable, we plot the predicted probability functions with the marginal effects of power plant distance, electricity price, and temperature in Figure 8. Distance from power plants plays a key role, with the closest locations having a predicted cryptomining probability of 0.35 as compared to less than 0.05 for those farthest away. Regarding temperature, we obtain a somewhat non-monotonic pattern, consistent with the fact that both colder coal-based regions and the warmer Sichuan river-valley host many mining operations. The hottest regions, however, are very unlikely to host cryptomining. Finally, turning to pricing, low electricity prices greatly draw cryptomining activities, with the cheapest areas having almost a 0.30 probability of hosting cryptomining.

What is perhaps most important is the fit of the model and, in particular, its predictive accuracy. The most compelling statistic is the area under the ROC curve, which captures the ability of the model to discriminate correct classifications into cryptomining locations versus false positives. The statistic is 0.905 for our model, strongly suggesting that our approach captures much of the cryptominers' location decisions.

5.2.2 Local Economy Results

"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."

Daily Mail, January 19, 2018

All of the local economy specifications have a similar column structure, regardless of the dependent variable. We first present OLS estimation of the economic outcome as a function of $cryptomining_c \times Post_t$, time and city fixed effects, and local economy controls. The second column introduces IPW weighting based on the inverse of the propensity scores from the selection model, balanced to provide equal propensity weighting for cryptomining being selected and not. The third column then includes an interaction of $cryptomining_c \times Post_t$ with whether the local power plant is $fossil-$fuel based (and including the necessary double interactions). The second and third columns have fewer observations since the IPW process drops cities that do not satisfy the common support assumption. In particular, cities that have warmer weather, have high electricity prices, and are farther away from power plants are dropped.

First, we look at energy consumption. Energy consumption at the city level should increase with the entry of cryptomining, implying that more of the production of local power plants is consumed in the local economy. As reported in Table 5, the R^2 statistics are extremely high, as energy consumption is very static year-to-year. While other economic indicators — population, GDP and electricity prices — do not emerge as powerful predictors in such a specification, we find some evidence for an effect of cryptomining, but only for those cities powered by fossil fuels. This increase is, however, modest. In fossil fuel-based cities, the introduction of cryptomining was accompanied by a 0.23% increase in energy consumption. The small magnitude of this effect suggests that other industries and commercial enterprises may be cutting back on energy use as cryptominers enter.

Next, we look at whether cryptomining induces any spillovers in the local economies. The potential for positive effects on the overall economy is indeed one of the arguments often put forth by advocates of cryptomining. In order to test this claim, we look at the impact of cryptomining on the local labor market (wages) and fixed investment by the commercial sector (fixed asset investment). Note that we cannot isolate the investment by the cryptominers themselves, so our estimates are biased toward finding a positive effect on investments. We first look at per capita wage levels in columns (1) to (3) of Table 6. We find that wages tend to *decrease* as a result of crypto operations. For these cities, the introduction of cryptomining is accompanied by a decrease in wages of 0.68%. It is perhaps not surprising that the labor market is not spurred by cryptomining investment, as cryptomining facilities employ very few workers. The negative effect may result from declining demand for workers by other commercial enterprises and industry due to cryptomining crowding out other energy uses. In columns (4) to (6), we consider whether cryptomining has any positive spillover effects on local business activity. The results indicate a negative impact on fixed asset investments. We include wages in this specification to show that this effect is independent of any other impacts mediated via the labor market. (The result does not change without this control.) In terms of economic magnitude, the introduction of cryptomining is accompanied by a decrease in local fixed asset investment of 0.36%. Taken together, these findings suggest that it is possible that local economies suffer as a result of crowding out in the electricity market.

6 Effects on Local Taxes

"It's good for the economy. We're seeing [bitcoin mining] really diversifying our economy. There are millions of dollars being invested in the economy. It's going to help our tax base...."

— Interview with Ron Cridlebaugh
Port of Douglas County economic development manager
Politico (3/9/2018)

Given the results in Section 4 for NY and Section 5 for China, it is natural to ask why local governments in the US or China might be willing to allow or even encourage cryptomining. The evidence thus far suggests only negative welfare effects on the local community through higher electricity prices and energy crowding out. However, it is possible that cryptomining benefits local governments by providing a more lucrative source of taxes. Testimonial evidence suggests that cryptomining is a very profitable (and thus very taxable) use of local electricity supply. This might provide a substantial source of tax revenues for local governments, especially 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.

In this section, we explore if and to what extent the entry of cryptomining in a community results in a change in local taxes and government expenditures. We perform this analysis both in NY and in China, using the production location choice IPW model discussed in Section 5.1.

6.1 China

In the context of China, we consider two measures of taxation collection — value-added and business income. As per Chinese tax law, software and technology companies are subject to value added taxation of production at a reduced rate of 6%.[27] Our analysis of the effect of cryptomining on local taxes follows exactly the estimating equations discussed in Section 5.1.

The results in Table 7 support the thesis that governments have an incentive to attract cryptomining due to the fact that it tends to increase business tax revenues. This result is weak except for cities for which the closest power plant is from clean energy, i.e. non-fossil fuel-based. Thus, we focus on columns (3) and (6) for clean cities. We find that in clean power cities, the introduction of cryptomining is accompanied by an *increase* in business taxes by 0.15%. Again, this is consistent with the fact that cryptomining is a highly profitable activity[28] and, thus, one that tends to yield more tax dollars per unit of electricity.

6.2 New York State

6.2.1 Results

We now study the effect of cryptomining on community-level taxes in NY. The tax data available to us are at a lower frequency compared to the electricity price and consumption data (annual rather than monthly). As a result, we cannot implement the same identification strategy discussed in Section 4.2, which exploits high-frequency variation both in the price of Bitcoin, and in the price and consumption of electricity. However, while the *time-series* variation is more limited, we are able to exploit granular variation in the *cross-section* of communities based on their exposure to cryptomining.

[27] Consultancy KPMG provides an informative report on Chinese VAT, which serves a large role in revenue collection for the government (KPMG, 2016).

[28] See, e.g., `digiconomist.com`.

We estimate a difference-in-differences specification on a yearly panel of communities in Upstate NY. Specifically, our estimating equation is given by:

$$Y_{ct} = \alpha cryptomining_c \times Post_t + \mu_c + \mu_t + \epsilon_{ct}, \tag{14}$$

where $cryptomining_c$ is a dummy equal to one if there is evidence of cryptomining operations in the county where community c is located. We allow tax benefits to accrue across towns within the same county government, because counties play a role in taxation and power contracting at the town level. $Post_t$ is a dummy equal to one if $t \geq 2017$; μ_c and μ_t are community and year fixed effects. The interaction of $cryptomining_c$ with $Post_t$ produces a standard difference-in-difference specification, with the coefficient α measuring how hosting cryptomining activities affects the outcome variables over time.

Following the approach for China, we account for time-varying factors via an IPW specification based on a location model akin to that in equation (12). In particular, we capture miners' location choice using information on county-level average temperature and power plant capacity in 2010 (the first year of our taxes and expenditures data). Figure 9 shows a map motivating our model. In Panel A on the lefthand side, we depict the cryptomining counties in Upstate NY. In Panel B, we show a heat map of the average temperature and power plant capacity by county in 2010. The Panel B maps reflect a strong correlation between cryptomining activity and both power plant capacity (higher capacity predicts cryptomining) and temperature (lower temperature predicts cryptomining).

More formally, Column (1) of Table 8 shows the estimates of the location choice model using the panel of communities. We allow all towns in cryptomining counties to be treated, as described above. We find that both power plant capacity and temperature have a significant effect on the probability of a town hosting cryptomining. The results are consistent with our estimates for the location choice model in China (see Table 4) and with climate and proximity to power plants being among the main determinants of cryptominers' location choice.[29] While very parsimonious, the fit of the model is quite good with an area under the ROC curve statistic of about 0.70.

The right-hand side of Panel A in Figure 9 shows the fitted probability that a county hosts cryptomining. Our prediction of cryptomining location closely tracks the power capacity distribution across counties. As robustness to unwind the tightness of the location-power capacity relationship, we also implement a model that just uses the common support requirement implied by the location model, but without the final probability weighting.

Columns (2) to (4) of Table 8 show the results using taxes per capita as the dependent variable. Columns (5) to (7) report results on the flip-side of taxation, i.e. government expenditures per capita. First, columns (2) and (5) reports the OLS estimates of the difference-in-difference model given by equation (14). We find that treated communities experience a differential increase in annual taxes per capita compared to control communities after the

[29] See, e.g., `https://www.techinasia.com/inner-mongolia-bitcoin-mine.`

introduction of cryptomining. The effect is statistically significant and the point estimate implies an increase of about $17 per capita. We cannot, however, identify and effect of cryptomining on expenditures in the OLS specification.

Columns (3) and (6), the main estimates, presents the tax results from the IPW-selection model. We again find a positive significant effect of cryptomining on tax generation, and the magnitude increases relative to the unweighted model. Treated communities experience a relative increase in taxes per capita by $29.5 dollars compared to control communities. In expenditures, the magnitudes and statistical power also increase. As robustness, columns (4) and (7) report the estimates using the common support. The effect is again significant and the magnitude of the coefficient straddles the OLS and IPW estimates.

To put these numbers in perspective, we start with the observation that the average community tax revenue per capita in Upstate NY is $500. If we take our main IPW result as a benchmark, we find that cryptomining is associated with a 6% increase in taxes per capita. Treated communities experience a relative increase in government expenditures by about $51.4 dollars compared to control communities. Given average expenditure per capita of about $800, we find that cryptomining is also associated with a 6% increase in expenditure per capita.

Overall, the results from Table 8 support the thesis that government may have an incentive to allow cryptominers to operate in their jurisdiction due to the prospect of increased tax revenues.

6.2.2 Updated Local Welfare Calculation

We conclude this section by updating our NY State welfare calculation from Section 4.4 to reflect the positive impact of cryptomining on local government finances. Table 9 shows the results. Column (1) in Panel A reports the estimated monthly cost faced by small businesses and households via higher electricity prices using the estimates from Table 3. Column (2) scales those losses up to the year level to be able to compare them with the annual gains in terms of tax revenues, which are reported in the same column in Panel (B). For this calculation, we use the difference-in-difference estimates with IPW weighting. In Panel B, we look at both taxes and government expenditures. The calculation using local government expenditure gives us an upper bound on the effect of cryptomining on local public finances.

In column (4), we obtain aggregate annual welfare costs for Upstate NY by multiplying the individual annual losses in column (2) by the number of affected individuals/small businesses.[30] Aggregating small businesses and households, we obtain a welfare cost of about $240 million happening via the electricity market spillovers. Higher tax revenues reduce this

[30]We compute the number of affected small businesses as the total number of small businesses in NY state times the population share of Upstate NY relative to the entire state. The number of affected households is the total population of Upstate NY in 2019 divided by the average number of people per households. The number of affected households/businesses in the tax and expenditure calculations is the population in treated towns.

cost by almost \$40 million, thus recovering slightly more than 15% of the losses. As a result, we estimate a welfare cost of about \$200 million in Upstate NY.

When accounting for the differential increase in government expenditures, we find that in the aggregate cryptomining towns in Upstate NY generate almost \$70 million in additional government expenditures, thus recovering about 28% of the losses. As a result, we estimate a lower bound on the welfare loss of about \$175 million.

Finally, in column (5) of Table 9 we provide an estimate of the aggregate losses for the entire US, under the assumption that about 25% of cryptomining is taking place in Upstate NY. We obtain welfare losses for households and business of almost \$1 billion. When taking additional tax revenues into account, the net losses are between \$700 to \$820 million.

7 Conclusion

In this paper, we have presented testimonial and empirical evidence of the effects of cryptomining on local economies. First, we focused on a setting — Upstate New York — where cryptomining led to an increase in electricity prices. We estimated the local community's demand for electricity and used this to quantify the welfare losses incurred by the community as a result of higher electricity prices. We find that the magnitude of the welfare losses is large. We then turned to China, the country hosting the most cryptomining operations in the world, to assess the impact of cryptomining on the broader economy. Consistent with the nature of cryptomining, we find a negative impact on the labor market as well as fixed asset investments. Finally, we investigated whether cryptomining benefits local economies via increased tax revenues. We find that this is indeed the case in both Upstate NY and China, which helps explain why local governments have been eager to welcome cryptominers in their jurisdictions despite the negative externalities we document. However, we find that the additional tax revenues are smaller than the cost imposed on households and small businesses through higher electricity prices.

Of course, cryptomining — just as any other technology advances — may enhance the welfare of society at large (e.g., by supporting more democratic payment systems). This is beyond the scope of this paper; our objective here is simply to draw attention to the impact that this technology has on local economies. Future research could provide a full assessment by comparing the results in this paper to any improvements in global welfare stemming from proof-of-work cryptocurrencies. We also have abstracted from the costs to local communities stemming from the pollution externality associated with cryptomining. Since we ignore this channel, our estimates may be viewed as a lower bound on the total cost borne by the local community.

Our contribution represents just the first step in the analysis of cryptomining — and more generally energy intensive technology processing — around the world. In particular, the pricing effects on local communities that we document in Upstate NY are likely to occur in several other contexts and the issue is made all the more important by the recent Covid-19 pandemic-induced crisis affecting small businesses and households.

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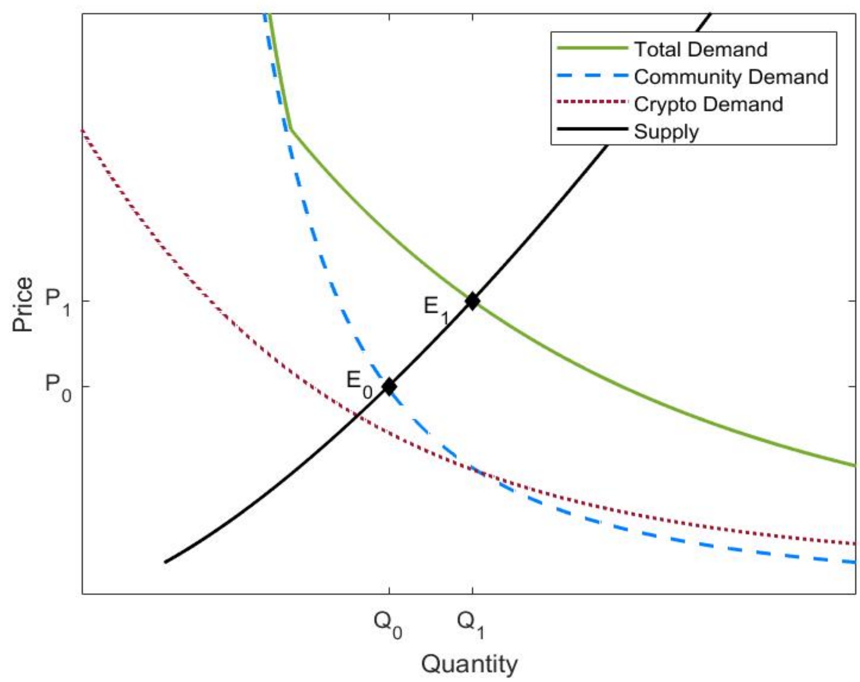
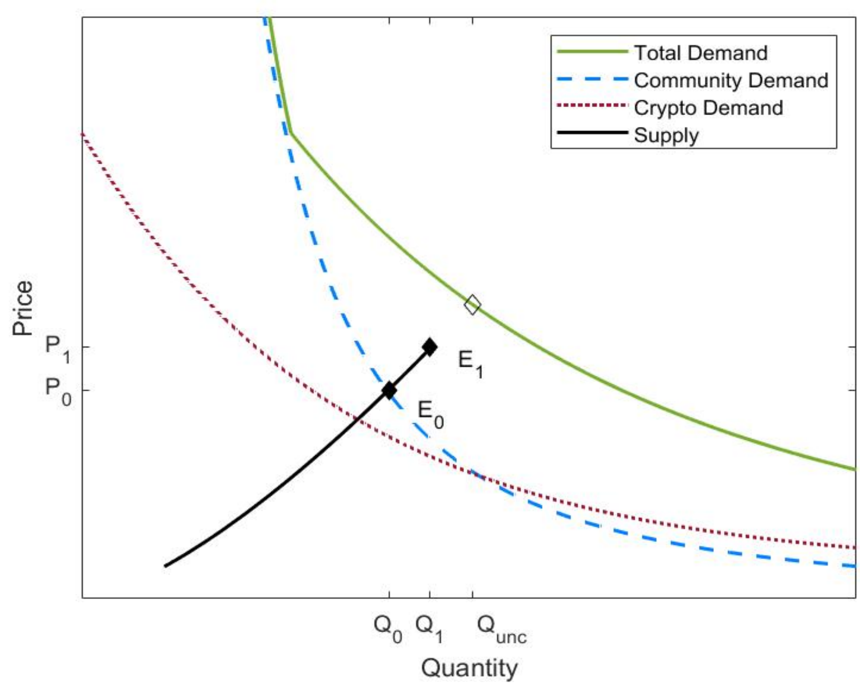
Figure 1: CRYPTOMINING WITH FLOATING ELECTRICITY PRICES

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

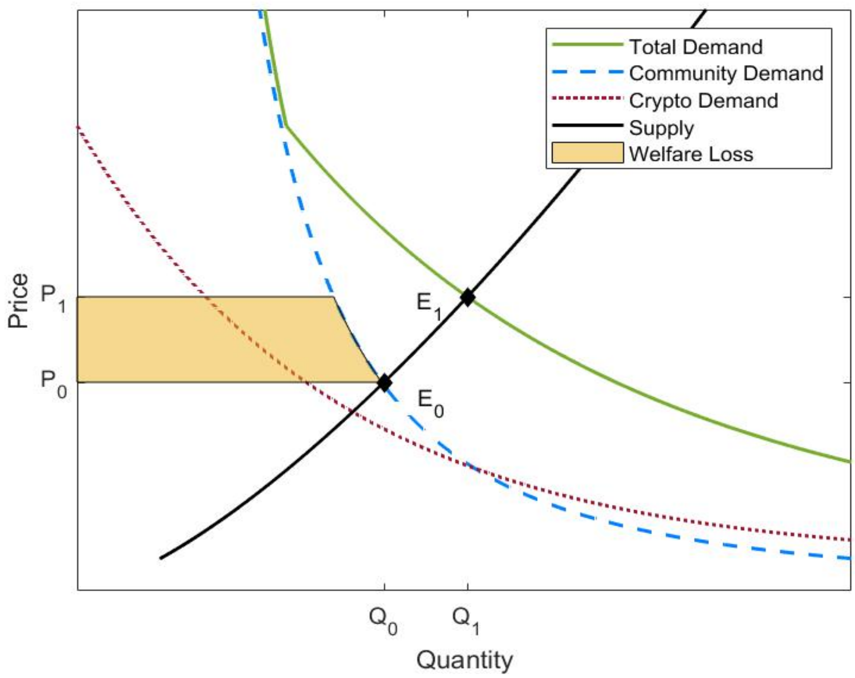


Panel B: Equilibrium in Local Electricity Market with Upward-Sloping Supply & Capacity Binding



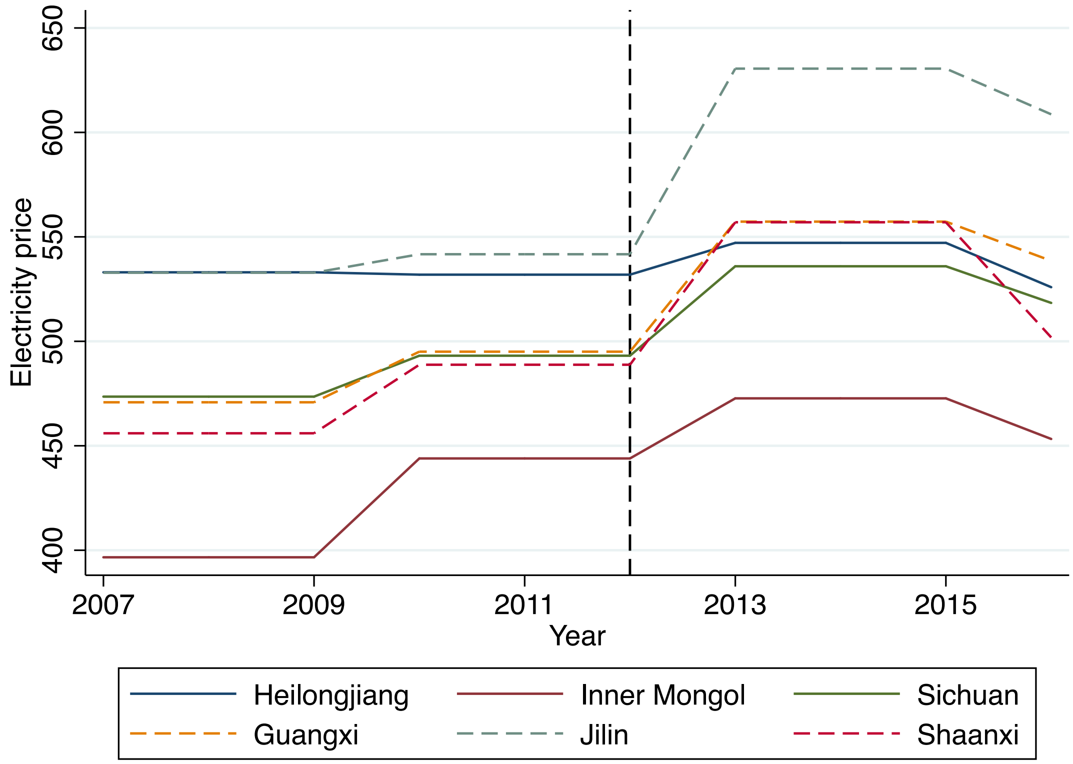
Note: The chart shows illustrations of supply and demand in markets with (Panel B) and without (Panel A) supply capacity binding. The figures depict the setting in which the local electricity supplier provides electricity up to capacity with a standard upward-sloping supply curve.

Figure 2: WELFARE LOSS FROM HIGHER PRICES



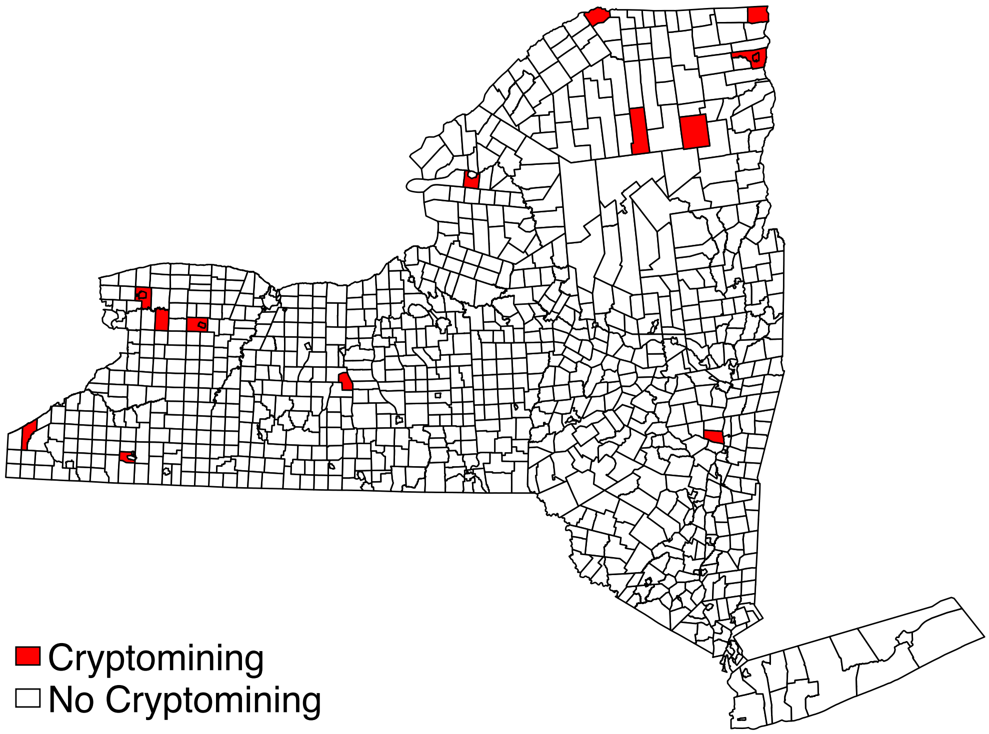
Note: The plot shows the equilibrium before (E_0) and after (E_1) the entry of cryptominers as well as the welfare loss incurred by the local community as a result of higher electricity prices.

Figure 3: ELECTRICITY PRICES OVER TIME IN CHINA



Note: Data on electricity prices in China 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 4: Mining communities in New York state

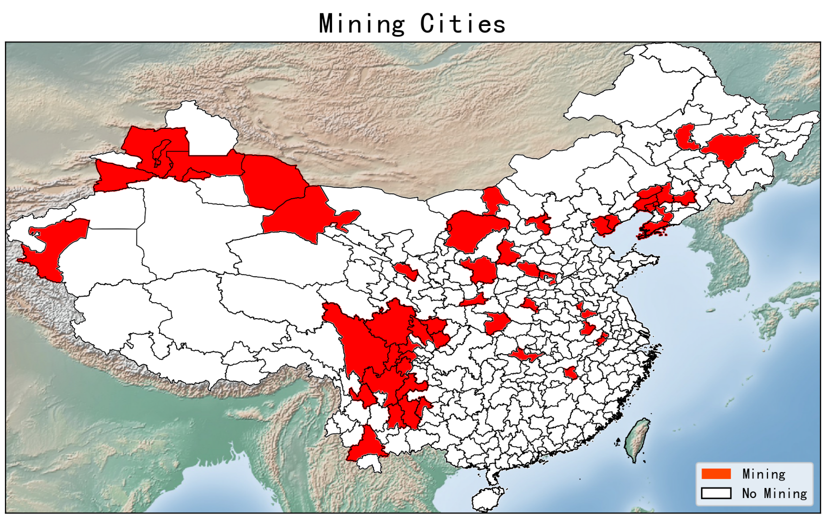


Note: Data on mining locations come from manual searches in local newspapers and newsources in English through Google. We present locations at our finer level of town in Upstate NY.

Figure 5: Mining cities in China

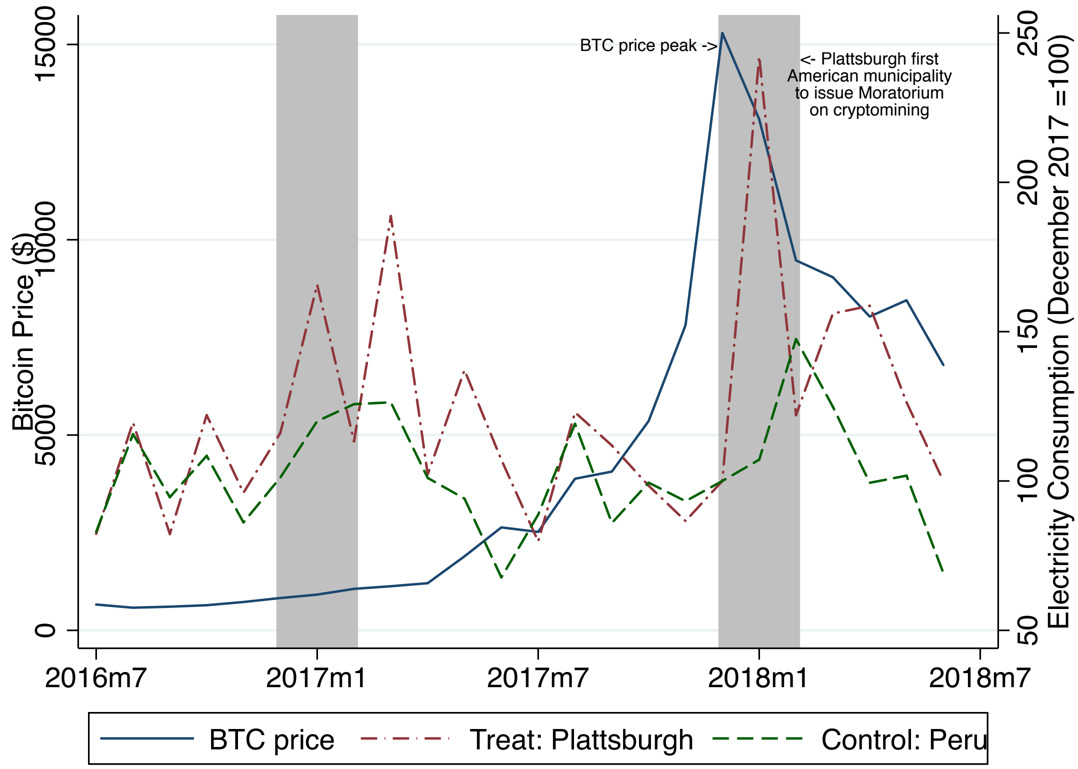
Panel A: Province-level locations of cryptomining

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).

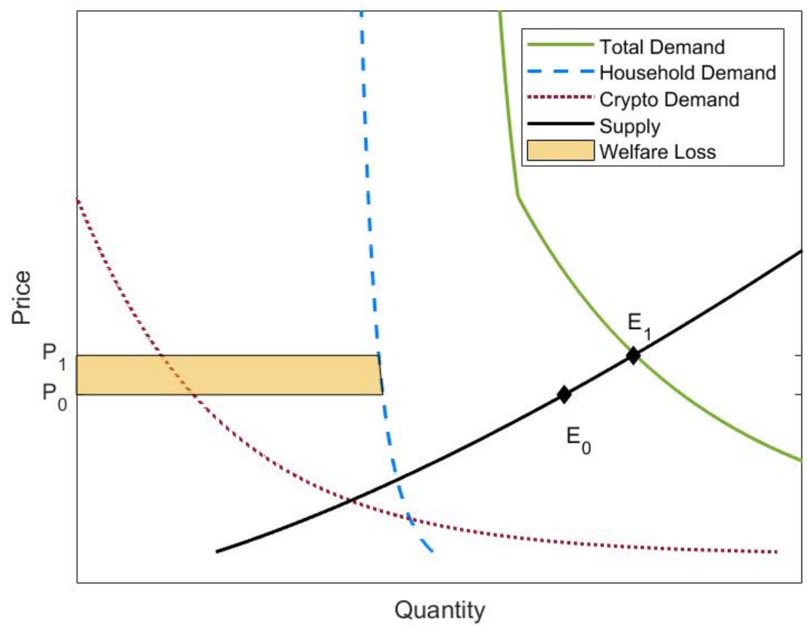
Figure 6: Bitcoin prices and electricity consumption



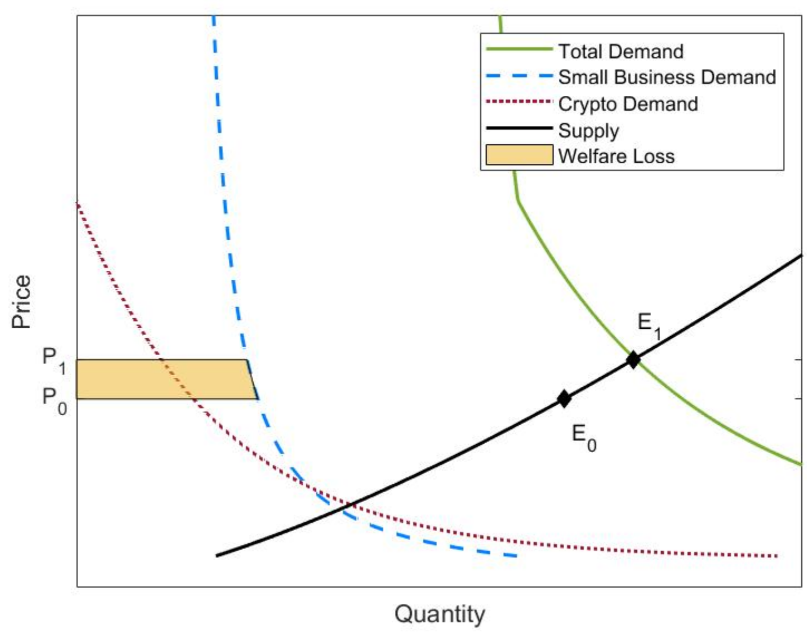
Note: Bitcoin price data comes from Coinmarketcap. Electricity consumption data comes from NYSERDA. The blue line shows the average price of Bitcoin each month. The red dash-dot line and the green dash line show total electricity consumption by small and industrial businesses in Plattsburgh and Peru, 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. Grey areas denote December, January and February of 2016-2017 and 2017-2018.

Figure 7: Welfare Effects of Cryptominers' Entry

Panel A: Households

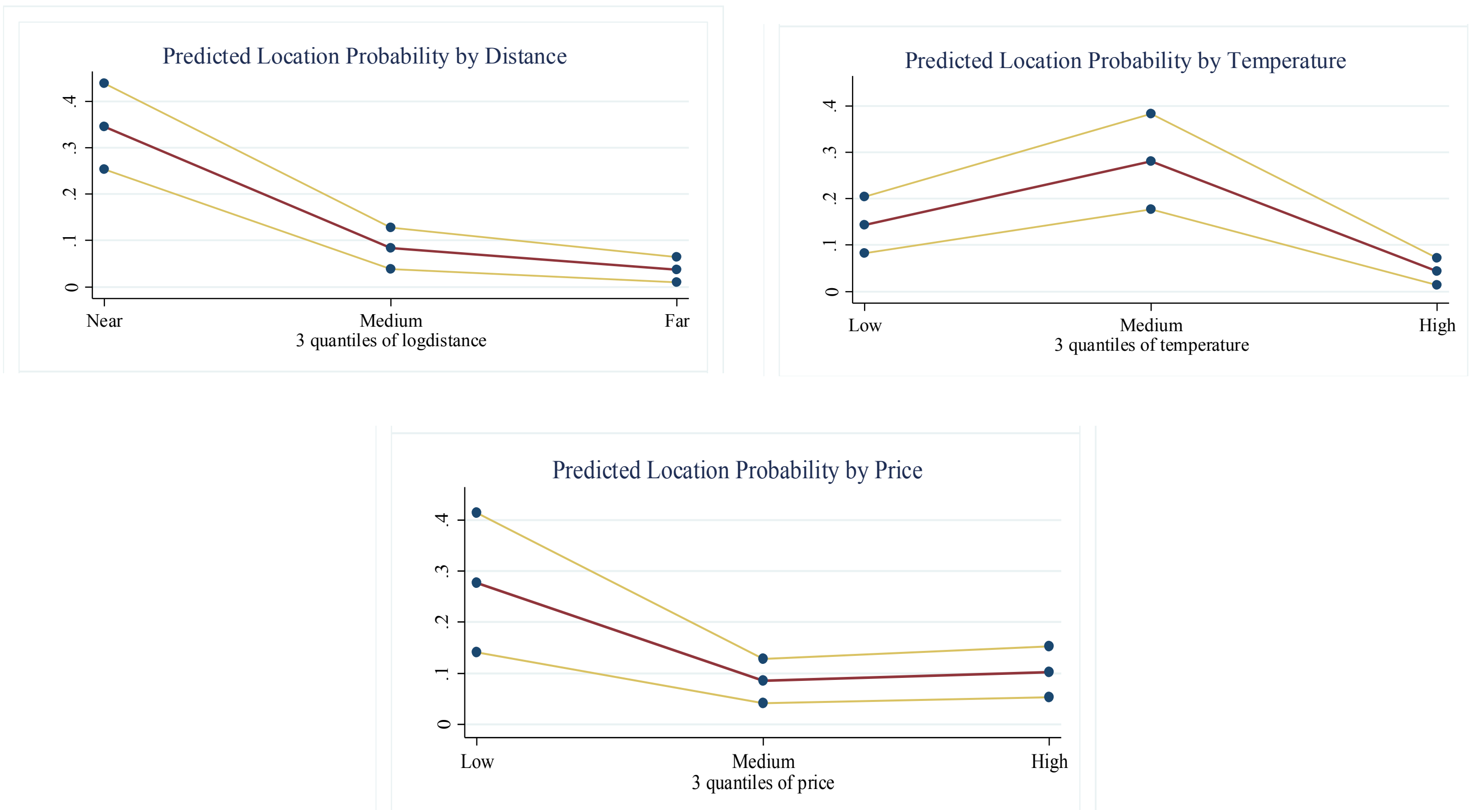


Panel B: Small Businesses



Note: Total demand is given by the sum of household, small business and crypto demand. E_0 represents the market equilibrium before the entry of cryptominers and is given by the intersection between supply and community demand (i.e. household plus small business). E_1 represents the market equilibrium after the entry of cryptominers and is given by the intersection between supply and total demand, inclusive of crypto demand. P_0 and P_1 are the associated equilibrium prices. Panel A shows the welfare change for households as the integral below the household demand curve between P_0 and P_1. Panel B does the same for small businesses.

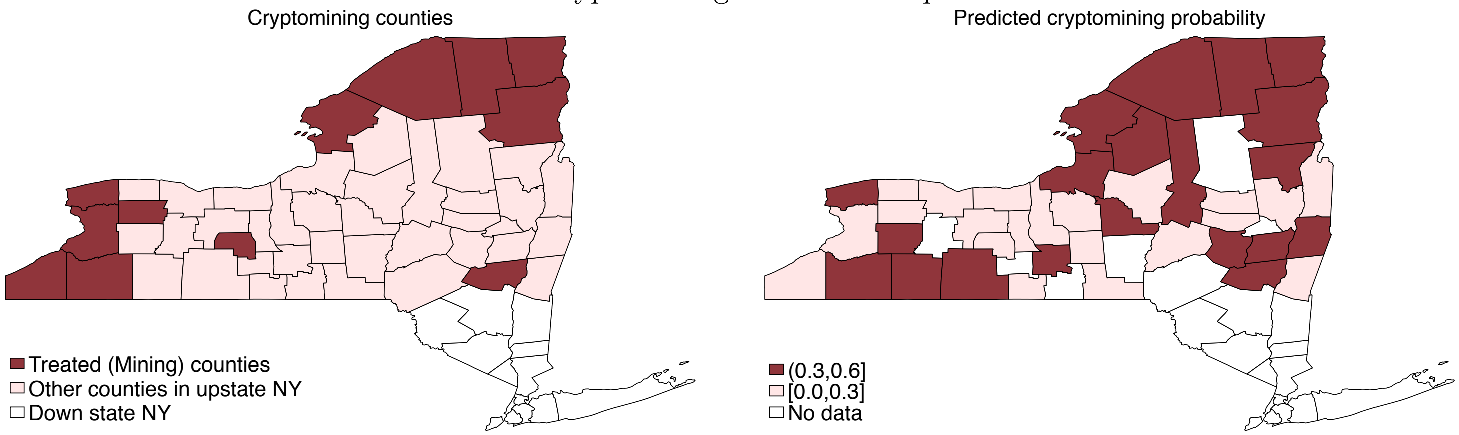
Figure 8: Marginal Effects of Distance to Power Plant, Temperature and Electricity Price on Location Decision of Cryptomining Facilities



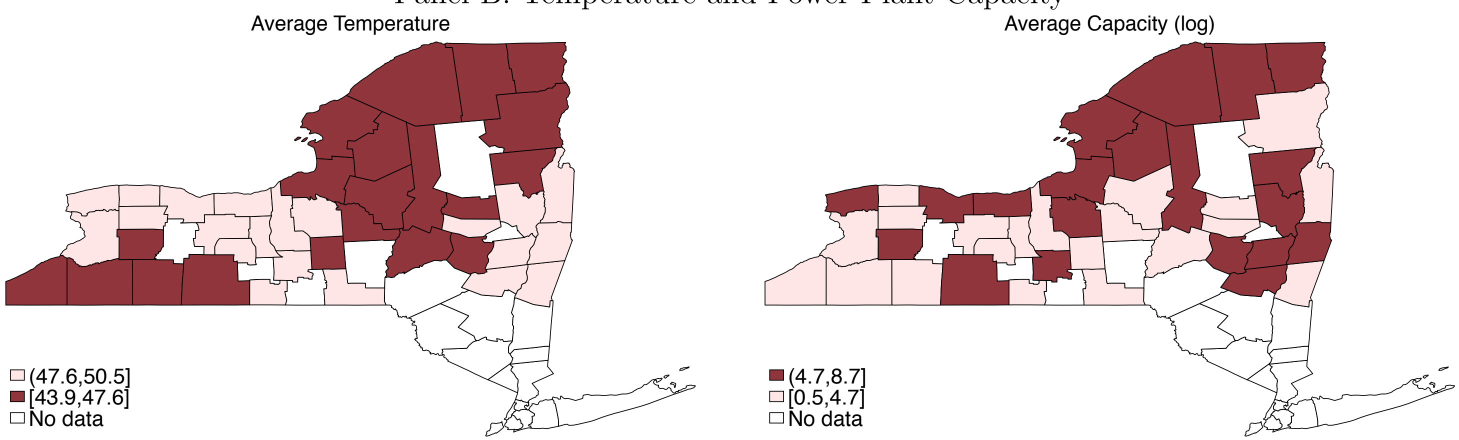
Note: Plotted are the results of spline estimation of the marginal effects of Log(Distance to a Power Plant), Average Annual Temperature, and Electricity Price on the location of cryptomining facilities in China. Economic variable data are from Province Yearbooks. The location of cryptomines are from manual news searches in Baidu using each city name and keywords for cryptomining. The data are from 2013-2014. Splines have three nodal points and a slope coefficient for each variable.

Figure 9: Mining counties, Temperature and Power Plant Capacity in Upstate New York

Panel A: Cryptomining - Actual and predicted



Panel B: Temperature and Power Plant Capacity



Note: Data on mining locations come from manual searches in local newspapers and newsources in English through Google. In panel A, we depict the counties with evidence of cryptomining and the predicted probability of mining based on our location choice model. In panel B, we show the average temperature and power plants capacity at the county level in 2010.

Table 1: **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. Panel A shows the variables for the electricity market. Sales and number of customers are collected by York State Energy Research and Development Authority (NYSERDA) and can be found here `https://www.nyserda.ny.gov/All-Programs/Programs/Clean-Energy-Communities/Community-Energy-Use-Data`. Data on the location-based marginal price are collected by New York Independent System Operator (NYISO) and can be found here `https://www.nyiso.com/energy-market-operational-data`. Panel B shows tax revenues and government expenditures at the year-town levels. Data can be found here `https://seethroughny.net/benchmarking/local-government-spending-and-revenue`. Panel C shows the temperature at the county-month level and the price of BTC which is available online (see among other sources `https://coinmarketcap.com`).

	Observations	Mean	St.Dev	Min	Median	Max
Panel A: Electricity market variables						
Residential						
Sales (MWh)	32818	1575.73	3558.89	0.00	666.87	74063.65
Customers (Count)	32818	2339.75	6180.76	0.00	889.00	109496.00
Small businesses						
Sales (MWh)	26836	470.50	1893.83	0.00	51.95	36752.82
Customers (Count)	26836	253.60	656.34	0.00	93.00	9974.00
Other industrial						
Sales (MWh)	16479	3572.28	14156.04	0.00	385.35	220115.51
Customers (Count)	16479	105.25	239.18	0.00	39.00	3522.00
Location-based marginal price ($/MWh)	14966	26.99	10.94	2.63	24.67	110.93
Panel B: Additional variables						
Temperature (Degrees Fahrenheit)	41965	46.99	16.97	13.50	48.60	75.40
BTC price ($)	36	4042.60	3935.75	404.41	2577.81	15294.27
Taxes per capita ($)	6854	524.37	505.83	66.43	419.99	9083.09
Expenditures per capita ($)	6854	819.94	773.88	42.86	641.11	15267.27

Table 2: **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 metropolitan 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 on Google and Baidu using each city name and keywords for cryptomining. ***, **, and * indicate statistical significance of a two-sample t-test at the 1%, 5%, and 10% levels.

	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 3: **Effect of Cryptomining on Electricity Prices and Demand**

Column (1) presents the estimates of the first stage regression given by equation (6). The dependent variable is the (log) location based marginal price (LBMP) in $/MWh. Column (2) presents the ordinary least square (OLS) estimates from equation (7). Column (3) presents the instrumental variable (IV) estimates from equation (8), using the first stage estimates from column (1). Panel A shows results for small businesses and Panel B shows results for households. In columns (2) and (3) the dependent variable is small businesses (Panel A) and household (Panel B) electricity consumption at the community level in log MWh. BTP price is the (log) average price of Bitcoin in a month-year. All columns control for (log) local temperature and include community, year and provider dummies. Errors are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	First Stage	OLS	IV
	(1)	(2)	(3)
Panel A: Small Businesses			
BTC price (log)	0.141***		
	(0.005)		
Price (log)		0.056***	-0.179***
		(0.021)	(0.057)
Temperature (log)	-0.200***	-0.088***	-0.133***
	(0.020)	(0.024)	(0.031)
Community Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Provider Fixed Effects	Y	Y	Y
Mean Y	3.22	5.70	5.70
SD Y	0.36	2.00	2.00
F stat	737.91		
Obs.	3071	2977	2977
R2adj	0.37	0.98	0.98
Panel B: Residential			
BTC price (log)	0.146***		
	(0.006)		
Price (log)		0.155***	-0.074**
		(0.015)	(0.031)
Temperature (log)	-0.234***	-0.093***	-0.145***
	(0.020)	(0.020)	(0.024)
Community Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Provider Fixed Effects	Y	Y	Y
Mean Y	3.23	7.56	7.56
SD Y	0.36	1.34	1.34
F stat	679.25		
Obs.	3309	3251	3251
R2adj	0.39	0.98	0.97

Table 4: **Cryptomining Location Decision**

Presented are logit coefficients from the choice of cryptomining city location, based on splines of the location predictor variables - log distance to the closest power plant, temperature, and province-year electricity price. 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:	Indicator for Cryptomining City
	(1)
Distance to Closest Power Plant	
Tercile 2	8.442**
	[4.112]
Tercile 3	-2.350
	[3.971]
Slope Node 0 to 1	-1.199***
	[0.437]
Slope Node 1 to 2	-4.237***
	[1.381]
Slope Node 2 to 3	-0.489
	[0.991]
Temperature	
Tercile 2	-3.815
	[3.454]
Tercile 3	23.53***
	[5.074]
Slope Node 0 to 1	0.0689
	[0.129]
Slope Node 1 to 2	0.467**
	[0.219]
Slope Node 2 to 3	-1.148***
	[0.269]
Electricity Price	
Tercile 2	-31.82**
	[13.43]
Tercile 3	13.56
	[13.40]
Slope Node 0 to 1	-0.0341
	[0.0219]
Slope Node 1 to 2	0.0321**
	[0.0148]
Slope Node 2 to 3	-0.0449***
	[0.0136]
Log Population	-1.389***
	[0.409]
Log Government Budget	2.639***
	[0.525]
Log GDP	-0.432
	[0.433]
Observations	376
Pseudo R-squared	0.409
Area under ROC Curve	0.905

Table 5: **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 at the city-seat level for all of the cities within the inland provinces of China. Economic variables data are from Province Yearbooks. Cryptomining 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. Fossil indicates that the city's closet power plant is coal-, oil-, or gas-powered. 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. All columns have control variables log GDP, log population, electricity price, and year dummies. Errors are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
Dependent Variable:	Log (Energy Consumption)		
Difference-in-differences Model:	OLS	IPW	IPW
Post * Cryptomining	-0.0374	0.0139	-0.173
	[0.0492]	[0.0567]	[0.108]
Post * Cryptomining * Fossil			0.231*
			[0.125]
Post * Fossil			0.0561
			[0.0780]
Log Population	0.137	0.112	0.108
	[0.139]	[0.106]	[0.109]
Log GDP	0.0707	0.0599	0.0611
	[0.0479]	[0.0478]	[0.0483]
Log Electricity Price	0.158	0.205	0.175
	[0.206]	[0.195]	[0.195]
City Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	941	721	721
R-squared	0.946	0.941	0.941

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 variables in columns (1)-(3) and columns (4)-(6) are, respectively, the per capita wage level and the log of fixed asset investment at the city-seat level for all of the cities within the inland provinces of China. Economic variables data are from Province Yearbooks. Cryptomining 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. Fossil indicates that the city's closet power plant is coal-, oil-, or gas-powered. Columns (1) and (4) are estimated via OLS. Columns (2), (3), (5) and (6) 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. All columns have control variables log GDP, log population, and year dummies. Columns (4) to (6) also include the wage level, to ensure identification of separate effects. Errors are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log (Wage level)			Log (Fixed Asset Investment)		
Difference-in-differences Model:	OLS	IPW	IPW	OLS	IPW	IPW
Post * Cryptomining	-0.426**	-0.678*	-1.662	-0.177***	-0.363***	-0.274**
	[0.209]	[0.373]	[1.180]	[0.0653]	[0.0918]	[0.132]
Post * Cryptomining * Fossil			1.17			-0.0969
			[1.226]			[0.166]
Post * Fossil			0.442*			-0.0599
			[0.242]			[0.0789]
Log Population	-1.025*	-1.128*	-1.174*	0.235	0.370**	0.388**
	[0.569]	[0.662]	[0.679]	[0.156]	[0.168]	[0.176]
Log GDP	-0.0519	-0.0792*	-0.0840**	0.368***	0.342***	0.344***
	[0.0393]	[0.0412]	[0.0421]	[0.0846]	[0.0906]	[0.0897]
Log Wages				-0.0486***	-0.0496***	-0.0448***
				[0.00923]	[0.00929]	[0.00942]
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	1262	883	883	1255	876	876
R-squared	0.253	0.249	0.281	0.877	0.856	0.857

Table 7: **Effect of Cryptomining on Local Business Taxes - China**

All models are difference-in-differences specifications, with varying methods to account for location selection. The dependent variables in columns (1) to (3) and (4) to (6) are, respectively the annual city value-added taxes collected and the annual business income taxes collected for cities in the inland provinces of China. Economic variables data are from Province Yearbooks. Cryptomining 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. Fossil indicates that the city's closet power plant is coal-, oil-, or gas-powered. Columns (1) and (4) are estimated with OLS. Columns (2), (3), (5) and (6) are estimated via 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.. All columns have control variables log population, log city government budget, and year dummies. Errors are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log (Value-Added Business Taxes)			Log (Business Taxes)		
Difference-in-differences Model:	OLS	IPW	IPW	OLS	IPW	IPW
Post * Cryptomining	0.0368	-0.0359	0.162*	0.0474	-0.0113	0.141*
	[0.0703]	[0.0960]	[0.0951]	[0.0764]	[0.110]	[0.0759]
Post * Cryptomining * Fossil			-0.205			-0.189
			[0.148]			[0.149]
Post * Fossil			-0.0509			0.058
			[0.0810]			[0.0894]
Log Population	-0.0513	0.0324	0.0146	0.0794	0.0581	0.046
	[0.242]	[0.344]	[0.348]	[0.125]	[0.188]	[0.203]
Log Budget	0.730***	0.701***	0.693***	0.248**	0.283**	0.289**
	[0.125]	[0.147]	[0.145]	[0.124]	[0.139]	[0.139]
City Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	408	376	376	318	306	306
R-squared	0.95	0.939	0.940	0.964	0.963	0.964

Table 8: **Effect of Cryptomining on Local Taxes - New York State**

Column (1) is a logit location choice model estimated at the town level. The dependent variable is a dummy equal to one if a town belongs to a county with evidence of cryptomining. Data on cryptomining are manually collected from news searches in Google and other sources using each town name and keywords for cryptomining. Capacity mw is the estimated total capacity in megawatts at the county level in 2010. The data on power plan capacity comes from the Global Power Plant Database. Temperature is the average temperature at the county level in 2010. The data on temperature comes from the National Centers for Environmental Information (NCEI). Models in columns (2) to (7) are difference-in-differences specifications, with varying methods to account for location selection. The dependent variables in columns (2) to (4) and (5) to (7) are, respectively the annual taxes per capita and expenditure per capita for towns in Upstate New York. Post indicates post-2016. Columns (2) and (5) are estimated with OLS. Columns (3) and (6) are estimated via 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. Columns (4) and (7) are based on a common support restriction using the estimates of the location-choice model in column (1). Errors are robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Cryptomining	Taxes			Expenditures		
	(1)	(2) OLS	(3) IPW	(4) Common Support	(5) OLS	(6) IPW	(7) Common Support
Capacity mw (log)	0.302***						
	(0.051)						
Temperature	-0.406***						
	(0.059)						
Post * Cryptomining		17.028**	29.461***	21.263***	35.030	51.368*	37.303*
		(6.780)	(8.894)	(6.735)	(22.263)	(29.734)	(22.340)
Community Fixed Effects		Y	Y	Y	Y	Y	Y
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Mean Y		524.37	498.60	508.79	819.97	784.18	806.96
SD Y		505.92	426.95	450.01	774.02	681.98	728.44
Obs.	719	6851	6135	6135	6851	6135	6135
R2adj		0.97	0.96	0.96	0.89	0.88	0.87
Pseudo R-squared	0.10						
Area under ROC Curve	.71						

Table 9: **Local Welfare Calculations**

In Panel A, monthly costs for small businesses and households comes from the procedure discussed in Section 4.4. Annual costs are monthly costs multiplied by twelve. Small businesses exposed is the number of total small businesses in NY state which we allocated to Upstate NY based on the share of its population relative to the total in NY state. Household exposed is the total population of upstate New York in 2019 divided by the average number of people per households. In Panel B annual costs are the tax revenues and government expenditures per capital from the difference-in-difference IPW estimates in Table 8. Count of exposed is the population in treated towns. Welfare cost upstate NY is the product of annual cost and count of exposed in million dollars. Welfare cost national scale up the welfare cost in upstate NY under the assumption that about 25% of cryptomining in the US is happening in Upstate NY.

	(1) Monthly Cost ($)	(2) Annual Cost ($)	(3) Count of Exposed (,000)	(4) Welfare Upstate NY ($M)	(5) Welfare National ($M)
Panel A: Cryptomining local spillover					
Small businesses	-12	-144	550	-79	-316
Households	-6	-71	2,321	-165	-661
				-244	-977
Panel B: Accounting for effect on local government					
Taxes		29	1,340	39	155
				-205	-821
Expenditures		51	1,340	68	273
				-176	-704