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WHEN CRYPTOMINING COMES TO TOWN:
HIGH ELECTRICITY-USE SPILLOVERS TO THE LOCAL ECONOMY

Matteo Benetton
Giovanni Compiani
Adair Morse

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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 electricity 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 part of the supply curve faced by the community, we estimate the electricity demand functions for small businesses and households. Based on our estimates, we calculate counterfactual electricity bills, finding that small businesses and households paid an extra $92 million and $204 million annually in Upstate NY because of increased electricity consumption from cryptominers. Local governments in Upstate NY realize more business taxes, but this only offsets a small portion of the costs from higher community electricity bills. Using data on China, where electricity 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. Our results point to a yet-unstudied negative spillover from technology processing to local communities, which would need to be considered against welfare benefits.

Matteo Benetton
University of California, Berkeley
1440 Montgomery Street
San Francisco, CA 94133
benetton@berkeley.edu

Giovanni Compiani
University of Chicago
Booth School of Business
5807 S. Woodlawn Ave
Chicago, IL 60605
gio1compiani@gmail.com

Adair Morse
University of California, Berkeley
5319 42nd Pl NW
Washington, DC 20015
and NBER
morse@haas.berkeley.edu

"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; rather, 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]

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 real effects 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.[2] 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 the validity of the transactions (Chen et al., 2019; Ciamac and Moallemi, 2020). This has led to an arms race among firms who run large cryptomines — essentially warehouses full of specialized computers crunching numbers — across the world.

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

[2] 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.

We begin with a conceptual framework to illustrate our simple story. The essence is as follows. 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. This implies that the incumbents pay higher rates for electricity. In markets in which the supply of electricity operates in a fixed-price regime, the new demand may induce shortfalls in the availability of electricity for the community.

Our main empirical analysis focuses on New York State, specifically Upstate NY, excluding New York City and Long Island. The U.S. represented about 8% of global cryptomining in 2020, and this share increased to more than 30% starting in July 2021, as a result of China's ban on cryptomining.[3] Within the U.S., Upstate NY attracted cryptomining operations early compared to other states, especially in the northern counties, due to its cold climate, cheap electricity, and proximity to large hydropower sources.

Upstate NY has a typical grid electricity system. The grid operator, NYISO, employs a marginal supply pricing algorithm, whereby upward pressure on prices from demand gets passed onto households and small businesses through a component of the electricity bill called the 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 combine detailed administrative data on these local electricity prices, electricity usage, and other economic outcomes with hand-collected data on the likely location of cryptominers to analyze whether the use of electricity by cryptominers affects local communities. In particular, the pathways we study are (i) small business and household consumption of electricity, (ii) electricity provider revenues, and (iii) local government taxes.

First, using provider-town-month level data, we estimate the local community demand for electricity from NY households and small businesses.[4] We address the well-known problem of quantities and prices being determined endogenously 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, a higher Bitcoin price increases the demand for electricity by cryptominers. In the first stage regressions of this relationship, we find an F-statistic of approximately 700, indicating that the instrument is strong. 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 except through the effect on electricity pricing.

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 -0.07 and -0.17, consistent with the literature

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

[4] Throughout the paper, we refer to households and small businesses as (electricity) consumers.

on electricity demand.[5] For example, Ito (2014) estimates medium-long run elasticities to be between -0.071 and -0.088 for California households.

Possible concerns for our estimation framework emerge from the proper handling of the role of temperature on electricity demand and from timing mechanisms that may be spuriously correlated with the Bitcoin price. We implement a series of robustness specifications that, including one where we first project electricity consumption on non-linear weather effects and then estimate price elasticities using the residuals from this regression. We also show that our results continue to hold in first difference collapses of the analysis, with the economic magnitudes of the effects being of the same order as in baseline specifications.

Second, using provider-year level data, we analyze the effect of crytomining-induced increased demand for electricity on local provider sales volumes and revenues coming from industrial and community (residential and small business) sectors.[6] Because we do not have month level data from electricity producers or data on these providers' revenues and sales by each city and town, we instead fit a continuous difference-in-differences specification where the treatment is the intensity of cryptomining communities within the portfolio of communities served. Because we do have data on municipal providers (cites with their own power plant), our identification comes more from these single-community providers, but the results also include large providers across Upstate NY. Since no public registries exist as to the location of cryptomines, we hand collected data on their *reported* location from local media coverage. We then estimate a model of how the treatment affects provider sales and revenues in the industrial and community sectors, interacting treatment with both a post dummy and the price of Bitcoin, to ensure that we are not picking up a selection on trends.

We find that the treatment interactions predict positive sales volumes and revenues from industrial users, consistent with cryptominers, who show up in the data as industrial users,[7] consuming more electricity, with an even larger pricing effect on all industrial clients. When we repeat the analysis for small businesses and residential customers, we find a negative (but noisy) effect on the quantity of electricity consumed, but a positive effect on the revenues providers generate from community electricity consumption. This result is consistent with higher demand from cryptominers shifting the total local demand outward and leading to higher equilibrium prices, and larger surplus for electricity producers.

Third, using town-year level data, we test whether the entrance of cryptomining in a community results in a change in tax revenues. 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)

[5] Since most households and businesses receive their electricity bill at the end of the month, we also estimate a lagged version of our model. Residential and small businesses show a larger elasticity to the moving average of current and recent prices, consistent with larger delayed responses.

[6] While our focus is on spillovers to other electricity consumers, we are interested in the production side as a source of further spillovers to household and small business surplus, because producer revenues could be at least partly redistributed to the local community through government taxation.

[7] See for example `https://crsreports.congress.gov/product/pdf/R/R45863`.

use of the local electricity supply. Our empirical design embeds the endogenous choice of cryptomining locations in a difference-in-difference identification strategy.[8] 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 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 government taxes.

Within the location selection model, we find a positive significant effect of cryptomining on tax generation. Treated communities experience a relative increase in taxes per capita by \$6 dollars compared to control communities when the price of Bitcoin increases by 100%. To put these numbers in perspective, the price of Bitcoin increased from about \$600 in 2016 to \$7,500 in 2018. According to our estimates, this increase could have lead to higher taxes per capita in cryptomining communities by about \$70, or 14% of the average tax revenue per capita.

Finally, we combine our empirical estimates in a consumer surplus calculation for Upstate NY.[9] We use the first stage regression to compute (counterfactual) prices for the equilibrium with and without cryptomining and then simply integrate the estimated demand curves between the lower no-cryptomining 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 the average household and small business in NY to pay an extra \$88 and \$168 in their electricity bills per year, respectively. In aggregate, NY households and small businesses pay \$204 million and \$92 million more per year, respectively. When accounting for the differential increase in government revenues, we find that, in the aggregate, cryptomining towns in Upstate NY generate almost \$40 million in additional government revenues, thus recovering about 14% of the losses. As a result, we estimate a net consumer surplus loss of \$257 million in Upstate NY. These estimates are robust to changes in the specification of the electricity demand model. Specifically, the welfare figures are essentially unaffected when (i) we allow households and small businesses to respond to a moving average of electricity prices (as opposed to just contemporaneous prices), and when (ii) we control for the effect of weather on electricity demand by deseasonalizing prices.

Producer revenues also increase due to cryptomining. Again using identification based

[8] Our dataset for taxes is at the town level, rather than the electricity provider level, which allows us to estimate a more robust difference-in-differences model relative to the case of electricity production data.

[9] 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.

on changes in the Bitcoin price, we estimate an upper bound on this effect of $415 million. Given margins of at least 15% in the electricity generation sector, this would imply a lower bound on the producer surplus gain of $62 million. Further, spillovers to the community through labor and other mechanisms may bring additional benefits.

Given the estimated net negative effects on local communities, we consider policy tools that governments could use to mitigate the impact on their jurisdictions. An intuitive intervention would be to simply ban cryptomining. This, however, would likely only shift the problem to other jurisdictions that did not impose a ban and would also prevent the local government from earning additional tax revenues from cryptominers. Another option is to implement electricity pricing schemes or dynamic quotas in order to minimize the adverse impact on the local community.

While our main analysis focuses on the negative externalities of the high electricity use of cryptomining through the price channel, local externalities may also occur through quantity rationing. An anecdote from a data center in Norway makes a compelling case. In March, 2023, the *Financial Times* reported on Nammo, an ammunition producer located two hours north of Oslo. Nammo was complaining that they were unable to expand production to meet the demand for ammunition for the war in Ukraine and Europe in general because of a TikTok data center's large electricity use. The local utility company responded that energy is provided on a first-come first-serve basis and capacity could not be increased without infrastructure investment. Nammo's CEO, Mortsen Bradtzaeg is quoted in the *FT* article as saying: "We are concerned because we see our future growth is challenged by the storage of cat videos."[10]

The possibility that cryptomining might likewise hinder access to electricity for other local business uses is important in many local economies, but might be particularly important in China, which hosted 65-82% of the world's cryptomining during the last decade before the ban in 2021.[11] In China, the pricing mechanism is shut down because provinces set fixed electricity prices, which are updated only infrequently. Further, electricity grids are governed at the province-level, resulting in supply impediments at borders and frictions to the updating of transmission networks (Kahrl et al. (2011)). 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). We focus on the 218 inland China city-areas, which have a mean population of 355,000, and do not include the large coastal metropolitan areas; we find evidence of cryptomining for 52 of them. Our empirical strategy follows the

[10] "European ammunition maker says plant expansion hit by energy-guzzling TikTok site," March 26, 2023, *The Financial Times*.

[11] This range is derived from Hileman and Rauchs (2017) and current information can be found on `https://digiconomist.net` and `https://cbeci.org/mining_map`.

same difference-in-differences approach used to study the effect on taxes in Upstate NY. Our setting leads to an average treatment on the treated interpretation rather than an average treatment effect (Ryan et al. (2015)), because we cannot claim to satisfy the common shock assumption of Angrist and Pischke (2009).

We find that after cryptomining enters a city, local fixed asset investments decline annually by 19%, and wage levels decline by 10%. These results, which are robust to a battery of robustness specifications and are consistent with parallel trends assumptions, suggest that cryptomining tends to crowd out other business uses of electricity. The results also suggest that these crowded-out industrial uses of electricity would have led to larger investments in the physical and human capital of the local economy in the years following the entry of cryptomining. The shock of cryptomining entry is associated with a statistically significant drop in local GDP of 8.2%, which could result if cryptomining's production does not contribute to the measurement of local GDP or if cryptomining uses more electricity per unit of GDP produced. Taken together, these findings suggest that it is possible that local economies suffer as a result of crowding out in the electricity market. These results are large yet plausible, given that we interpret the results as the average treatment effect only on the 52 treated city-areas in inland China, which represent only a small, but meaningful, part of the overall Chinese economy. In contrast, we would not expect our estimates to apply to much larger cities, such as Beijing, which are not treated in our sample.

Our analysis abstracts from the possible advantages of proof-of-work cryptocurrencies for users worldwide, which include 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)).[12] While this comparison is beyond the scope of this paper, we contribute to the discussion by highlighting and quantifying the physical footprint of virtual currencies 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 via the electricity market. 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 the supply and demand of 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 communities, 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

[12]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.

and Climate Change (2014)) Yet, 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, 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 the broader and growing literature on proof-of-work cryptocurrencies (e.g., Budish (2018), Biais et al. (2018), Easley et al. (2018), Liu and Tsyvinski (2018), Li et al. (2019), Chiu and Koeppl (2019), Twomey and Mann (2019), Makarov and Schoar (2020)).[13] 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 increasingly important role given the rise of high energy-use technologies. Thus, our paper is closely related to the emerging literature studying the determinants and effects of the entry of data centers (Goiri et al., 2011).

In the next section, we lay out the conceptual framework that we use throughout the paper. Section 3 describes the data. In Section 4, we discuss our empirical analysis for Upstate NY and in Section 5 we present the results for China. Section 6 concludes.

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

[13]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).

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., air quality could deteriorate due to increased activity of a local power plant) and globally (notably, climate change).[14]

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.[15] In Panel A of Figure 1, the 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, anecdotes suggest that it is often local businesses or even households that bear the brunt. This is consistent with the fact that cryptomining is a highly profitable business and is thus likely to be prioritized by tax revenue-maximizing local governments, who may have binding contracts with cryptominers. The resulting potential blackouts imply another negative externality.

[14]The impact of cryptomining in the environment has been relatively more studied than the impact on the local economy via the price and availability of electricity. For a recent analysis of the effect of cryptocurrency mining for air pollution in the the US see Goodkind et al. (2020).

[15]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 the effects of cryptomining on communities in China.

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

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

Local consumer surplus decreases if electricity prices increase due to the entry of cryptominers. Figure 2 provides a visual representation of the consumer welfare loss from higher electricity prices that mirrors the expression in (3): the consumer welfare loss is obtained by integrating the community demand function between the initial price and the new higher price, which corresponds to the area shaded in dark gray.

One countervailing effect is that the local tax revenues might increase if local governments are able to tax the cryptomining taking place in their jurisdictions and/or the additional sales of electricity in a way that offsets potential concurrent decreases in tax revenues. We denote this by

$$\Delta\text{Tax Revenues} = \tau_c \times \pi_c\left(D_{crypto}\right) + \tau_e \times \pi_e\left(D_{crypto}\right), \tag{4}$$

where τ_c is the local tax rate on profits from cryptomining, π_c denotes the mapping from energy used as an input to cryptomining into profits, and similarly τ_e is the local tax rate on profits from electricity sales and π_e denotes the profit function for the electric utilities. To the extent that tax revenues are rebated to local consumers, this will have a positive effect on their surplus.

Putting this together, the net change for the local consumer surplus will be given by the increase in tax revenues minus the decrease in consumer surplus due to higher electricity prices. The goal of our empirical analysis will be to quantify each of these effects, thus providing a measure of the overall impact of cryptomining on local consumer welfare.

In addition to the above, the surplus of electricity producers increases when cryptominers enter the market:

$$\underbrace{\Delta\text{Producer Surplus}}_{(+)} = \pi_e\left(D_{crypto}\right).$$

Specifically, since both quantity and price are higher in equilibrium, producer revenues and profits increase, as shown in the light gray shaded area in Figure 2. We quantify this effect in our empirical analysis, but we keep it separate from the analysis of the local consumer surplus, assuming that electricity producer profits benefit local consumers only via taxes, which we already account for in equation (4).

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 was the country hosting the most cryptomining in the World before the ban in 2021, and thus an important market to understand the impact of cryptomining on local communities. 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.[16] Therefore, the price channel is shut down in China, and the 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)

[16] Figure A1 in the Appendix 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 the entry of cryptocurrencies in specific markets. If anything, in the provinces where we find more evidence of cryptomining presence (Heilongjiang, Inner Mongolia and Sichuan), electricity prices increased by less than in provinces without cryptomining activity (Guangxi, Jilin and Shaanxi).

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.[17] 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 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.[18] 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, favorable electricity rates in Upstate New York may have encouraged cryptominers to relocate their operations to the area.[19]

The electricity price faced by end users is the combination of a number of line items appearing on a monthly statement. A statement will have a fixed monthly service charge, a delivery charge per kilowatt, adjustment and legacy charges, and an electricity supply charge.[20] 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.[21] The grid revolves around a pricing mechanism called 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 for any location. The generators have projections and real-time updating for these calculations, so that they can plan ahead to bring supply online or offline as demand warrants. Importantly, the marginal price is adjusted for each demand location according to transmission distance and congestion on the lines, thus ending with a location-based marginal price.[22]

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

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

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

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

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

[22] 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.

Putting these mechanics together, we see that the LBMP — which dictates the electricity supply charge and is thus passed onto end users — is affected by an increase in demand relative to the usual level. Electricity prices fluctuate by location, and this fluctuation varies according to proximity to the generator serving as the marginal supplier. Yet, because of the marginal pricing supply system, demand increases in specific locations can affect the entire grid if they change the locations and/or supply pricing schedule point of the marginal supplier. 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. Note that this mechanism plays out in the same way irrespective of what the source of the increase in electricity demand is. As a result, the same logic would apply to the case of, e.g., energy-intensive data centers moving into a community.

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 (NYSERDA), and high-frequency data on location-based marginal prices at the generator level collected by the New York Independent System Operator (NYISO).[23]

Panel A of Table 1 reports summary statistics from our combined dataset. Data on electricity consumption are collected by New York State at the level of the town or city, hereafter 'community'. 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 700 MWh. The average number of residents per community-provider is about 2,300, while the median is approximately 900. The average consumption of electricity by small businesses is lower than for households, while industrial businesses consume about eight times as much as small businesses (500 and 4,000 MWh, respectively). The difference between small and industrial businesses is even starker if we look at per capita consumption. The average (median) number of small business electricity customers per community is about 250 (90), while the average (median) number of industrial 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

[23]The two datasets 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.

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 around \$2.5/MWh to more than 100\$/MWh, varying over time and by communities and providers.

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. Third, 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, obtained from publicly available data,[24] are on average \$520, ranging from a minimum of \$66 to a maximum of \$9,000.

Finally, since no public registries exist as to the location of cryptomines, we hand 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 cryptomining 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 mentioned cryptomining operations in the community. We find evidence of cryptomining in 15 communities which are located in 12 different counties. Figure 3 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 locations with colder weather (because the machines become hot and malfunction without cooling), and with an affordable and reliable energy supply.

In addition to having the community-level locations of cryptomines, we also create an electricity provider-level cryptomining intensity variable, where the intensity is measured as the extent to which the communities served by the providers are also host to cryptomining. We do this at the community level rather than production volume level to abstract from production endogeneity. In Upstate NY, since there are large multi-community providers as

[24]`https://seethroughny.net/benchmarking/local-government-spending-and-revenue/#`.

well as small municipal providers, focused on the community specifically, the variable takes the form of 0 or 1 for the local-only municipal providers and a percentage of locations for the large providers.

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 the 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 key 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), as well as 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 performed 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 we found 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 4 shows a map that summarizes our data on cryptomining in China. Panel A displays 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 distance to the closest power plant (calculated using GIS mapping) and the power source (hydro, coal, solar, gas, wind, or oil). The data on the location of power plants comes from the Global Power Plant Database, which is a comprehensive, global, open source database of power plants.[25]

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. Whether cryptomining is supported by fossil fuels as opposed to hydropower (NY is largely, but not entirely, hydropower) may be important for our business activity tests. Thus, we create a variable capturing whether each community is primarily powered by fossil fuels or renewable energy.

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

In doing so, we uncover 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.[26]

3.2.2 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 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.[27] 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

[26] If 48.2% of Chinese cryptomining is powered by coal, and 80% (60% in 2020) of the world's cryptomining happened in China during our sample period, this implies that at least 39% (29% in 2020) 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 taking place. Thus, we conservatively conclude that one-half to two-thirds of cryptomining involved fossil fuels during this time period.

[27] See `ndrc.gov.cn`

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

In this section we study the effect of cryptomining on communities – i.e., households and small businesses – in Upstate NY. Our primarily analysis focuses on the effects of cryptomining on community electricity consumption and the community's implied consumer surplus, based on the conceptual framework in Section 2. We then study electricity provider revenues and local government taxes, especially how these aspects factor into a local welfare calculation for the incumbent community.

4.1 Cryptomining and Community Electricity Consumption

4.1.1 Empirical Strategy: Electricity Consumption

Identification strategy. Our identification strategy leverages exogenous shocks associated with changes in 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 demand for electricity — the main input into cryptomining production — increases. In turn, if suppliers of electricity have upward sloping supply curves, an increase in electricity demand by cryptominers would affect the incumbent community because the new electricity demand would change the portion of the supply curve faced by the (non-cryptomining) community demand, driving up the equilibrium price. Thus, we can use the price of Bitcoin as an instrument for the price of electricity in an estimation of community demand.

To illustrate our identification, consider the city of Plattsburgh, NY, which attracted cryptomining operations early in the growth of cryptomining due to its cold climate and cheap electricity. Figure 5 shows monthly electricity consumption for businesses in the town of Plattsburgh and the neighboring town of Peru. Before the end of 2017, Plattsburgh and Peru experienced a similar pattern in electricity consumption for businesses. However, in January 2018 — when the Bitcoin price peaked — electricity consumption by Plattsburgh businesses increased by almost 150%, whereas almost no change to the seasonal pattern occurred in Peru. This corroborates evidence in the media and from a Congressional Research Service report 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.[28] ,[29]

The exclusion restriction for our IV setup is that the Bitcoin price does not affect community electricity demand except through the electricity pricing mechanism. This assumption seems quite plausible since it is unlikely that many households or small business owners in Upstate New York would adjust electricity consumption on a month-by-month basis because of the Bitcoin price. The exclusion restriction is seemingly intuitive at face value for small businesses, yet it is worth a pause here on the household side, as some households may own Bitcoin even in 2018. Two possible confounding stories come to mind. First, to the extent that households do hold Bitcoins, the Bitcoin price increase may induce a wealth effect. An increase in the Bitcoin price may create wealth that induces individuals to purchase other high-electricity use leisure goods (e.g., gaming systems). While this is plausible, both the timing of the estimation and the magnitude of the implication suggest that this mechanism is unlikely to be material. If operable, a wealth effect would seemingly cause a one-time purchase of leisure goods, which would not likely track ex post price declines since the leisure activity is likely to be sticky. In addition, the channel would not hold for small business, where we find comparable estimation results with the same pricing mechanism.

A second possible confounding effect is that households themselves could be Bitcoin miners. However, over time, household mining because less and less prevalent as larger players grew in technological advantage. Furthermore, the electricity price in New York is high for households but low for industrial customers. Thus, any individual who was mining in volume in NY would have been incentivized to become an industrial customer. Thus, although we cannot rule out such mining, the volume is likely to be small. These arguments together suggest that our exclusion restriction is quite likely to hold.

Estimating equations. We estimate our model separately for each user type $u \in \{household, small\ business\}$. Note that because of the electricity grid system described previously, the price of Bitcoin is likely to affect prices across the entire Upstate grid. Our first stage equation is as follows:

$$\log p_{ct} = \alpha^u \log p_t^{BTC} + \gamma_1^u X_{ct} + \mu_{1,p}^u + \mu_{1,c}^u + \varepsilon_{pct}^u, \tag{5}$$

where p_{ct} is the location-based marginal price in community c at time (month-year) t; X_{ct} includes other community-time specific predictors of electricity consumption such as local weather; $\mu_{1,p}^u$ 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.

Our outcome equation, which follows directly from the framework presented in Section

[28]See Congressional Research Service (2019) and Ana Alexandre, "New York State Regulators Approve New Power Rate Structure for Crypto Miners," Cointelegraph, July 13, 2018.

[29]Soon after this spike, Plattsburgh issued a moratorium on cryptomining, and energy consumption returned to a pattern similar to that of neighboring Peru.

2, is as follows. For each user type u:

$$\log q_{pct}^u = \beta^u \log p_{ct} + \gamma^u X_{ct} + \mu_p^u + \mu_c^u + \epsilon_{pct}^u, \tag{6}$$

where q_{pct}^u is the electricity consumption 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 of electricity. 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:

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

where $\widehat{p_{ct}}$ is instrumented using the Bitcoin price, and all other variables are as in equation (6).

The effect of weather. Weather plays a key role in the consumption of electricity, and thus also its price. Temperature, as the key measure, is likely to have a nonlinear effect on electricity consumption, since communities demand more energy for both heating (in low temperatures) and air conditioning (in high temperatures). Such a statement would suggest that we control for temperature using a quadratic specification, allowing for a U shaped consumption over temperature. However, a strong correlation among consumption, price, and temperature in our data poses an issue of multicollinearity. For example, the variance inflation factor (VIF) estimates for the temperature and temperature squared variables in the OLS specification reported above are over 80; a VIF of five or above is conventionally considered to give rise to multicollinearity issues. A piecewise linear specification in temperature, allowing for five different slopes at the 10th, 30th, 70th, and 90th percentiles of temperature, produces VIFs ranging from 73 to 202. This raises concerns about the interpretability of coefficients, as our price variable is also structurally correlated with temperature.

Our analysis thus involves several steps. First, we present a model of electricity consumption linear in log temperature. This model does not account for the nonlinearity of the effect of temperature, but we view it as a helpful baseline with low multicollinearity concerns in that the VIFs fall to less than two.

Second, we present a three-period moving average (MA3) specification. Because this specification works on averages in an otherwise high collinearity setting, we are able to solve our VIF issue, while allowing us to estimate a separate coefficient on temperature for the winter months as opposed to other seasons. The downside of a moving average is that aggregating over time periods leads to a loss of information.

Third, we take out the seasonality from the price variable, by projecting the historical electricity price on month dummy variables and use the residual from the projection. This method does not solve collinearity in the temperature specification, but orthogonalizes price to avoid mulicollinearity-induced inflation of the absolute values of the price coefficients.

Finally, our preferred method involves projecting electricity consumption itself on temperature. We project electricity consumption on a quadratic of temperature (including community fixed effects) and then take the residual from this regression (i.e., orthogonalized electricity consumption) and regress it on the electricity price instrumented using the Bitcoin price. This method is, in essence, giving preference to temperature as the driver of electricity demand and then quantifies how price affects the unexplained component of consumption. We interpret our price elasticity estimates as reflecting the effect of price on demand after controlling for temperature in a way that is not compromised by multicollinearity. Our method is consistent with recent advances in econometrics and machine learning that handle many possibly collinear variables, including LASSO and ridge regression, as well as with the idea of accounting for the effect of a high-dimensional confounding factor (temperature in our example) via orthogonalization (see, e.g., Chetverikov et al. (2016), Mullainathan and Spiess (2017) and Athey and Imbens (2019)).

4.1.2 Results: Electricity Consumption

Relevance evidence. The relevance evidence, motivated by the Plattsburgh case study, is confirmed in the IV first stage (labeled FS) across Upstate NY. As shown in column (2) of Table 3 (4), we find an elasticity of the location-based marginal electricity price to the price of Bitcoin of 0.145 (0.139) for residents (small businesses). A 10% increase in the price of Bitcoin is associated with approximately a 1.4% increase in the location-based marginal price. The estimation includes year, community, and provider fixed effects, and controls for temperature. Importantly, the $F-$statistic for the inclusion of the instrument in the first stage is approximately 700 (varying slightly across the tables), suggesting that demand by cryptominers has a strong positive association with electricity prices.

Main result. We now turn to the main results of the IV system. First, Column (1) of Table 3 for residential customers, and likewise that of Table 4 for small business customers, report the results from the non-instrumented OLS regression of electricity quantity demanded on the location-based marginal price (LBMP). The estimations include log temperature as a control plus community, utility provider, and year fixed effects. The OLS specifications produce a positive coefficient on the electricity price, which is consistent with an upward bias in estimating demand elasticities from data generated by the equilibrium interaction of demand and supply without exogenous variation.

Column (3) of Table 3 shows the IV baseline results for households following from equation (7), with weather being controlled for by the log of temperature. Under our maintained exclusion restriction, the instrumental variable strategy allows us to interpret the price coefficient as an estimate of the true elasticity of community demand to price changes. The coefficient is now negative and significant. As prices increase exogenously, the quantity of electricity demanded declines. In particular, residential customers exhibit an elasticity of -0.074, reducing consumption of electricity by 0.74% for every 10% increase in price. For comparison, Ito (2014) estimates medium-long run elasticities to be between -0.071 and -0.088 for California households.

Likewise, Table 4 shows the estimates of electricity demand for small businesses. The OLS estimates in Column (1) show again an upward bias coming from the equilibrium interaction of demand and supply. The IV estimates in Column (3) are instead in line with a downward sloping electricity demand curve. Small businesses exhibit a more reactive demand elasticity of -0.18, reducing consumption of electricity by 1.8% for every 10% increase in price. Overall, these findings highlight that community demand for electricity is somewhat responsive to prices leading to lower consumption — and thus surplus — when prices are pushed up by cryptominers' entry.

The remaining columns refine our baseline specification to test robustness on two fronts: (i) the way we are controlling for weather, and (ii) the timing assumptions embedded in the IV fixed effects methodology. Columns (4) and (5) of Tables 3 and 4 report estimates from the first-stage equation (5) and the IV equation (7) using a MA3 specification. Since most households and businesses receive their electricity bill at the end of the month, there may be some lag between price increases and adjustment in demand if they react in the subsequent months. At the same time, it may still be that households are aware of concurrent price changes. The three-month averaging allows for concurrent as well as delayed effects. We include a winter dummy and its interaction with temperature to model the role of temperature on electricity demand more flexibly. When including the moving average of prices and an improved specification of temperature, we see a larger elasticity to the moving average of current and recent prices, consistent with larger delayed responses. In particular, both residential and small business customers have an elasticity of around -0.28, indicating that consumers reduce consumption of electricity by 2.8% for every 10% increase in price. Furthermore, the increased magnitude relative to column (3) suggests an interpretation counter to the concern that our results are being driven by the timing of consumers' response or the spurious effect of temperature.

Columns (6) and (7) approach the weather multicollinearity concern by projecting the price variable onto seasonal effects. We implement this specification as concurrent, with a quadratic in temperature. The coefficients are statistically strong and fall in the range bound by columns (3) and (5), namely, households exhibit an electricity consumption elasticity of -0.256 to price; and small businesses, an elasticity of -0.240.

We pause to look at the first stage results for the IV systems of columns (4-5) and (6-7). We find the expected negative interaction between winter and temperature (column (4)) and the expected U-shaped effect of temperature on prices (column (6)), indicating that colder and hotter weather are both associated with higher electricity prices. In these specifications, the F-statistics for the instrument are still very robust.

Finally, in columns (8) and (9), we present our preferred specification to pin down the price elasticity controlling for weather, with electricity consumption now being defined as the component orthogonal to quadratic temperature variables. We present the form of the projection of electricity consumption on temperature graphically as Figure 6. In this figure, we have plotted a histogram of the temperature distribution (averages per month), showing the four seasons in Upstate NY, as background. Then, we plot the predicted relationship between temperature and electricity consumption. We do this plot in quadratic of temperature as well as a piece-wise linear. The lines are very similar. We take the residuals from regressing electricity consumption on quadratic temperature and community fixed effects.[30]

Returning to Tables 3 and 4, we find that despite this very different specification, the elasticities in columns 9 of the two tables are very similar to the prior columns. Residential (small business) consumers reduce consumption of electricity by 2.70% (3.17%) for every 10% increase in price.

First differences results. One concern with the first stage regression (5) is that, since the Bitcoin price may follow a nonstationary distribution over time (Ciaian et al. (2016)), the estimate of the coefficient on Bitcoin price might be spurious. This could in turn affect our estimates of the electricity price elasticities. One natural solution is to take first differences of the variables in both the first stage and the main outcome equation and run the regressions using those differences. This addresses the above concern since first differences of the Bitcoin price time series tend to be stationary (Ciaian et al. (2016)).

Table 5 reports first differences specifications for both residential (columns (1) to (4)) and small business (columns (5) to (8)) customers. As before, we present both the first stage and the second stage IV results. In columns (1-2) and (5-6), we present the results for the case where first differences are taken over one month, whereas columns (3-4) and (7-8) are for the case where first differences are based on a 3 month moving average. To form the moving average version, we take the average of each variable over month $t, t+1$, and $t+2$ and subtract from it the average over month $t-3, t-2$ and $t-1$. Despite the first differencing, we still allow for community and provider fixed effects, in order to absorb any differing growth trends systematic to a community or provider.

We find results, presented in Table 5, that are very consistent with the main results, with slightly muted economic magnitudes for small businesses. In particular, residents exhibit an elasticity of electricity consumption to instrumented electricity price ranging from -0.078 to -0.211, while the same elasticity ranges from -0.126 to -0.137 for small businesses.

4.2 Cryptomining and Electricity Provider Revenues

4.2.1 Electricity Providers

The focus of this study is primarily the effect of cryptomining on the consumer side: what happens to households and small businesses when cryptomining comes to town, abstracting from producer surplus. Yet, the analysis of community surplus is incomplete without some consideration of the presumably positive effect whereby the increased demand for electricity from cryptominers increases local provider revenues. Furthermore, we are interested in the

[30]Implementing the orthogonalization in a community fixed effects model, temperature explains an additional 2.2% (small business) to 9.4% (residential) percent of the variation over the sample period. Also, note that because we implement a community fixed effects model in the residualization, the R-square is substantially lower in column (9).

production side, as a source of further spillovers to household and small business surplus, because electricity producer revenues are likely to be at least partly redistributed back to the community through government taxation.

Most electricity providers in Upstate NY are large, multi-county corporations, with co-mingled revenues, making precise location-specific revenues and production difficult, but not impossible because the electricity market in Upstate NY also has a set of smaller municipal providers.[31] Municipal providers would presumably have been attractive for cryptominers due to their competitive pricing of electricity, as we can see in Figure 7, which shows the average electricity price in $/kWh for investor-owned and municipal electricity providers by different customers. For investor-owned providers, there is a steep negative gradient in the price going from residential, with an average price of around 17 cent/kWh, to industrial users, who pay less than 10 cent/kWh. This gradient is not as pronounced for municipal electricity providers; industrial customers can obtain electricity for less than 5 cent/kWh, which is consistent with the evidence documenting cryptominers registering as industrial users in towns with municipal providers.[32]

In our data section, we described the collection of the community locations of cryptomining operations. We match these locations with the municipal providers, identifying treatment locations. Of course, not all municipalities host cryptomining; thus giving us a cross-section of importance for estimating the role of cryptomining in electricity production. The large utility providers also have cryptomining operations working off their grids. For the large municipalities, we identify a treatment intensity, consisting of the percentage of communities served experiencing cryptomining. This simple averaging abstracts from a weighting of the importance of volumes with endogeneous production quantities.

A final, and not insignificant, data hindrance we face is that small municipal providers do not provide sub-annual data on revenues and production sales. Thus, we cannot implement a monthly IV specification based on the bitcoin price, instead using techniques that exploit the location of cryptomining over time as Bitcoin prices grew, and mining operations came online. Given data deficiencies, we thus view this analysis as suggestive, but still important to the overall takeaways.

4.2.2 Empirical Strategy: Electricity Providers

We estimate a continuous difference-in-differences specification following Acemoglu et al. (2004), where the treatment variable, the location of cryptomines, is a continuous variable differenced around a post period. We also implement a differencing version of this where we do not difference around time, but rather interact the cryptomining treatment with the average Bitcoin price for the year. This specification helps us to argue that any effects we

[31] Figure A2 in the Appendix shows the operation areas of the four large investor-owned electricity providers (Panel A) and several smaller municipal providers (Panel B).

[32] See for example the report by the Congressional Research Service, which can be found here: `https://crsreports.congress.gov/product/pdf/R/R45863`.

are identifying are not likely to be due to selection as follows. Whereas in the standard difference-in-differences specification, it could be that that our treatment interaction with post is picking up a selection of communities having a differential trend, causing a spurious loading on the post-treatment variable. Yet, there is not a linear trend in the Bitcoin price. The price of Bitcoin increased by 109% from 2015-2016 and by 89% from 2017- 2018, but by 605% from the intermediate period 2016-2017, implying an entirely different trend pattern.

A potential residual selection concern would emerge if the locations selecting into being hosts of cryptomining exhibited a pattern of economic activity, and hence electricity consumption, that varies in time in a way correlated with the price of Bitcoin. Yet, a counterfactual test would be as follows: in a setting of a town with a nonlinear but rapid growth rate, one would expect that the growth of industrial electricity use would be accompanied by growth in the small business and residential electricity use. By contrast, in our theoretical framing with increases in cryptomining demand for electricity, the industrial customers (incorporating the cryptominers) would experience positive growth in cryptomining, whereas the residential and small business consumption of electricity would decline. In that setting, community electricity consumption would exhibit a different pattern from industrial electricity consumption. Such a result would be inconsistent with location selection.

Our specification is based on yearly provider-level industrial and community production segments. We refer to the segments of clients (industrial and community) with a superscript j.[33] Within the $j = community$ segment of clients, we have provider-year observations for residential and small business customers. We pool these observations for the community estimating equation, allowing for two observations for each provider-year for the community segment. We refer to these sub-segments with subscript i (residential, small business). We do this pooling for reasons of power and the ability to estimate the effect of the treatment on provider community production with a single parameter. The prediction from our model is that the industrial segment, which contains the new cryptominers, should increase in sales and revenues. By contrast, the households should reduce their consumption.

Our estimating equation is given by:

$$\log y_{pit}^{j} = \theta^{j}\, cryptomining\ treatment_{p} \times Z_{t} + \mu_{pi}^{j} + \mu_{t}^{j} + \epsilon_{pit}^{j}, \tag{8}$$

where $cryptomining\ treatment_p$ is a continuous variable; Z_t is either p_t^{BTC}, the average price of Bitcoin in year t, or $post_t$, an indicator for being post 2016, the period after which cryptomining arose in these communities; and μ_p^u and μ_t^u are provider and year fixed effects. The dependent variables covered by $\log y_{pit}^{j}$ are the log of total sales volume in megawatt hours or the log of total revenues of electricity providers. We estimate equation (8) separately for each market segment j (industrial, community). The main coefficient θ^j represents the effect on producer sales (or revenues) of an increase in the treatment – the cryptomining intensity.

[33] The data at the provider level comes from the US Energy Information Administration (EIA).

4.2.3 Results: Electricity Providers

Tables 6 and 7 show the electricity provider results for the industrial and community segments respectively. In each table, columns (1) to (4) present results concerning the sales volumes (log megawatt hours) dependent variable, and columns (5) to (8) present results on revenues (log dollars). In the odd numbered columns, we present the estimations with the continuous treatment variable of provider-level cryptomining intensity, which can be 0 or 1 for the local-only municipal providers but is a percentage of locations for the large providers. The mean cryptomining treatment intensity across providers is 0.326. In the even numbered columns, we restrict the cryptomining treatment to be the 0-1 indicator for the municipal providers. Because of our small sample, this restriction does not imply that the large providers do not matter, but rather with only 4 such organizations, we simply do not have the power or precision to identify from their cross-section. The mean dummy indication of treatment is 0.229. Finally, whereas in columns (1), (2), (5), and (6) we use the Bitcoin price specification — interacting the Bitcoin price with the treatment variable — in the other columns, we use the standard difference-in-differences specification with a post dummy.

In Table 6, we include provider and year fixed effects and cluster by provider. In Table 7, we include provider-by-subsegment (residential or small business) fixed effects as well as year fixed effects, again clustering by provider. These fixed effects almost fully saturate the model, as seen in the high R^2 coefficients in both panels. We also control for the minimum and maximum monthly average temperature, to capture the effect of cold and high temperatures that vary by provider-year (averaging within the large providers across communities) and for the log volume of electricity sourced from the wholesale market.

In Table 6, we find evidence for higher volumes of industrial segment sales and revenues by providers servicing cryptomining locations for years when cryptomining demand increased, either measured by the price of Bitcoin being higher or by the post period dummy. The θ^j coefficient on the interaction of interest is positive across all eight columns, and significant in six of the eight, including all specifications for industrial revenues.

Overall, being in a cryptomining location in the post period or when the price of Bitcoin increased by 100% is associated with approximately 9-12% higher sales and 10-14% higher revenues from industrial users for treated electricity providers. This result is consistent with higher demand from cryptominers shifting the total local demand outward and leading to higher equilibrium quantities and prices, and larger revenues for electricity producers, as depicted in Figure 2.

Table 7 reports the estimates of equation (8) for pooled community accounts, small businesses and households. Our framework suggested that a positive shock to the electricity price induced by an increase in the Bitcoin price would reduce sales volume coming from small businesses and residents (the incumbent community in our framework), but could increase revenues as the price of electricity supplied increases.

Empirically, although the signs on the coefficients in columns (1) to (4) are negative, we fail to find any statistically significant negative sales volume effects between treated and control providers. This lack of a finding could be due to the coarseness of our data at the provider level, which is a very different dataset than the community-month level data for residential and small business consumption used in prior analyses. We do not take this evidence as being inconsistent with demand-side results, but rather reflective of a lack of precision because of annual averaging.

For revenues, however, we find significant estimates for the predicted effect that providers generate more revenues from the community, even if the community residents and small businesses cut back on consumption. It is however noteworthy that the magnitudes in Table 7 are lower compared to those in Table 6. Because the industrial users increase volume consumed, in particular the cryptominers using electricity, the combination of increased volumes and increased prices generates larger increased provider segment revenues compared to the same calculation for the community segment, where the increased revenues emerge only from a pricing effect. Specifically, the revenue coefficient (comparable to a percentage change) has a 2.5 - 5 times larger effect in Table 6 compared to Table 7.

4.3 Cryptomining and Community Tax Revenues

"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)

The evidence in the producer revenue section is consistent with our illustrating framework: electricity provider revenues from industrial users substantially increase due to the electricity demand from cryptomining operations. Given our goal of understanding the implications for community consumer surplus, here we consider the possibility that these added revenues may partly come back to the community in the form of government services from added tax revenues paid out of production revenues. The added government revenues need not be from electricity producers, but could be from taxing the cryptomining itself. Indeed, testimonial evidence suggests that cryptomining is a very profitable (and thus very taxable) use of local electricity supply.

We assume that all added local government revenues benefit local community households and small businesses, although in practice it could be that some of the extra tax revenues do not translate into community benefit. Thus, our estimates provide an upper bound on the benefit to the local community via the tax channel, which allows us to provide a conservative estimate of any negative impact on communities.

4.3.1 Empirical Strategy: Tax Revenues

As in our provider revenue estimation, we estimate a continuous variable difference-in-differences specification following Acemoglu et al. (2004). The treatment variable, the price of Bitcoin, is a continuous variable. The dependent variable is annual tax revenues. Our tax revenues dataset is at the town level, rather than the electricity provider level, which constrains our estimation for provider results. These town-level data allow us to estimate the continuous variable difference-in-differences model using the granular *cross-sectional* exposure to cryptomining. In particular, we difference around whether the town (versus the provider) is in a county with cryptomining. We allow towns to share in cryptomining tax benefits across the county because these towns share the same county government, and counties play a role in taxation and power contracting at the town level.

Specifically, our estimating model is given by:

$$\log TaxRevenues_{ct} = \lambda cryptomining_c \times \log p_t^{BTC} + \gamma X_{ct} + \mu_c + \mu_t + \epsilon_{ct}, \tag{9}$$

where $cryptomining_c$ is a dummy equal to one if there is evidence of cryptomining operations in the county where community (town) c is located; p_t^{BTC} is the average price of Bitcoin in year t; μ_c and μ_t are community and year fixed effects; and X_{ct} is a vector of time-varying community level controls. The main coefficient λ represents the effect on local government tax revenues of an increase in the intensity of treatment — the Bitcoin price.

In specification (9), if cryptominers' location decisions were only based on time-invariant factors, we could consistently recover λ. 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, estimated in the pre-cryptomining period, according to:

$$cryptomining_c = f\left(X_c, Z_c, \eta_c\right), \tag{10}$$

where X_c are the same covariates included in the tax outcome equation (9), and Z_c are additional factors affecting cryptominers' location decisions that are excluded from the tax outcome equation. We maintain the selection on observables assumption that the observables included in the location model be rich enough that all remaining variation in the location choice (η_c) is independent of potential outcomes. We cannot prove this claim, but in the robustness section, we break out the effect over the post period time. Recall that the Bitcoin price is lower on average in 2016 than in 2017 or 2018. If the run-up in Bitcoin prices was spuriously related to an unobservable location selection, our results should vary in a standard difference in differences in the post period by year. We offer such a test for robustness.

Location choice. We capture miners' location choice using information on county-level average temperature and power plant capacity in 2010 (the first year of our taxes data). Figure 8 shows a map motivating our model. In Panel A on the left-hand 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 depict a strong spatial correlation between cryptomining activity and both power plant capacity (higher capacity predicts cryptomining) and temperature (lower temperature predicts cryptomining due to machinery cooling costs).

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 included as treated locations, 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 forthcoming estimates for the location choice model in China (see Table A2) and with the arguments that climate and power plant proximity are main determinants of cryptominers' location choice.[34] While very parsimonious, the fit of the model is quite good with an area under the ROC curve statistic of 0.71. The right-hand side of Panel A in Figure 8 shows the fitted probability that a county hosts cryptomining, with a clear positive spatial correlation to the actual location of cryptomining counties.

4.3.2 Results: Tax Revenues

Main result: Tax Revenues. Columns (2) and (3) of Table 8 show the main results of our tax revenue estimations. First, column (2) reports the OLS estimates of the difference-in-differences model given by equation (9). We find that treated communities experience a differential increase in annual taxes per capita compared to control communities after the introduction of cryptomining. The effect is statistically significant and the point estimate implies that a 10% increase in the price of Bitcoin is associated with an increase of \$0.41 per capita in taxes in cryptomining communities.

Column (3) 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 \$0.61 compared to control communities when the price of Bitcoin increases by 10%. To put these numbers in perspective, we start with the observation that the average community tax revenue per capita in Upstate NY is \$500. The price of Bitcoin increased from about \$600 in 2016 to \$7,500 in 2018. According to our estimates, this increase could have led to higher taxes per capita in cryptomining communities by about \$70, or 14% of the average tax revenue per capita. Overall, the results from Table 8 support the thesis that governments may have an incentive to allow cryptominers to operate in their jurisdiction due to the prospect of increased tax revenues.

Robustness: Tax Revenues. In columns (4) to (6) of Tables 8, we report the estimates of equation 9, but substituting the price of Bitcoin with time dummies equal to one after 2016, 2017 and 2018, respectively. The interaction $cryptomining_c \times post_t$ produces a standard difference-in-differences specification, measuring how hosting cryptomining activities affects

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

local government taxes over time. Treated communities experience a relative increase in taxes per capita by approximately $30 dollars (or 6% of the average community tax revenues per capita) compared to control communities, and the results are robust to the choice of the post period. This consistency across time in a standard difference-in-differences serves to support our assumption that any residual location selection is not driving our results.

As we discussed, cryptominers are not the only electricity-thirsty players in the market. In particular, data centers have been using increasing amounts of electricity over the last few years. Thus, one concern could be that our estimates capture increased electricity demand from data centers' entry into communities as well. This could bias our estimates if (i) cryptominers and data centers location decisions are highly correlated; (ii) events that increase electricity demand from cryptominers also increase electricity demand from data centers. Since there are no public registries on the location of data centers (similarly to the case of cryptominers), we proxy for this information in two ways. First, we count the number of firms in each county in Upstate NY that engage in data processing, hosting, and related services (corresponding to the NAICS code 518210). Second, within this NAICS category, we identify firms engaging in computer data storage, data processing services and website hosting. The latter gives us a narrower (more conservative) measure of where data centers might be located.

Figure A3 in the Appendix shows the maps of (i) counties with a number of firms in data processing, hosting, and related services above and below the median, and (ii) counties with firms that are likely data centers. While there is some overlap between cryptominers and data centers, which is expected given the common incentives to locate close to energy sources, we also observe substantial variation. To test the robustness of our estimates to the inclusion of data centers, we estimate equation (9) horse-racing $cryptomining_c \times \log p_t^{BTC}$ against $data\ center_c \times \log p_t^{BTC}$, using our broader and narrower measures for the presence of data centers. Table A1 in the Appendix reports the results for both the OLS specification (columns (1) and (2)) and the IPW specification (columns (3) and (4)). The effect of higher Bitcoin prices on local tax revenues in cryptomining communities is robust to the inclusion of controls for data centers.

4.4 Cryptomining and Consumer Surplus

4.4.1 Approach

Using our framework in Section 2 and our empirical results, we quantify the impact of cryptomining on local consumer surplus. We implement several steps.

First, for each location, we use the estimates from the first stage regression (5) to compute the predicted marginal price before and after the entry of cryptominers. Specifically, for each community c and month-year t, we calculate

$$\widehat{\log} p_{ct,nocrypto} = \hat{\alpha}^u_{FS} \log p^{BTC}_{2016} + \hat{\gamma}^u_{1,FS} X_{ct} + \hat{\mu}^u_{1,FS,p} + \hat{\mu}^u_{1,FS,c}, \tag{11}$$

where the coefficients are the estimates from the first stage regression (column (1) of Tables 3 and 4) and p_{2016}^{BTC} 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

$$\widehat{\log p}_{ct,crypto} = \hat{\alpha}_{FS}^{u} \log p_{2018}^{BTC} + \hat{\gamma}_{1,FS}^{u} X_{ct} + \hat{\mu}_{1,FS,p}^{u} + \hat{\mu}_{1,FS,c}^{u}, \tag{12}$$

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

Second, given $\widehat{p}_{ct,nocrypto}$ and $\widehat{p}_{ct,crypto}$ (the non-logged versions of (11) and (12)), we calculate the change in local consumer surplus using the integral in equation (3) as follows

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

where the coefficients $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ are the estimates from the IV regression (column (3) of Tables 3 and 4). In words, the decrease in consumer surplus is simply the integral of the community demand function between $\widehat{p}_{ct,nocrypto}$ and $\widehat{p}_{ct,crypto}$.

Third, for each location, we divide the total change in consumer surplus by the number of accounts to obtain per-capita (or per-business) welfare changes.

Finally, we incorporate our estimates of the increases in tax revenues from cryptomining. We provide an estimate of the effect of cryptomining on consumer surplus under the assumption that the additional tax revenues are entirely rebated to the consumers, i.e. we report ΔConsumer Surplus + ΔTax Revenues. For the calculation of the additional tax revenues, we use the difference-in-differences estimates with IPW weighting from column (3) of Table 8.

4.4.2 Local Surplus Calculation

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. We find that households experience an extra cost of over \$7 per month, or \$88 per year. While the amount might seem small, we doubt that any resident 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;[35] thus, the welfare cost in percentage terms is 6.6%. 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 almost \$14 per month on average, adding up to \$168

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

per year. The average monthly electricity bill in NY for businesses is $919,[36] implying a 1.5% 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.[37]

Column (2) of Table 9 scales those losses up to the year level to be able to compare them with the annual gains in terms of tax revenues. 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.[38]

The aggregate implication is that households in Upstate New York pay over $200 million extra annually in electricity costs. Small businesses in Upstate New York pay $90 million more in aggregate because of cryptomining. We represent these effects in Figure 10. 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 consumer surplus 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. Aggregating small businesses and households, we obtain consumer surplus losses of over $290 million happening via electricity market spillovers.

When accounting for the differential increase in government revenues, we find that in the aggregate cryptomining towns in Upstate NY generate almost $40 million in additional government revenues, thus recovering about 14% of the losses. As a result, we estimate a net consumer surplus loss of $257 million in Upstate NY. In Panel B of Table 9, we replicate the analysis using the electricity demand elasticities from column (5) of Tables 3 and 4 (corresponding to the moving average robustness check). In Panel C, we do the same using the electricity demand elasticities from column (7) of Tables 3 and 4 (corresponding to the deseasonalized price robustness check). The estimated magnitudes are highly robust.[39] Note that we do not perform the welfare calculation for the robustness analysis that uses orthogonalized demand as the dependent variable (the last column of Tables 3 and 4). This

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

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

[38] 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 household. The number of affected households/businesses in the tax and expenditure calculations is the population of the treated towns.

[39] Note that the estimates of the welfare effects can be similar even if the magnitudes of the price elasticities differ. This is because the welfare loss formula in (3) depends not just on the price coefficient, but also on the coefficients on the other drivers of demand (e.g., fixed effects), which are also re-estimated across our specifications.

is because in that case the demand curve we are estimating is a scaled down version of the actual demand curve (since we are taking out temperature and community fixed effects) and thus we would need to adjust the calculation accordingly. We do not pursue this and instead rely on the fact that the price elasticities in that specification are in line with those from the other specifications, which suggests that the welfare figures are also similar.

Our focus so far has been on the effect of cryptomining on local consumer welfare (consumer surplus and the related government revenues) and not on electricity provider surplus. This is motivated by the limitations in our analysis of electricity provider revenues discussed in Section 4.2 and the fact that several providers are investor-owned and unlikely to contribute to *local* surplus, which is the main object of our analysis. However, here we briefly discuss how we can account for the supply side within our framework. As shown in Table 6, electricity providers increase their revenues when cryptominers enter the market. This is because, as we documented empirically, both quantities and prices increase in the new equilibrium with cryptominers. The increase in revenue is represented by the gray shaded area with dashed contours in Figure 2.

In order to calculate the corresponding increase in electricity provider revenues in our data, we proceed as follows. First, we compute average revenues in 2016 (prior to the cryptomining boom) across different providers and users and take it as the baseline. Second, we use our estimates from column (2) of Table 6 to compute the average increase in revenues for different providers and users associated with a 100% increase in the price of Bitcoin. This step assumes that the increase in revenues that we identify with differential variation based on exposure to cryptomining of some providers applies to all providers. If other providers experience a smaller increase in revenue, this figure will overstate the additional revenues of electricity providers. Third, we multiply the average increase in revenues for the number of providers and sum across all providers to obtain the overall increase in revenues with cryptomining.

We find that total provider revenues in Upstate New York increase by about $415 million. Translating this increase in revenues to producer surplus requires more assumptions. Perhaps the most natural path is to assume a profit margin consistent with industry evidence. Assuming a profit margin of 15% for electric utilities (Froelich and McLagan II, 2008), the increase in revenues leads to a $62 million increase in profits, a local community benefit. We note that this is likely to be a lower bound on the additional provider profits from cryptomining. This is because the 15% figure reflects operating margins, which are net of all operating costs, including fixed costs. However, in our analysis, producers only incur marginal costs as they expand their supply and therefore the increase in provider profits is likely to be higher. Beyond profit margins, one might consider other local benefits working through the provider revenues, such as additional labor opportunities or returns, a higher utilization of capitalizing but unused production capacity, etc. These effects may be material; yet they would have to amount to 58% of providers' revenues (= $241/$415) in order to offset the losses to consumers. Given these considerations, we conclude that the total positive spillover through electricity providers for any year in our time period is at least $62 million. This is fairly small relative to the net decrease in consumer surplus of $241 million. In contrast, we note that our theoretical framework predicts an increase in the total (consumer and producer) surplus. Indeed, as depicted in Figure 2, since the electricity market is expanding, the size of the overall pie increases. Thus, the actual increase in producer profits is likely to be substantially higher than our coarse lower bound of $62 million.

4.4.3 Policy Alternatives

Taken together, we have estimated there to be $250 million in local consumer surplus losses due to cryptomining after accounting for increased local tax revenues. On the other hand, electricity providers earn at least $62 million in extra profits. We cannot observe the non-local benefits to cryptomining firms or others; however, by limiting our scope to a study of local externalities, these effects do not concern our agenda. Also, as mentioned at the onset, we are not speaking to any local negative externalities on the environment. Further, note that we are only considering a small portion of global cryptomining, studied in a specific location at a specific point in time. With these scope definitions and caveats in mind, we briefly consider what policies might help mitigate the transfer of surplus away from local consumers. While providing a full-fledged analysis of possible policy solutions is beyond our scope, our framework does afford us the opportunity for a qualitative comparison of a few alternatives.

First, we consider a policy that banned cryptomining altogether, akin to that which occurred in Plattsburgh, NY. A limitation to this policy is that cryptomining could just move to other communities that didn't impose such a ban. Thus, unless the policy is coordinated among jurisdictions, the negative effects for local consumers would be moved geographically, rather than being eliminated. Since coordinating among jurisdictions is often difficult, such a solution would inherently be a local one. It is also important to note that such a solution would remove not only any consumer surplus losses but also any gains. In our estimation, NY exhibited $415 million in electricity provider revenue gains (a fraction of which represented net profits), and governments realized $40 million in annual government revenue increases from cryptomining. If, as predicted by our theoretical framework, the overall effect on the combined surplus of consumers and producers is positive, then banning cryptomining would be suboptimal, even from the perspective of the individual community.

Given this, one could consider solutions that allow cryptominers to operate while better aligning their incentives with those of the local communities or redistributing some of the extra surplus generated. For example, an option is a windfall profit tax on the extra profit earned by electricity companies due to cryptomining. Our calculations indicate that the tax should transfer at least $250 million a year to consumers in order to leave them as well off as before the entry of cryptominers. Of course, whether full or only partial redistribution is desirable is a political decision that should be made based on the local communities' preferences.

Another solution is to implement a pricing scheme sensitive to community demand. For instance, imagine a pricing scheme that incentivizes cryptominers to use electricity when the cryptomining price impacts on local consumers are at their lowest. Based on historical, seasonal usage data, electricity providers might set a price that cryptominers pay for electricity that is correlated with small business and household demand. Such a technique is already being considered and implemented in many industrial contracts and electric vehicle charging schemes. In our context, cryptominers do have the flexibility to cut usage of electricity by engaging in mining only when it is expected to be profitable, although switching on and off may impose some machinery toil. Such a pricing scheme is akin to a Pigouvian tax, defined in a local sense, if the pricing adjustment to cryptominers is calibrated to offset increases in prices to small businesses and households.

Finally, as an alternative to pricing-based mechanisms, electricity providers could enforce dynamic quotas on cryptominers. In either of these cases, the objective would be to keep the price impact on households or small businesses as minimal as possible while allowing cryptominers to operate.

5 Empirical Analysis: China

"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

We now turn to the case of China, the country hosting the most cryptomining in the world until 2021.[40] Beyond its importance because of its market share, China is relevant for our study in that, during our period of study, electricity prices in China act as if fixed at the province level in the medium-run, allowing us to focus on the impact of cryptomining on local economy activity happening through quantity channels as opposed to price channels. When crytomining comes to town, the quantity channel presents an ambiguous sign on its effect on community welfare. Despite cryptomining's low job creation, cryptomining might boost local economies with profit and tax spillovers. Conversely, the entry of highly energy-intensive players might crowd out other electricity uses and have a negative impact on non-cryptomining economic activity.

5.1 Empirical Strategy

We consider several outcome variables, denoted y_{ct}, for each city c and year t. Specifically, we look at city-level gross domestic product, fixed asset investments, and wage rate as

[40] The Cambridge Bitcoin Electricity Consumption Index (CBECI) shows that up until 2021 more than 50% of the global hashrate was taking place in China (See: `https://ccaf.io/cbeci/mining_map`).

measures of the commercial and industrial side of $D_{community}$. We also consider government budgets, which mirror our tax revenue measures in NY.

Our estimating equation is given by:

$$\log y_{ct} = \alpha \, cryptomining_c \times Post_t + \gamma X_{ct} + \mu_c + \mu_t + \epsilon_{ct}, \tag{13}$$

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 $t > 2015$; μ_c and μ_t are city and year fixed effects; and X_{ct} is a vector of time-varying city level controls.

We focus on the 218 inland China city-areas (with a mean population of 355,000) of which 52 have evidence of cryptomining. We choose 2016 as the start of the post period, marking the point in time when cryptominers began ramping up industrial cryptomining in China.[41], [42] We later consider robustness to that choice; in particular, we use 2017 as the start of the post period, while dropping the data from 2016 for comparability. We use weighted least squares to ensure equal contribution of each city irrespective of the panel balance and cluster standard errors at the city-level to account for the possibility of correlation in the error terms over time within a city, while also allowing for heteroskedasticity. We estimate our model in logarithms, leading to an interpretation of the coefficients as percentage changes.

The interaction $cryptomining_c \times Post_t$ yields a standard difference-in-difference specification, with the coefficient α measuring how hosting cryptomining activities affects the outcome variables over time. Our setting leads to an average treatment on the treated interpretation rather than an average treatment effect (Ryan et al. (2015)), because we cannot claim to support the common shock assumption of Angrist and Pischke (2009). We first present the baseline results and then go through a number of robustness checks.

5.2 Results

Main Results. Table 10 presents our baseline weighted least squares, difference-in-differences model. The unit of observation is a city-year. We begin by considering what happens to GDP in our panel, only controlling for the city population. Under the model's assumptions, we find that the introduction of cryptomining results in a statistically significant decrease in local GDP of 8.2%. Such a result might be indicative of a setting where either cryptomining operations generate lower GDP per unit of electricity compared with other production uses or where cryptomining GDP is not captured in local measurement because of remote

[41] The Economist (January 8, 2015, The Magic of Mining) reports: *"Chances are that many of these mystery machines live in China. At any rate, mining is likely to grow rapidly there. Miners in Inner Mongolia – where electricity is cheap thanks to abundant coal, over-investment in power plants and lax environmental rules – are reportedly building data centres much bigger than any in the West."*

[42] Kaiser et al. (2018) show that the growth of Chinese cryptomining in late 2015 and 2016 shifted China to being the dominant producer by 2016. Yet, cryptomining continued to grow, with China participating in that growth, past 2016. Some of that growth tapped into fully utilizing and expanding facilities in places like Ordos, Inner Mongolia, which had been built in 2015 or 2016.

corporate headquarters accounting.

In columns 2–4, we introduce controls for local economic growth. The key economic growth variable is GDP itself; thus, heretofore we focus on the economic mechanism of investment, wages, and government revenues. We find that investment and wage levels both exhibit a statistically significant decline when cryptomining enters a city, under the model interpretation. However, local cities exhibit no negative effects on government revenue due to economic activity switching to cryptomining.

In terms of economic magnitude, starting from 2016, local fixed assets investment falls by 19.5% and local wage rates decreased by 10.0% in cryptomining cities. These results are consistent with the possibility that cryptomining leads to retractions in investment by other industries in the years following cryptomining's entrance, and that, because cryptomining uses very few workers, this leads to downward pressure on labor, as other more labor-intensive uses of electricity are crowded out. A possible reason why we do not see an accompanying decline in government revenues comes from the evidence documenting that cryptomining is a highly profitable activity[43] and, thus, one that tends to yield more tax dollars per unit of electricity.

Taken together, these findings suggest that it is possible that local economies suffer as a result of crowding out in the electricity market. The economic magnitude of the results is large, yet plausible, given that we interpret the results as the average treatment effect only on the 52 treated city-areas in inland China, which represent only a small, but relevant, portion of the overall Chinese economy. In contrast, we would not expect our estimates to apply to much larger cities, such as Beijing, which are not treated in our sample.

Robustness Specifications - Parallel Trends and Location Selection. Next, in order to address the concern that the location of cryptomining facilities is related to growth pattern differentials in any of the dependent variables, we take two steps. First, we look at whether those variables exhibited parallel trends in the pre-period. Second, we re-estimate the model with a location selection correction. Panels (A) to (D) in Figure 11 display the pre-trends, confirming no difference in the trend for each of the dependent variables. Specifically, the background bars with green (dark) outline and no fill color depict the raw across-city means of each outcome variable by year for the control group of cities with no cryptomining. The pink (light) shaded bars are the raw means of the outcome variables by year for cities with cryptomining. For the pre-period, we include the standard error whiskers so as to visually assess the parallel trends assumption. In the same figure, we also plot a counterfactual estimate of the effects of cryptomining (the darker bars). Specifically, we calculate the predicted outcomes (in logarithms) from the estimates, subtract the interaction term between the post period and the cryptomining dummy, and exponentiate.

Next, Table A3 in the Appendix reproduces our specifications, under a location choice model. Using pre-period data from 2013-2015, we model location choice of cryptominers as a

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

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 of these variables as well as the log of population, the city government budget, and GDP. We plot the predicted probability functions with the marginal effects of power plant distance, electricity price, and temperature in Appendix Figure A4.[44] The area under the ROC curve statistic, which captures the ability of the model to correctly classify locations in the cryptomining vs. no cryptomining category, is 0.905, suggesting that our approach captures much of the cryptominers' location decisions. We take the probability of being a cryptomining city as predicted by the model, and implement an inverse probability weighting (IPW) difference-in-differences model as a robustness check. Three results are reported in Table A3 in the Appendix. In all cases, the coefficients are larger in absolute value and consistent with those in Table 10.

A separate concern arises because of potential electricity grid spillovers. In particular, the control cities may also be exposed to shortfalls in electricity if supply is diverted away from them and towards cities hosting cryptomining operations. Although this muddying of the control group would lead to a conservative attenuation of our estimates, ideally we would like the control to exist in a different policy environment.

Such a setting is reminiscent of the Twin Counties Model of Chirinko and Wilson (2008), who study counties whose region crosses multiple jurisdiction borders, in turn implying different policy treatment environments. In our case, because electricity transmission is controlled by province governments, their borders limit the possibility of treatment spillovers. This test uses the assumption that electricity grids are not integrated (Kahrl et al. (2011)).

To operationalize this robustness test, we construct a refinement to the control group consisting of cities with a very low likelihood of exhibiting any cryptomining spillovers. In particular, we limit the control cities to those that: (i) are located in the provinces in Figure 4, Panel A with no or low cryptomining (yellow or mustard), and (ii) do not border any cryptomining city-seats (marked in red in Figure 4, Panel B) unless across province lines. The empirical results from this limiting of the control group appear in columns 5–7 of Table 10. Again, our results are quite robust and consistent with those in columns 2–4, despite a tighter control sample.

Robustness Specifications - Post Period. Columns 8–10 of Table 10 present the final robustness specification.[45] Although cryptomining began at scale as an industry in 2016,

[44] 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.

[45] Columns 5–7 of Table A3 present the same robustness specification for the probability weighting (IPW) difference-in-differences model.

it might be that its effects started playing out on local communities with some delay. To accommodate this, we re-estimate our regressions dropping 2016 and using 2017 as the beginning of the post period. Our results are robust to this alternative timeline. If anything, the magnitudes are slightly larger, especially for wages, consistent with 2017 reflecting the period of large scaling-up (the 2017 massive growth in Bitcoin activities) serving as a focal point for community effects.

Summary of the China Analysis. We return to the interpretation of columns 1-4 of Table 10. We find that fixed asset investment, GDP and wage rates tend to *decrease* as a result of cryptomining operations locally. This is consistent with the possibility that manufacturers and other industrial activities may be crowded out in access to cheap electricity, thus resulting in the fixed asset and GDP decline. Further, 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 reduced demand for workers by other commercial enterprises and industry due to cryptomining crowding out alternative energy uses. Taken together, these findings suggest that it is possible that local economies suffer as a result of crowding out in the electricity market.

6 Conclusion

In this paper, we have presented novel empirical evidence of the real 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 consumer surplus losses incurred by the community as a result of higher electricity prices. We then turned to China, the country hosting the most cryptomining operations in the world in the last decade, 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. We also 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 in Upstate NY are smaller than the cost imposed on households and small businesses through higher electricity prices.

Of course, cryptomining — just like any other technological 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 real 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 away from the costs to local communities stemming from the carbon 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.

In addition to this, our analysis of the real effects of energy-intensive technologies on local communities could be expanded in several directions. First, we ignore cryptomining in all other locations globally. For instance, recently, an army of cryptocurrency miners has migrated to Texas. Because Texas has the most vulnerable power grid in the U.S., the mining in Texas may force peak pricing effects in an even more costly way to Texas's households and small businesses.[46] Second, cryptomining is just the tip of the iceberg among technology processing industries around the world. Thus, we view our work as just the first step towards quantifying the real effects of energy-intensive technologies on local communities.

[46]See https://www.bloomberg.com/news/articles/2021-11-19/texas-plans-to-become-the-u-s-bitcoin-capital-can-its-grid-ercot-handle-itand https://www.cnbc.com/2021/10/31/bitcoin-mining-giants-bitdeer-riot-blockchain-in-rockdale-texas.html.

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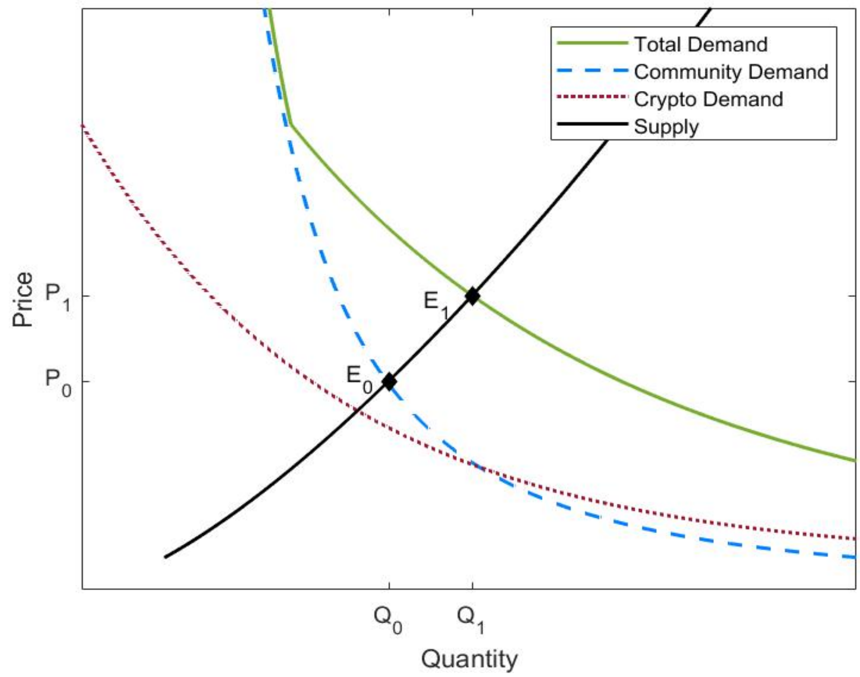
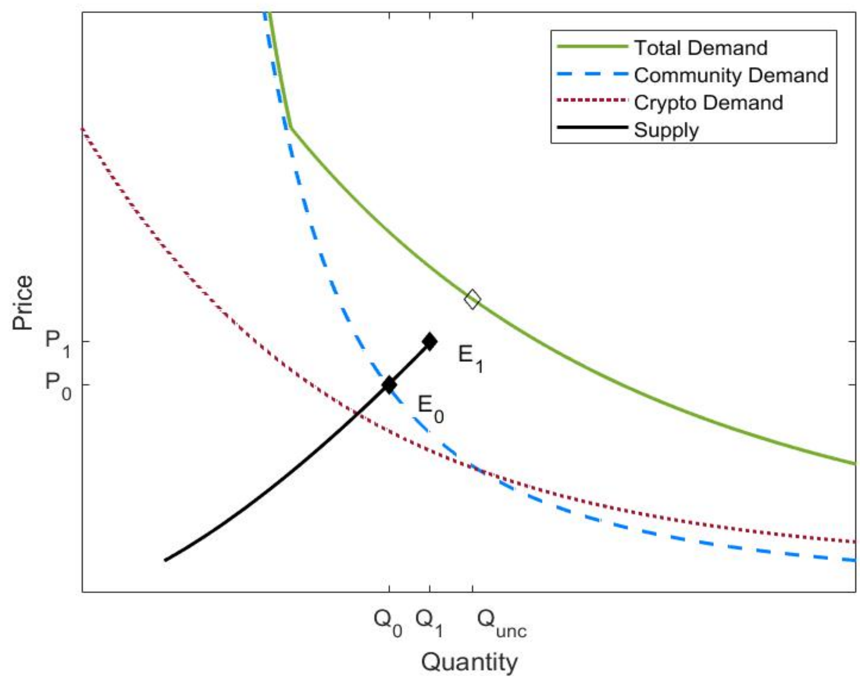
Figure 1: Cryptomining with floating electricity prices

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

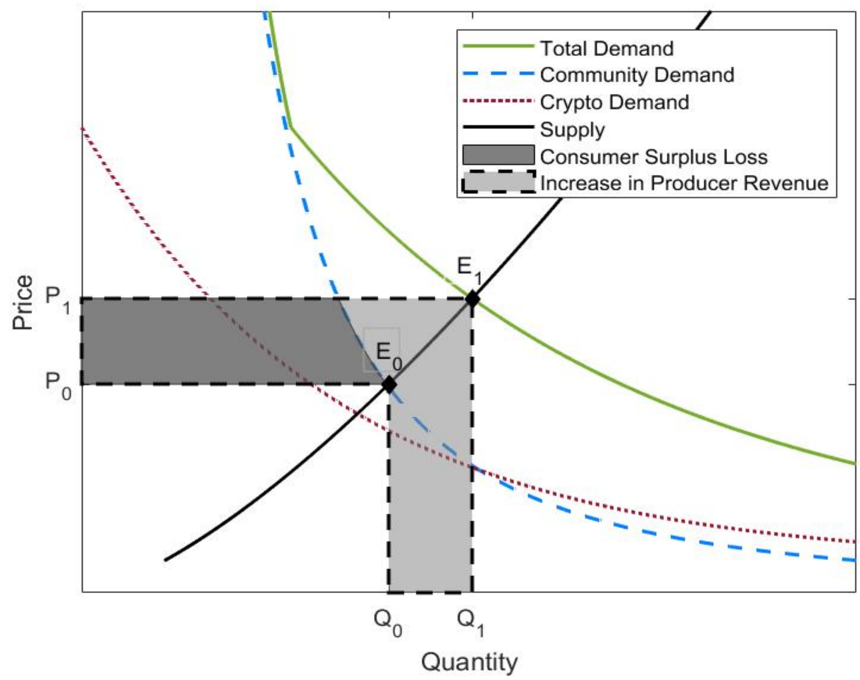


Panel B: Equilibrium in Local Electricity Market with Upward-Sloping Supply & Capacity Binding



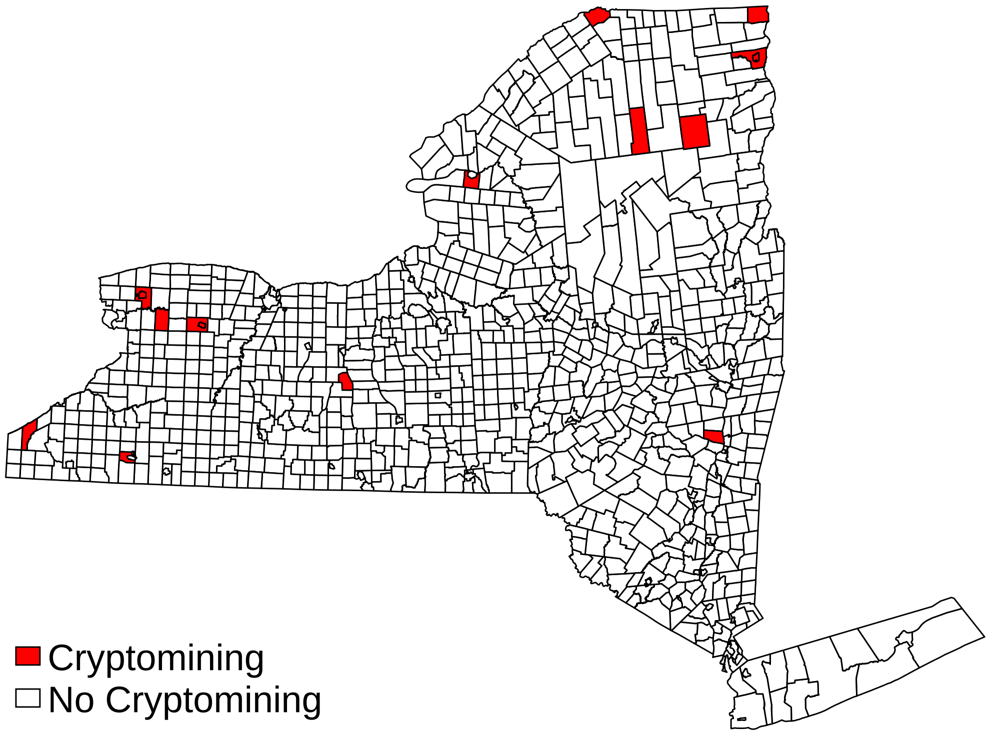
Note: The chart shows illustrations of supply and demand in markets with (Panel B) and without (Panel A) supply capacity binding. The figures depict the setting in which the local electricity supplier provides electricity up to capacity with a standard upward-sloping supply curve.

Figure 2: Equilibrium Effects of Cryptomining on Local Welfare



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 consumers as a result of higher electricity prices (in darker gray) and the associated increase in producer revenue (darker and lighter gray areas combined).

Figure 3: Mining communities in New York state

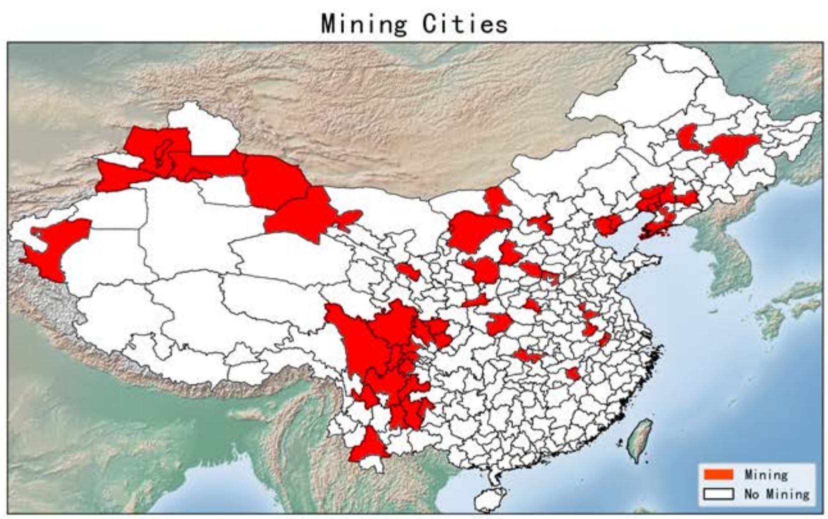


Note: Data on mining locations come from manual searches in local newspapers and newsources in English through Google. We present locations at the finer town level in Upstate NY.

Figure 4: Mining cities in China

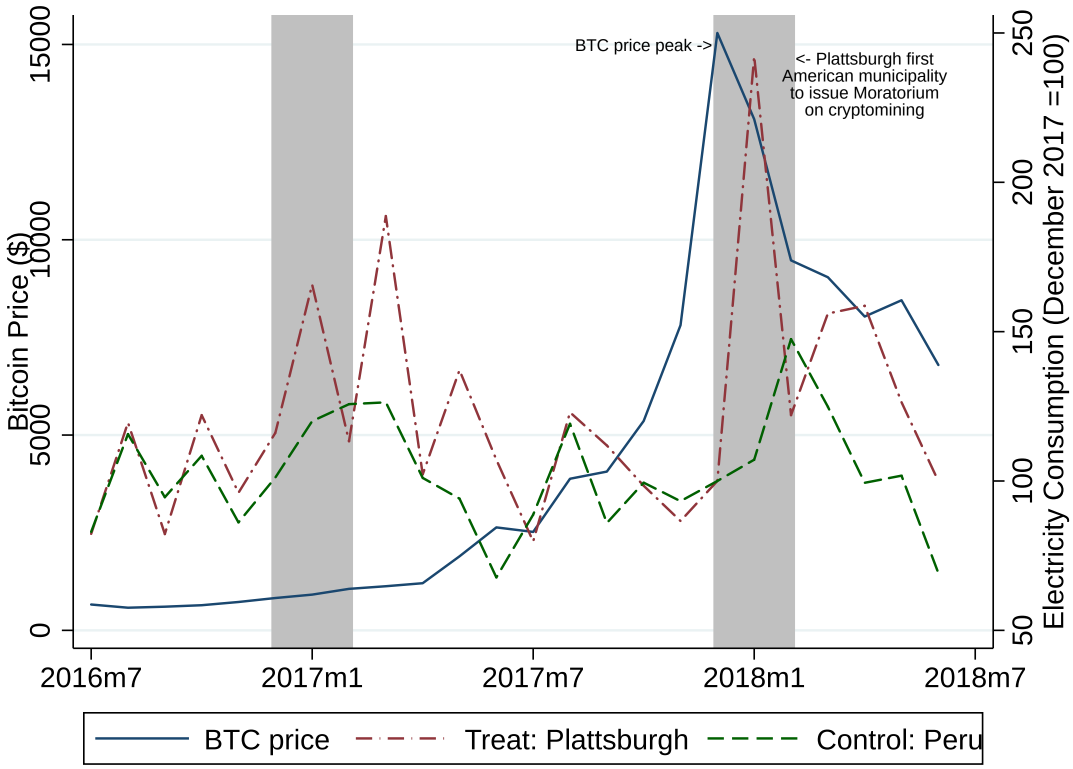
Panel A: Province-level locations of cryptomining

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 city-seat, where a city-seat is the main city with its controlling surrounding areas (akin to counties).

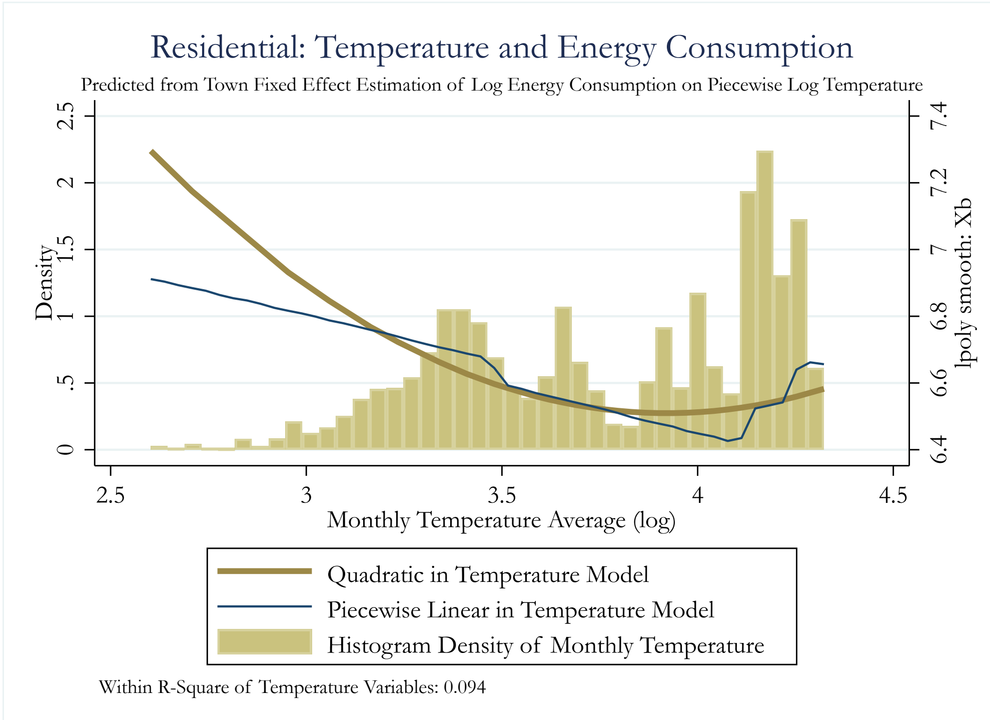
Figure 5: Bitcoin prices and electricity consumption



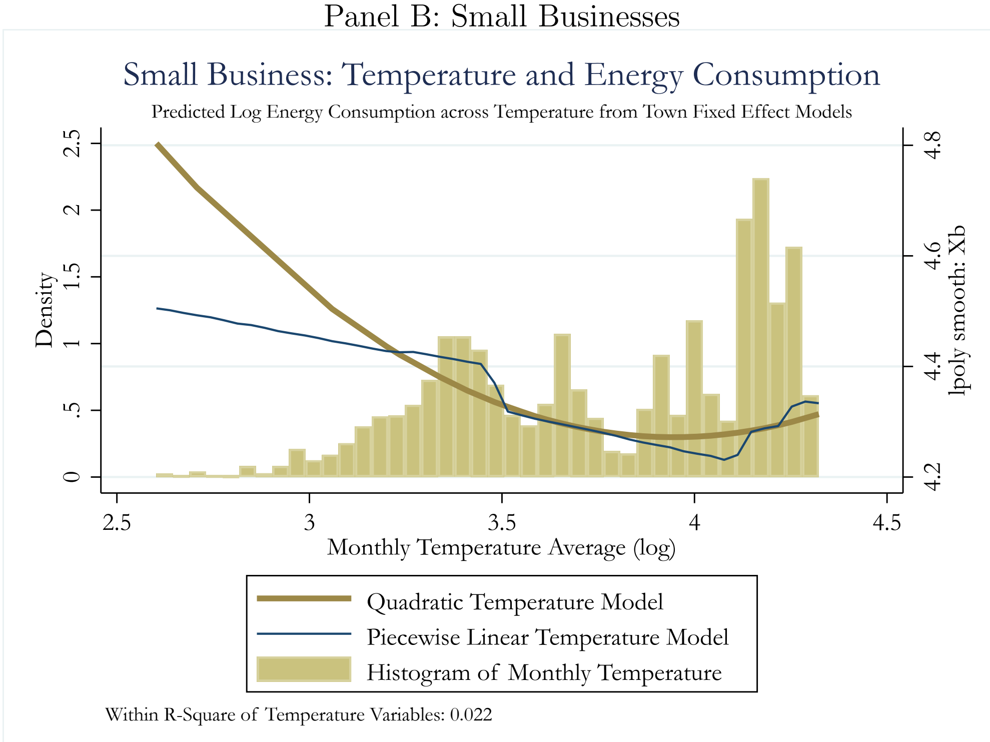
Note: Bitcoin price data comes from Coinmarketcap. Electricity consumption data comes from NYSERDA. The blue line shows the average price of Bitcoin each month. The red dash-dot line and the green dash line show total electricity consumption by small and industrial businesses in Plattsburgh and Peru, respectively. We normalize electricity consumption in each town to 100 in December 2017, which is the month is which Bitcoin prices reached their maximum of around $15,000. Grey areas denote December, January and February of 2016-2017 and 2017-2018.

Figure 6: Effect of temperature on electricity consumption

Panel A: Residential

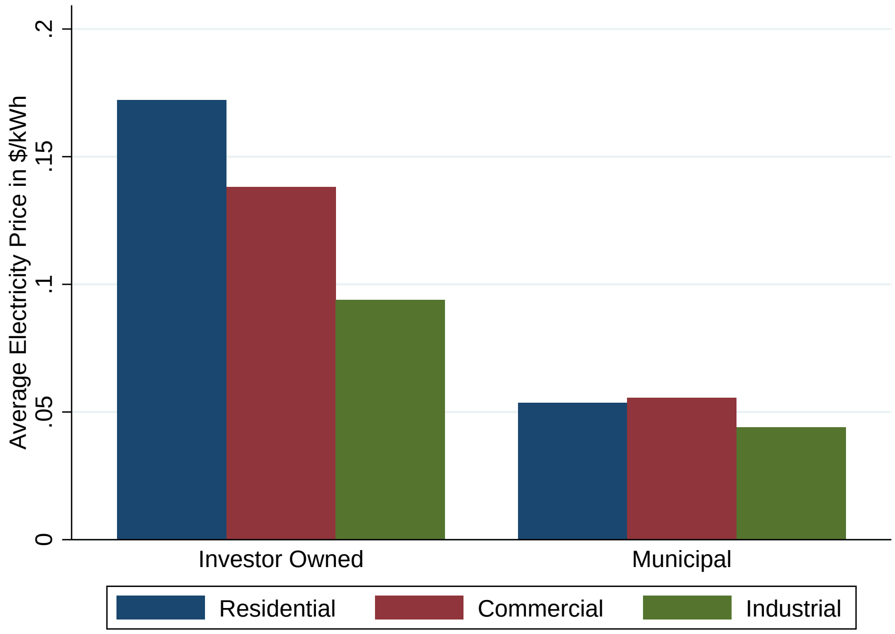


Panel B: Small Businesses



Note: The figures show the histogram of the temperature distribution (averages per month) and the predicted relationship between temperature and electricity consumption, using both a quadratic of temperature as well as a piecewise linear. Panel A shows the energy consumption for residential. Panel B shows the energy consumption for small businesses.

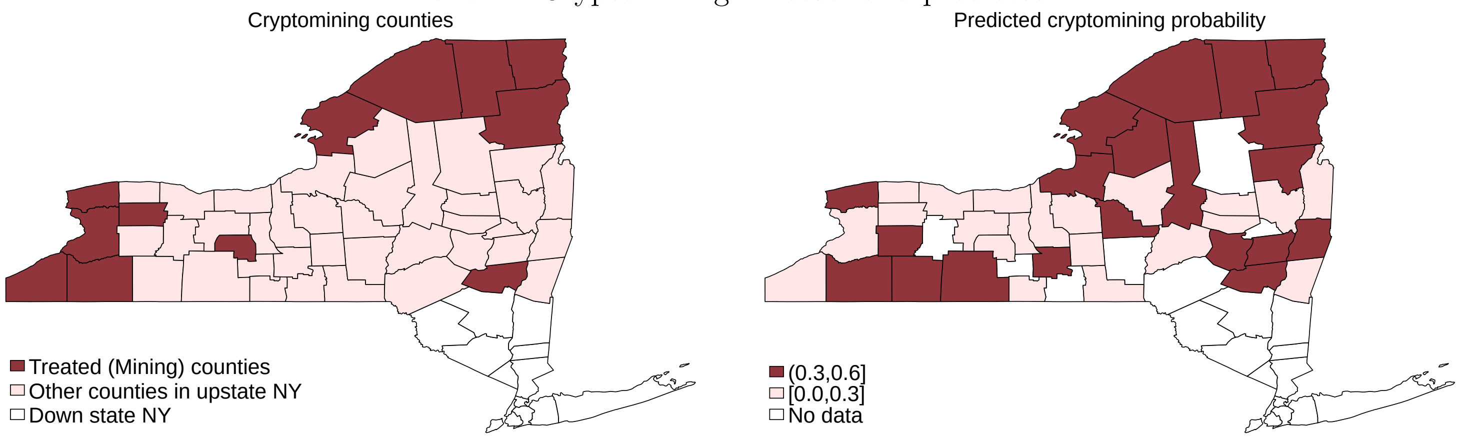
Figure 7: Electricity prices by provider type in Upstate NY



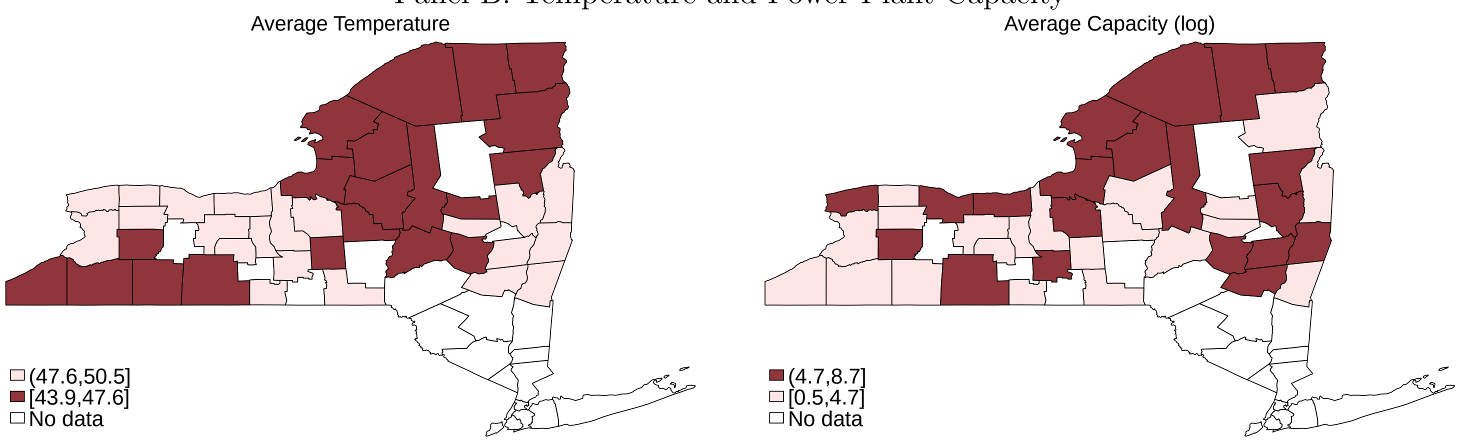
Note: The chart shows the average electricity price for different customer types and electricity providers.

Figure 8: Mining counties, Temperature and Power Plant Capacity in Upstate New York

Panel A: Cryptomining - Actual and predicted

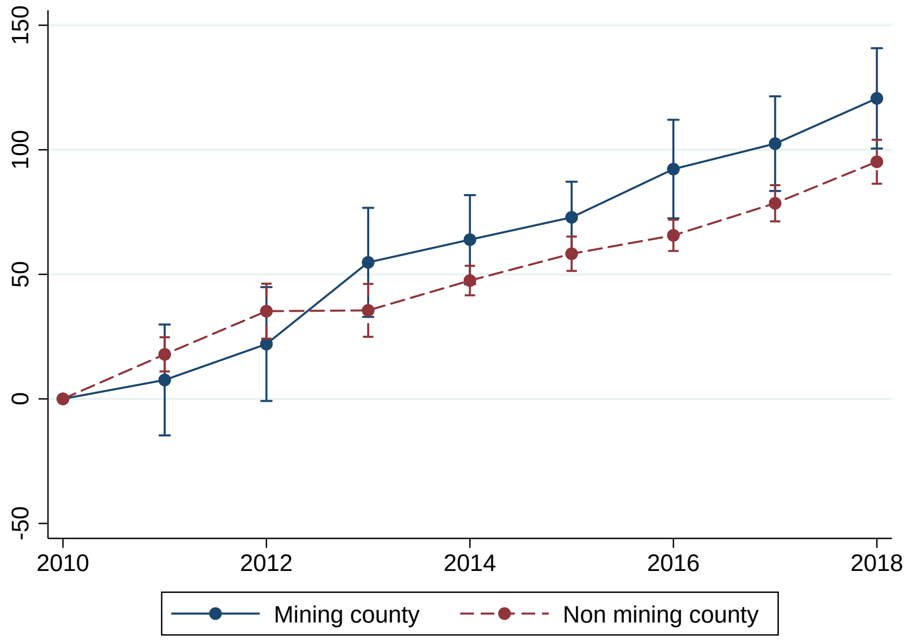


Panel B: Temperature and Power Plant Capacity



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 plant capacity at the county level in 2010.

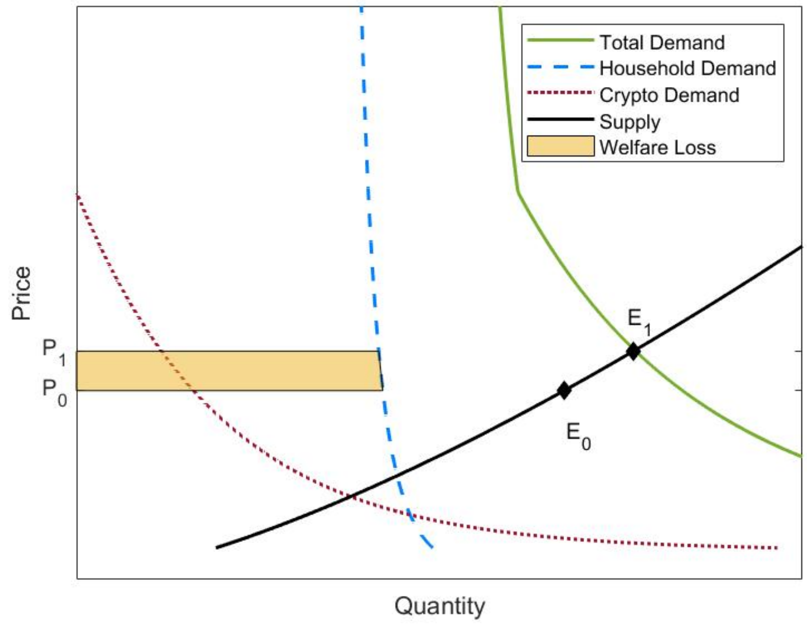
Figure 9: Local Taxes - Parallel Trends



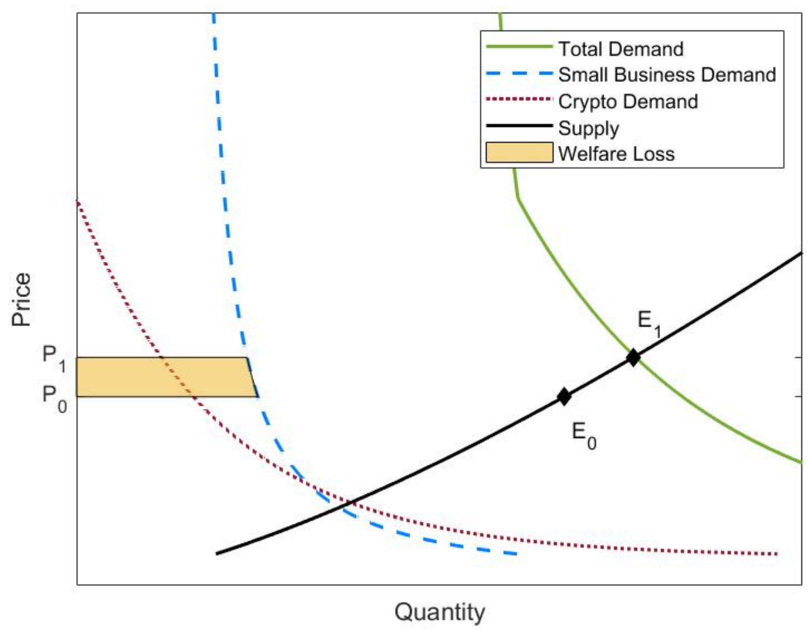
Note: The chart shows the average tax revenues in towns with and without cryptomining in the county. The y-axis captures the growth in tax revenues (in dollars per capita) from the baseline year of 2010.

Figure 10: 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., households 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 11: Parallel Trends

Note: The background bars with green (dark) outline and no fill color depict the raw across-city mean of an outcome variable by year for the control group of cities with no cryptomining. The pink (light) shaded bars are the raw mean of outcome variable by year for cities with cryptomining. For the pre-period, we also include the standard error whiskers so as to visually assess the parallel trends assumption. For the post period, we instead include a dark (black) bar, which is the counterfactual prediction from the estimation model of columns 1 to 4 of Table 10 for the respective panel figure, calculated by taking the prediction from the estimation (in logarithms), adjusting to remove the interaction term between the post period and the cryptomining dummy, and exponentiating.

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 New 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 B shows the temperature at the county-month level, the price of BTC, which is available online (see among other sources `https://coinmarketcap.com`), and taxes per capita at the town-year level from `https://seethroughny.net/benchmarking/local-government-spending-and-revenue/#`.

	Observations	Mean	Std. Dev.	Minimum	Median	Maximum
Panel A: Electricity market variables						
Residential						
Sales (MWh)	32,447	1,593.74	3,575.17	6.71	676.44	74,063.65
Customers (Count)	32,447	2,366.50	6,210.91	15.00	905.00	109,496.00
Small businesses						
Sales (MWh)	26,059	484.53	1,920.09	0.43	55.52	36,752.82
Customers (Count)	26,059	261.16	664.57	6.00	96.00	9,974.00
Other industrial						
Sales (MWh)	15,080	3,903.68	14,754.38	0.21	452.93	220,115.51
Customers (Count)	15,080	115.02	247.77	6.00	44.00	3,522.00
Location-based marginal price ($/MWh)	14,744	27.08	10.95	2.63	24.70	110.93
Panel B: Additional variables						
Temperature (Degrees Fahrenheit)	41,469	47.00	16.96	13.50	48.60	75.40
BTC price ($)	36	4,042.60	3,935.75	404.41	2,577.81	15,294.27
Taxes per capita ($)	6854	524.37	505.83	66.43	419.99	9083.09

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 does the same for cities with cryptomining. Data on economic variables 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: Residential**
Columns (2), (4), (6) and (8) present the estimates of the first stage regression given by equation (5). The dependent variable is the (log) location based marginal price (LBMP) in \$/MWh. Column (1) presents the ordinary least square (OLS) estimates from equation (6). Columns (3), (5), (7) and (9) presents the instrumental variable (IV) estimates from equation (7), using the respective first stage estimates. The dependent variable is the (log) household electricity consumption at the community level in MWh. BTC price is the (log) average price of Bitcoin in a month-year. Columns (4) and (5) report the specification with three-month averaging. Columns (6) and (7) project the price variable onto seasonal effects. In Columns (8) and (9) electricity consumption is defined as the component orthogonal to quadratic temperature variables. Errors are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Baseline			Moving Average		Deseasonalized Price		Orthogonalized Demand	
	OLS	FS	IV	FS	IV	FS	IV	FS	IV
Instruments:									
BTC price (log)		0.145***				0.195***		0.140***	
		(0.006)				(0.005)		(0.005)	
BTC price (log, MA3)				0.105***					
				(0.007)					
Electricity price:									
Price (log)	0.155***		-0.074**						-0.270***
	(0.015)		(0.031)						(0.034)
Price (log, MA3)					-0.279***				
					(0.092)				
Price (log, deseasonalized)							-0.256***		
							(0.022)		
Controls:									
Temperature (log)	-0.093***	-0.233***	-0.145***			-3.121***	-5.555***		
	(0.020)	(0.020)	(0.024)			(0.165)	(0.351)		
Winter				0.663***	1.178***				
				(0.203)	(0.222)				
Temperature (log, MA3)				0.220***	0.085**				
				(0.018)	(0.035)				
Winter × Temperature (log, MA3)				-0.095	-0.275***				
				(0.058)	(0.059)				
Temperature (log^2)						0.435***	0.735***		
						(0.022)	(0.048)		
Year Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Community Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Provider Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	7.56	3.23	7.56	3.23	7.56	3.23	7.56	3.23	0.00
SD Y	1.34	0.36	1.34	0.36	1.34	0.36	1.34	0.36	0.21
F stat			656.89		74.28		1631.42		689.64
Observations	3251	3251	3252	3251	3252	3251	3252	3251	3252
Adjusted R-squared	0.98	0.39	0.97	0.41	0.97	0.46	0.98	0.33	-0.03

Table 4: **Effect of Cryptomining on Electricity Prices and Demand: Small Businesses**

Columns (2), (4), (6) and (8) present the estimates of the first stage regression given by equation (5). The dependent variable is the (log) location based marginal price (LBMP) in \$/MWh. Column (1) presents the ordinary least square (OLS) estimates from equation (6). Columns (3), (5), (7) and (9) presents the instrumental variable (IV) estimates from equation (7), using the respective first stage estimates. The dependent variable is the (log) small business electricity consumption at the community level in MWh. BTC price is the (log) average price of Bitcoin in a month-year. Columns (4) and (5) report the specification with three-month averaging. Columns (6) and (7) project the price variable onto seasonal effects. In Columns (8) and (9) electricity consumption is defined as the component orthogonal to quadratic temperature variables. Errors are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Baseline			Moving Average		Deseasonalized Price		Orthogonalized Demand	
	OLS	FS	IV	FS	IV	FS	IV	FS	IV
Instruments:									
BTC price (log)		0.139***				0.188***		0.135***	
		(0.005)				(0.005)		(0.005)	
BTC price (log, MA3)				0.101***					
				(0.006)					
Electricity price:									
Price (log)	0.056***		-0.179***						-0.317***
	(0.021)		(0.057)						(0.061)
Price (log, MA3)					-0.292***				
					(0.113)				
Price (log, deseasonalized)							-0.240***		
							(0.044)		
Controls:									
Temperature (log)	-0.088***	-0.195***	-0.133***			-2.902***	-3.176***		
	(0.024)	(0.020)	(0.031)			(0.214)	(0.378)		
Winter				0.704***	0.707***				
				(0.203)	(0.217)				
Temperature (log, MA3)				0.228***	-0.021				
				(0.016)	(0.035)				
Winter $\times$ Temperature (log, MA3)				-0.115**	-0.171***				
				(0.058)	(0.058)				
Temperature ($\log^2$)						0.410***	0.419***		
						(0.028)	(0.050)		
Year Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Community Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Provider Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	5.70	3.23	5.70	3.23	5.70	3.23	5.70	3.23	0.00
SD Y	2.00	0.35	2.00	0.35	2.00	0.35	2.00	0.35	0.27
F stat			713.88		103.78		1644.88		773.52
Observations	2977	2977	2978	2977	2978	2977	2978	2977	2978
Adjusted R-squared	0.98	0.37	0.98	0.40	0.98	0.46	0.98	0.32	-0.10

Table 5: **Effect of Cryptomining on Electricity Prices and Demand: First Difference**

Columns (1), (3), (5) and (7) present the estimates of the first stage regression given by equation (5) in first differences. The dependent variable is the change in (log) location based marginal price (LBMP) in \$/MWh. Columns (2), (4), (6) and (8) present the instrumental variable (IV) estimates from equation (7) in first differences, using the respective first stage estimates also in first differences. The dependent variable is the change in (log) household electricity consumption at the community level in MWh. BTP price is the (log) average price of Bitcoin in a month-year. Columns (3), (4), (7) and (8) report the specification with three-month averaging. To form the moving average version, we take the average of each variable over month $t, t+1$, and $t+2$ and subtract from it the average over month $t-3, t-2$ and $t-1$. Columns (1) to (4) report the results for residential. Columns (5) to (8) report the results for small businesses. Errors are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Residential				Small Businesses			
	FS	IV	FS	IV	FS	IV	FS	IV
Instruments:								
BTC price (Delta)	0.473***				0.472***			
	(0.017)				(0.019)			
BTC Price (Delta, MA3)			0.964***				0.915***	
			(0.033)				(0.035)	
Electricity price:								
Price (Delta)		-0.211***				-0.137*		
		(0.062)				(0.073)		
Price (Delta, MA3)				-0.078***				-0.126***
				(0.015)				(0.022)
Year Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Community Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Provider Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	-0.004	-0.000	0.085	-0.015	0.001	0.001	0.108	0.005
SD Y	0.36	0.26	0.91	0.42	0.35	0.27	0.84	0.45
F stat		798.84		868.72		596.17		695.03
Observations	2895	2895	2429	2429	2660	2660	2229	2229
Adjusted R-squared	0.02	-0.10	0.41	-0.02	0.02	-0.03	0.39	-0.01

Table 6: **Effect of Cryptomining on Electricity Provider Revenues: Industrial**

All columns present the estimates of the regression given by equation (8). The dependent variable in columns (1), (2), (3) and (4) is the (log) sales in MWh; and the dependent variable in columns (5), (6), (7) and (8) is the (log) revenues in thousands of dollars. Continuous treatment is a variable of provider-level cryptomining intensity, which can be 0 or 1 for the local-only municipal providers but is a percentage of locations for the large providers. Dummy treatment is a dummy equal to one for the treated municipal providers. BTC price is the (log) average price of Bitcoin in a year. Post is a dummy equal to one after 2016. Errors are clustered at the provider level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Sales (log)				Revenues (log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment:								
Treatment (continuous)	0.5664		-2.1605		0.9090		-1.8260	
	(7.2676)		(6.5955)		(5.6455)		(5.1619)	
Treatment (continuous) X BTC price (log)	0.0958				0.1013*			
	(0.0648)				(0.0556)			
Treatment (dummy) X BTC price (log)		0.0905				0.0957*		
		(0.0569)				(0.0489)		
Treatment (continuous) X Post			0.1205*				0.1364**	
			(0.0673)				(0.0584)	
Treatment (dummy) X Post				0.1220*				0.1364**
				(0.0644)				(0.0561)
Controls:								
Min temperature (log)	1.0311*	1.0278*	0.8221*	0.8169*	1.0283*	1.0274*	0.8261**	0.8210**
	(0.5594)	(0.5524)	(0.4266)	(0.4359)	(0.5091)	(0.4943)	(0.3522)	(0.3583)
Max temperature (log)	-2.4705	-2.1553	-0.4579	-0.5534	-3.9830	-3.6324	-1.9357	-1.9933
	(4.5012)	(4.0468)	(4.1289)	(3.9011)	(3.6941)	(3.2705)	(3.2476)	(3.0336)
Wholesale sources (log)	1.5371*	1.5450**	1.4537*	1.4452*	1.9043***	1.9148***	1.8198***	1.8131***
	(0.7155)	(0.7014)	(0.7391)	(0.7166)	(0.4987)	(0.4891)	(0.5265)	(0.5098)
Provider Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	11.62	11.62	11.62	11.62	8.68	8.68	8.68	8.68
SD Y	2.32	2.32	2.32	2.32	2.12	2.12	2.12	2.12
Obs.	50	50	50	50	50	50	50	50
Adjusted R-squared	0.9071	0.9103	0.9065	0.9097	0.9217	0.9244	0.9209	0.9237

Table 7: **Effect of Cryptomining on Electricity Provider Revenues: Community**

All columns present the estimates of the regression given by equation (8). The dependent variable in columns (1), (2), (3) and (4) is the (log) sales in MWh; and the dependent variable in columns (5), (6), (7) and (8) is the (log) revenues in thousands of dollars. Continuous treatment is a variable of provider-level cryptomining intensity, which can be 0 or 1 for the local-only municipal providers but is a percentage of locations for the large providers. Dummy treatment is a dummy equal to one for the treated municipal providers. BTC price is the (log) average price of Bitcoin in a year. Post is a dummy equal to one after 2016. Errors are clustered at the provider level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Sales (log)				Revenues (log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment:								
Treatment (continuous)	2.8759***		2.8937***		5.7404***		5.5700***	
	(0.7969)		(0.7665)		(1.5794)		(1.5185)	
Treatment (continuous) X BTC price (log)	-0.0031				0.0222**			
	(0.0051)				(0.0092)			
Treatment (dummy) X BTC price (log)		-0.0049				0.0183*		
		(0.0052)				(0.0092)		
Treatment (continuous) X Post			-0.0078				0.0531**	
			(0.0131)				(0.0221)	
Treatment (dummy) X Post				-0.0116				0.0448*
				(0.0132)				(0.0221)
Controls:								
Min temperature (log)	-0.2780***	-0.2691***	-0.2797***	-0.2693***	-0.1100	-0.0895	-0.1056	-0.0851
	(0.0873)	(0.0869)	(0.0887)	(0.0885)	(0.1377)	(0.1345)	(0.1445)	(0.1413)
Max temperature (log)	0.0920	0.2546	0.0650	0.2089	-0.0601	0.2990	0.1603	0.4610
	(0.4837)	(0.5014)	(0.4670)	(0.4804)	(0.5487)	(0.6160)	(0.5455)	(0.6104)
Wholesale sources (log)	-0.0027	0.0100	-0.0013	0.0130	0.2441*	0.2725**	0.2329*	0.2620**
	(0.0859)	(0.0850)	(0.0865)	(0.0856)	(0.1233)	(0.1256)	(0.1211)	(0.1231)
Provider-User Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	12.13	12.13	12.13	12.13	9.54	9.54	9.54	9.54
SD Y	1.96	1.96	1.96	1.96	2.23	2.23	2.23	2.23
Obs.	116	116	116	116	116	116	116	116
Adjusted R-squared	0.9996	0.9996	0.9996	0.9996	0.9993	0.9992	0.9993	0.9992

Table 8: **Effect of Cryptomining on Local Taxes**

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 (6) are difference-in-differences specifications, with varying methods to account for location selection. The dependent variables in columns (2) to (6) is the annual taxes per capita for towns in Upstate New York. Column (2) is estimated with OLS. Columns (3) to (6) are estimated with inverse probability weighting. Robust standard errors in parenthesis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

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

Table 9: **Consumer Surplus Calculations**

Monthly Δ consumer surplus for small businesses and households comes from the procedure discussed in Section 4.4. Annual Δ consumer surplus are monthly costs multiplied by twelve. Small businesses exposed is the total number of 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. Households exposed is the total population of upstate New York in 2019 divided by the average number of people per household. Total Δ consumer surplus (in million dollars) is obtained by multiplying the count of exposed by annual Δ consumer surplus. The figures for taxes are obtained via the procedure in Section 4.3. Panel A shows the estimates using the demand elasticities from column (3) of Tables 3 and 4; Panel B shows the estimates using the demand elasticities from column (5) of Tables 3 and 4; Panel C shows the estimates using the demand elasticities from column (7) of Tables 3 and 4.

	(1) Monthly Δ ($)	(2) Annual Δ ($)	(3) Count of Exposed (,000)	(4) Total Δ ($M)
Panel A: Baseline Estimates				
Consumer surplus				
Households	-7.33	-88	2,321	-204
Small businesses	-13.96	-168	550	-92
				-296
Taxes		29	1,340	39
Net consumer surplus				-257
Panel B: Robustness Estimates (Moving Average)				
Consumer surplus				
Households	-7.32	-88	2,321	-204
Small businesses	-13.97	-168	550	-92
				-296
Taxes		29	1,340	39
Net consumer surplus				-257
Panel C: Robustness Estimates (Deseasonalized Price))				
Consumer surplus				
Households	-7.33	-88	2,321	-204
Small businesses	-13.97	-168	550	-92
				-296
Taxes		29	1,340	39
Net consumer surplus				-257

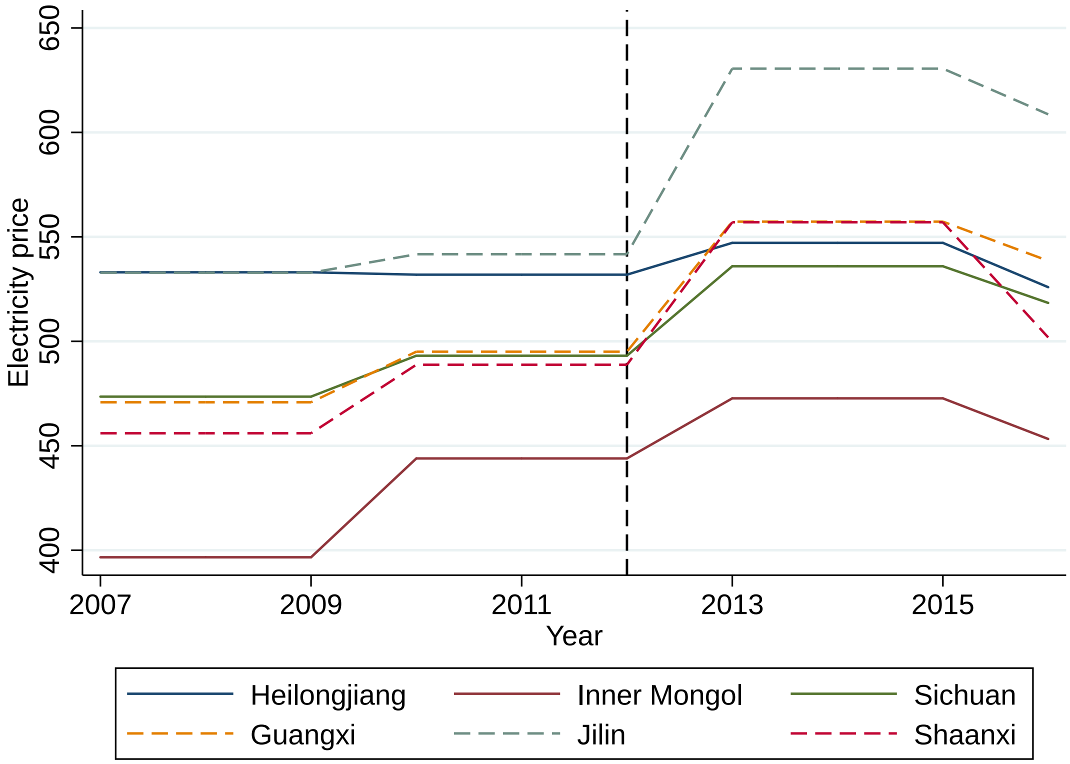
Table 10: **Effect of Cryptomining in China**

All columns present the estimates of the weighted least squares difference-in-differences model given by equation (13). The dependent variables are (log) GDP, (log) fixed assets investment, (log) wages and (log) government budget at the city-seat level for all of the cities within the inland provinces of China. Data on economic variables 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 and post-2016 in the last three columns. In the matched sample we limit the control cities to those that: (i) are located in the provinces in Figure 4, Panel A with no or low cryptomining (yellow or mustard), and (ii) do not border any cryptomining city-seats (marked in red in Figure 4, Panel B) unless across province lines. All specifications control for log population, city and year dummies. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Baseline				Robustness: matched sample			Robustness: post 2016		
	(1) GDP	(2) Investment	(3) Wages	(4) Budget	(5) Investment	(6) Wages	(7) Budget	(8) Investment	(9) Wages	(10) Budget
Treatment:										
Post × Cryptomining	-0.082**	-0.195**	-0.101***	0.039	-0.255***	-0.063**	0.045	-0.256*	-0.173***	0.063
	(0.032)	(0.096)	(0.025)	(0.035)	(0.091)	(0.026)	(0.048)	(0.138)	(0.052)	(0.053)
Controls:										
Population (log)	0.154**	0.021	-0.199*	0.272	-0.110	-0.090	0.173	-0.063	-0.336*	0.494*
	(0.071)	(0.198)	(0.109)	(0.165)	(0.173)	(0.188)	(0.215)	(0.392)	(0.172)	(0.285)
GDP (log)		0.225**	0.014	0.116***	0.555**	0.044	0.227*	0.291**	0.022*	0.105***
		(0.109)	(0.012)	(0.034)	(0.227)	(0.027)	(0.127)	(0.124)	(0.012)	(0.036)
Investment (log)			-0.023	0.244***		-0.057	0.218***		-0.036*	0.229***
			(0.016)	(0.034)		(0.034)	(0.057)		(0.019)	(0.038)
Wages (log)		-0.192		0.196**	-0.287		0.102	-0.294**		0.164*
		(0.117)		(0.080)	(0.176)		(0.089)	(0.130)		(0.085)
Year Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Y	6.77	6.70	10.71	4.31	7.03	10.76	4.75	6.67	10.68	4.29
SD Y	0.94	0.86	0.25	0.89	0.83	0.25	0.92	0.85	0.24	0.89
Observations	1300	1162	1162	1162	355	355	355	992	992	992
Adjusted R-squared	0.92	0.88	0.82	0.96	0.90	0.77	0.97	0.88	0.82	0.96

Online Appendix to "When cryptomining comes to town: High electricity-use spillovers to the local economy"

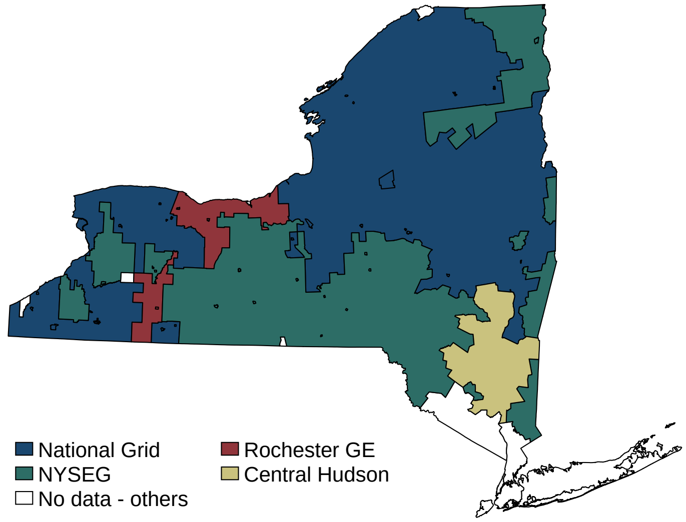
Figure A1: Electricity prices over time in China



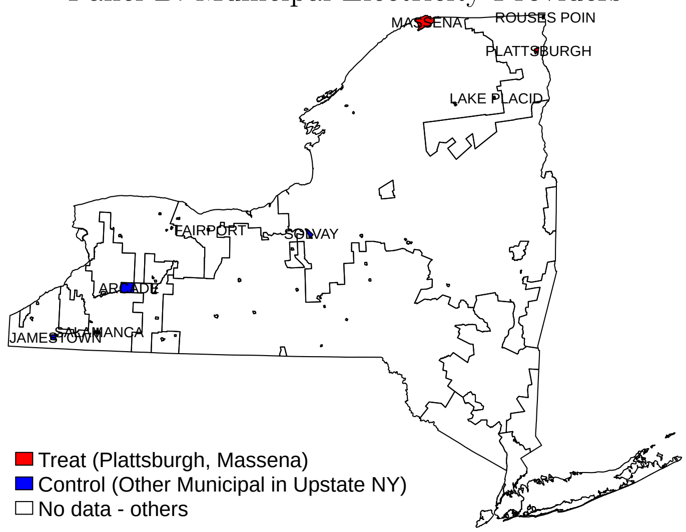
Note: Data on electricity prices in China from the government agency National Development and Reform Commission (URL: `ndrc.gov.cn`). We collected data for all provinces in China for 2009-2010 and 2015-2016. We fill the missing years in the following way. We attribute 2009 prices for all years up to 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 4.

Figure A2: Electricity providers

Panel A: Investor-owned Electricity Providers

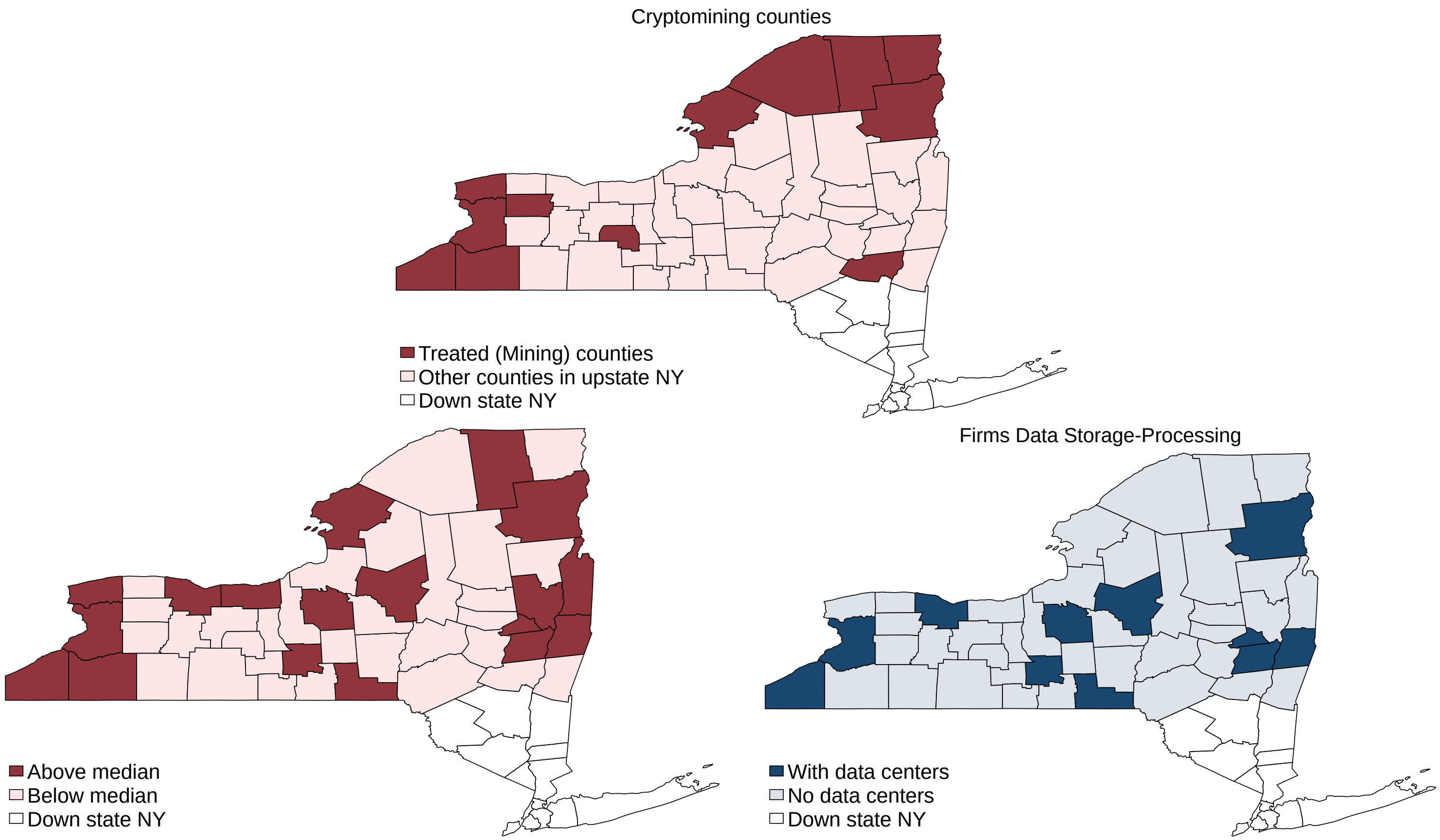


Panel B: Municipal Electricity Providers



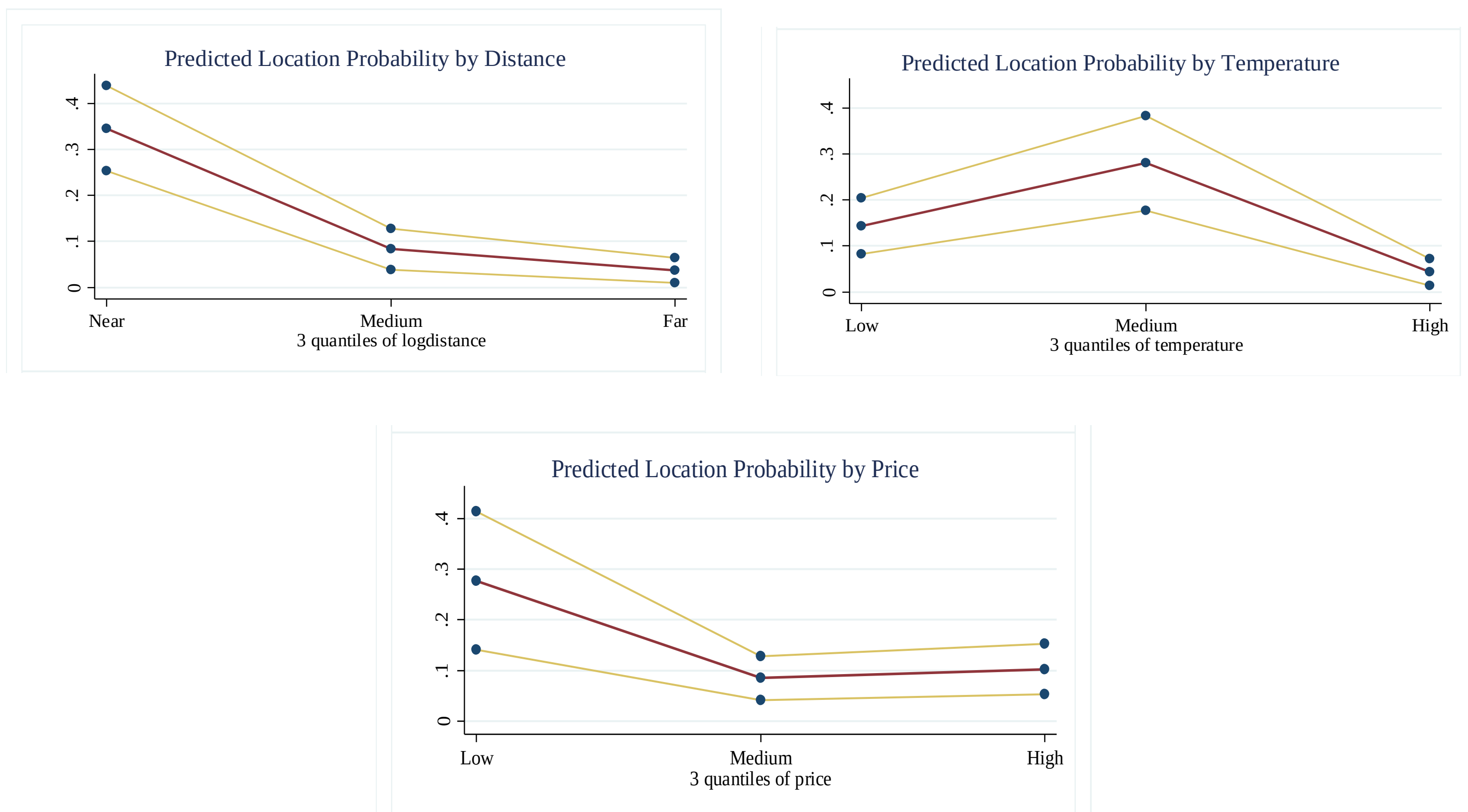
Note: The chart shows the operating areas of large (Investor-owned) Electricity Providers (Panel A) and small municipal electricity providers (Panel B) in Upstate NY.

Figure A3: Likely data centers



Note: In the top map, we depict the counties with evidence of cryptomining. The bottom left map depicts the counties with a number of firms in data processing, hosting, and related services (NAICS = 518210) above and below the median. The bottom right map show the counties with firms within data processing, hosting, and related services that are likely data centers (subcategories: computer data storage, data processing service and website hosting). Data on mining locations come from manual searches in local newspapers and newsources in English through Google. Data on firms comes from https://siccode.com.

Figure A4: 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. Data on economic variables are from Province Yearbooks. The location of cryptomines are from manual news searches on 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.

Table A1: **Effect of Cryptomining on Local Taxes - Robustness**

Models in columns (1) and (2) are difference-in-differences; models in columns (3) and (4) are difference-in-differences specifications estimated via inverse probability weighting. The dependent variable is the annual tax revenue per capita for towns in Upstate New York. Cryptomining is a dummy equal to one if a town belongs to a county with evidence of cryptomining. Firms NAICS 518210 (Firm Data Storage-Processing) are counties with a number of firms in data processing, hosting, and related services (computer data storage, data processing service and website hosting) above the median. Robust standard errors in parenthesis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	OLS		IPW	
	(1)	(2)	(3)	(4)
BTC price (log) X Cryptomining	4.632***	4.206***	6.243***	6.087***
	(0.903)	(0.977)	(1.118)	(1.160)
BTC price (log) X Firms NAICS 518210	-1.450**		-0.620	
	(0.658)		(0.608)	
BTC price (log) X Firm Data Storage-Processing		-1.075		0.030
		(0.792)		(0.744)
Community Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Mean Y	524.37	524.37	498.60	498.60
SD Y	505.92	505.92	426.95	426.95
Observations	6851	6851	6135	6135
Adjusted R-squared	0.97	0.97	0.96	0.96

Table A2: **Cryptomining Location Decision in China**

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. Data on economic variables 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 A3: **Effect of Cryptomining in China - Robustness**

All columns present the estimates of the inverse probability weighting difference-in-differences model given by equation (13). The dependent variables are (log) GDP, (log) fixed assets investment, (log) wages and (log) government budget at the city-seat level for all of the cities within the inland provinces of China. Data on economic variables 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 and post-2016 in the last three columns. All specifications control for log population, city and year dummies. Errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Baseline				Robustness: post 2016		
	(1) GDP	(2) Investment	(3) Wages	(4) Budget	(5) Investment	(6) Wages	(7) Budget
Treatment:							
Post × Cryptomining	-0.096**	-0.253**	-0.131***	0.057	-0.306*	-0.205***	0.082
	(0.039)	(0.123)	(0.032)	(0.040)	(0.162)	(0.071)	(0.056)
Controls:							
Population (log)	0.173*	0.054	-0.211**	0.270*	0.001	-0.302*	0.417
	(0.090)	(0.221)	(0.104)	(0.160)	(0.383)	(0.158)	(0.259)
GDP (log)		0.200*	0.014	0.107***	0.268**	0.024*	0.099***
		(0.105)	(0.013)	(0.031)	(0.124)	(0.013)	(0.035)
Investment (log)			-0.020	0.244***		-0.032*	0.226***
			(0.016)	(0.037)		(0.019)	(0.041)
Wages (log)		-0.182		0.220**	-0.269**		0.171*
		(0.126)		(0.090)	(0.134)		(0.092)
Year Fixed effects	Y	Y	Y	Y	Y	Y	Y
City Fixed effects	Y	Y	Y	Y	Y	Y	Y
Mean Y	6.82	6.68	10.71	4.28	6.65	10.67	4.25
SD Y	0.91	0.87	0.25	0.90	0.86	0.24	0.90
Observations	1191	1162	1162	1162	992	992	992
Adjusted R-squared	0.91	0.88	0.84	0.96	0.88	0.83	0.96