Resource and Energy Economics 74 (2023) 101376

Contents lists available at ScienceDirect

Resource and Energy Economics

journal homepage: www.elsevier.com/locate/ree

Can Bitcoin mining increase renewable electricity capacity?☆

August Bruno, Paige Weber, Andrew J. Yates *

University of North Carolina at Chapel Hill, USA

A R T I C L E I N F O

Article history:
Received 28 October 2022
Received in revised form 17 May 2023
Accepted 30 May 2023
Available online 3 June 2023

A B S T R A C T

Proponents of Bitcoin argue that demand for electricity from Bitcoin miners can lead to an increase in renewable electricity capacity. We rigorously evaluate this claim by estimating a Bitcoin electricity demand curve and include this demand curve in a long-run model of the Texas electricity market. We find that while Bitcoin mining can indeed increase renewable capacity, it also increases carbon emissions. When Bitcoin miners provide grid management services in the form of demand response, their emissions impact is largely mitigated.

1. Introduction

Bitcoin and cryptocurrency are attracting increasing attention from investors and environmentalists alike. The size of the market is dramatically expanding, reaching a market capitalization of over 1000 billion USD at points in 2021 (Statista, 2022). Increased concern about the energy and environmental impacts of Bitcoin and cryptocurrency warranted the Intergovernmental Panel on Climate Change to call cyptocurrency an area of "growing concern" in a recent Climate Change Assessment Report (Intergovernmental Panel on Climate Change, 2022).

Bitcoin proponents claim that the coin can benefit the electricity grid, by both increasing renewable energy and supporting grid management. We rigorously test these claims using a long-run model of electricity markets. We find that increased electricity demand from Bitcoin increases the optimal quantity of renewable capacity investment, and the share of generation provided by renewable resources also modestly increases. However, carbon emissions from an electricity grid with Bitcoin electricity demand are 1.6 times the emissions without Bitcoin. Bitcoin miners can significantly attenuate this emissions impact by providing grid management services that help ameliorate unexpected decreases in renewable generation.

Bitcoin requires energy for both the mining of new coins as well as the maintenance of Bitcoin's digital ledger, called a blockchain. Bitcoin miners use computing power to solve mathematical puzzles, which verify transactions. Miners are rewarded for solving puzzles with new Bitcoin. Other cryptocurrencies (e.g. Ethereum, Chia, Litecoin, Cardano), which offer similar

☆ We thank Maura Coughlin, Cailin Slattery, Jake Fan, Justin Phillips, and the participants at the 2022 Berkeley Energy Camp and the 2022 Texas A & M Bitcoin Conference for helpful comments and suggestions. This research was partially funded by the United States National Science Foundation under Grant 2009726 entitled CNH2-L: The coupled, co-evolving roles of drought and electricity systems in humans' exposure to air pollution.

* Corresponding author.
E-mail addresses: aabruno@live.unc.edu (A. Bruno), paigeweber@unc.edu (P. Weber), ajyates@email.unc.edu (A.J. Yates).

https://doi.org/10.1016/j.reseneeco.2023.101376

platforms for digital currency exchange, have also been expanding. While the specifics of the algorithms used to mine and verify the alternative cryptocurrencies differ, their broad implications on energy markets are consistent: digital currencies require significant amounts of electricity (Badea and Mungiu-Pupazan, 2021).[1]

Increases in mining for Bitcoin come with increases in the negative externalities from electricity production, which vary depending on the source of electricity used. The predominance of mining in China in previous years garnered much attention, where miners had concentrated to take advantage of cheap electricity fueled by coal (de Vries Alex, 2018; Badea and Mungiu-Pupazan, 2021). In the summer of 2021, the Chinese government began ordering Bitcoin miners to cease operating. Mining operations moved elsewhere, and the U.S. took over as the largest location of Bitcoin mining across the globe, accounting for 38 % of the global hashrate in January 2022 (Cambridge, 2021.).[2]

A recent set of arguments claims that Bitcoin can have positive environmental impacts. One argument is that the increase in demand from miners can increase the profitability of wind and solar resources, increasing the amount of renewable capacity on the electric grid (Li et al., 2019). At a U.S. Congress House Committee on Energy and Commerce hearing on the energy impacts of cryptocurrency, expert witnesses argued that Bitcoin can offer secure returns to wind investors concerned about not having enough traditional demand during hours in which wind production is high (Belizaire, 2022; Brooks Brian, 2022). A related claim is that Bitcoin can increase not just the total, but the *share* of electricity provided by renewable energy (Findijs, 2021; Initiative Bitcoin Clean Energy, 2021; Stein, 2022), in essence claiming that electricity demand from miners would increase the profitability and entry of wind and solar resources at a rate that exceeds the increase in entry from other traditional generation resources. These claims implicitly involve entry and exit of alternative generation technologies, and so require a long-run framework to evaluate their veracity.

Bitcoin has also been cited as being able to help with the management of the electric grid. Texas Governor Greg Abbott has welcomed miners to Texas, highlighting that miners can offer grid management in the form of demand response. Miners could make up for unexpected shortfalls in renewable generation by reducing demand, which may be particularly appealing to Texas given its increasing wind portfolio. In fact, miners have already been observed to provide demand response at times in Texas (Cision, 2022; Halaburda and David, 2023).

This paper quantifies Bitcoin's impact on long-run renewable capacity investment, carbon emissions, and grid management. We utilize and extend a new model of long-run equilibrium capacity investment in the electricity market in the United States, Holland Stephen et al. (2022), which we refer to as HMY (2022). We apply the extended HMY (2022) model to Texas's electricity grid. Texas is an ideal environment to test the implication of Bitcoin mining on renewable generating capacity because it has potential for both wind and solar resources, and it is essentially isolated from other parts of the country. As a result, we can study the long-run equilibrium without needing to account for import or export of electricity from other regions. Further, the state has already seen an increase in electricity demand from Bitcoin miners—as of December 2021 it was the state with the third largest amount of Bitcoin electricity demand in the U.S. (Cambridge, 2021).

In the HMY (2022) model, the capacities of various generation technologies are endogenously determined in a long-run equilibrium that incorporates demand, prices, and technology costs. We incorporate Bitcoin into this model by adding global Bitcoin demand into the Texas electricity grid.[3] We estimate global Bitcoin electricity demand first using observed data of miners' electricity consumption and prices. We then compare this demand estimate with a bottom-up engineering approach, which estimates Bitcoin electricity demand based on the technical components of Bitcoin mining profitability, and we find that these two approaches yield comparable results. Finally, we estimate a distribution of hourly capacity factors for wind and solar, which we use to extend HMY (2022) to include uncertainty in renewable energy generation.

We formalize and study the claims about Bitcoin by simulating optimal long-run technology investment, generation, and carbon emissions across several experiments. We first find the outcomes in a baseline experiment without Bitcoin electricity demand and then with Bitcoin. Next, we study the potential for Bitcoin to support grid management as a type of demand response product. Demand response refers to the suite of incentives used to reduce electricity consumption or move it to other hours of the day, providing a tool for grid operators to manage uncertainty in generation (U.S. Department of Energy, 2022), which is anticipated to be increasingly important with more penetration of wind and solar resources (Jaquelin and Denhom, 2015). From a technical operations perspective, Bitcoin miners can be turned off close to instantaneously with near zero adjustment costs (Menati and Xie, 2021), making miners good candidates for demand response.[4] Specifically, we allow grid

[1] That said, Bitcoin uses an algorithm called "proof-of-work", which has a larger energy footprint per transaction than algorithms used by other coins such as "proof-of-stake" (Lunie, 2019; Coinbase, 2023; Digiconomist, 2022). Given this and the fact that Bitcoin remains the dominant cyptocurrency in the market with almost three times the size in market capitalization compared to its closest competitor (Ethereum), this paper focuses on electricity demand from Bitcoin.

[2] Global hashrate shares are shown in Fig. A.1 in the Appendix. Mining in the U.S. occurs predominantly in nine states, with Georgia, Texas, Kentucky, and New York having the most mining, in that order (Cambridge, 2021).

[3] We include the entire global Bitcoin electricity demand in the Texas interconnection region since miners are geographically flexible and in theory could be incentivized to reallocate to Texas for sufficiently low electricity prices. Even with frictions in miners' geographic flexibility, generating reliable regional or sub-global Bitcoin demand curves is difficult. If one assumes that miners would not move operations in response to electricity price changes in the short term, and if data were available, one could use observed miner responses to changes in electricity prices within electricity grids to estimate regional Bitcoin demand curves. However, this paper is concerned with long-run outcomes and hence we do not attempt to do this. At the end of Section 5 we discuss the results from two scaling exercises which provide robustness checks for this modeling choice.

[4] Flexible generation resources such as natural gas peaker plants (peakers) may also be increasingly needed to manage more intermittent renewable resources; peaker plants are included in HMY (2022) and will be reviewed in the results.

operators to turn the demand from miners off whenever there is an unexpected shortfall in renewable generation, and compare these results to our other experiments.

The results from the experiments show that increased electricity demand from Bitcoin leads to a more than doubling of wind capacity and a modest increase in solar capacity. Despite the increase in renewable capacity, total carbon emissions increase by around 1.6 times the emissions without Bitcoin due to an increase in generation from natural gas plants. These extra carbon emissions, however, can almost completely be eliminated if Bitcoin also provides demand response. We find similar qualitative results when a storage technology is included in the model. In addition, we find that while the median daily price variation increases when adding electricity demand from Bitcoin, extreme price spikes are substantially mitigated, and the mean price variation actually decreases in the experiments with Bitcoin.

Our paper contributes to a nascent body of literature on the energy impacts of cryptocurrency—see Badea and Mungiu-Pupazan (2021) for a summary. Li et al. (2019) study the impact of regional variation in electricity prices on miner location decisions, and de Vries Alex (2018) shows that the energy required to mine has been increasing, indicating that understanding the interaction between Bitcoin and electricity markets will be an increasingly important aspect of cryptocurrencies' impact on our economy and the environment. Our paper also contributes to the recent literature on the economics of Bitcoin and blockchain digital currencies (Prat and Benjamin, 2021; Charles et al., 2021; William et al., 2021; Bruno et al., 2019; Hanna et al., 2022). While there is continued debate in the economics community about the underlying value of cryptocurrencies (Dirk et al., 2018; Fernández-Villaverde, 2018), the premise of this paper is only that Bitcoin is a new and growing source of electricity demand, and its future impacts on outcomes in the electricity grid are important and understudied.

2. Model

HMY (2022) develop a long-run model of the electricity sector which accounts for consumers' demand for electricity, the capital and marginal cost of generating capacity for a variety of technologies, the intermittency of renewable generation, and battery storage technology. We augment this model to account for electricity demand from Bitcoin miners and uncertainty about renewable generation. For a given hour t in a representative year, we let Q_t denote the consumers' consumption of electricity and $U_t(Q_t)$ denote the consumers' benefit of this consumption. Similarly, we let M_t denote the miners' consumption of electricity and $W_t(M_t)$ denote the miners' benefit of this consumption.[5]

There are several different technologies that can be used to generate electricity. For a given technology i we denote the capacity by K_i and the generation in each hour by q_{it}. These variables are related by the constraint:

$$q_{it} \le f_{it} K_i, \tag{1}$$

where the f_{it} indicates the capacity factor in hour t. Fossil fuel generation technologies generally have capacity factors equal to one in each hour. In contrast, renewable energy technologies have capacity factors that are less than or equal to one, and these capacity factors capture the intermittency of renewable energy. In HMY (2022), the capacity factors are deterministic. Here we assume the capacity factors for renewable generation are random variables that are independent across periods but may be correlated within period. Technology i has constant marginal cost of production c_i and capital costs r_i per unit of capacity.

The model allows for a storage technology, which we refer to as a battery, that than can be used to transfer electricity across periods. Let the capacity of the battery be given by $\bar{S}$ and the state of charge in period t be given by S_t. Each unit of battery capacity has capital costs r_s. The state of charge is constrained by:

$$0 \le S_t \le \bar{S}. \tag{2}$$

In each period, the battery can be charged or discharged, as described by the variable b_t, where a negative value indicates discharge. This leads to a dynamic constraint:

$$S_t = S_{t-1} + b_t. \tag{3}$$

Following HMY (2022), we assume the battery is perfect in that there are no charging losses.[6]

In each hour, the total demand for electricity from consumers, miners, and battery charging must equal the total electricity generated by all of the technologies. Thus we have the following final constraint:

$$M_t + Q_t + b_t = \sum_i q_{it}. \tag{4}$$

The long-run competitive equilibrium is defined by two conditions. First, there is a short run equilibrium in each period t which has supply equal to demand. Second, the capacities are such that all technologies, including the battery, earn zero profit. Batteries earn profits by arbitraging price differences. But as with the other technologies, any such profits attract entry and therefore must become zero in the long run equilibrium. To find this equilibrium, we use a two step nested algorithm. In the inner step, we consider capacities to be fixed and we determine the short run equilibrium in each period by solving a dynamic programming problem, which is required because periods are linked through the dynamic constraint for the battery. This

[5] The demand function for consumers and miners is given by the inverse functions of U' and W', respectively.

[6] The effect of charging losses would be very similar to an increase in the cost of the battery.

formulation takes advantage of the equivalence between the short run equilibrium and a planner's problem. In the outer step we adjust the capacities until the zero profit condition holds.[7]

The inner step dynamic program has two state variables: the state of the battery S_t and the state of a joint random variable σ_t that describes the uncertainty about the solar and wind capacity factors. The Bellman Equation for the planner's problem is:

$$V_t(S_t, \sigma_t) = \max_{M_t, Q_t, q_{it}, b_t} W_t(M_t) + U_t(Q_t) - \sum_i c_i q_{it} + E_t[V_{t+1}(S_{t+1}, \sigma_{t+1})], \tag{5}$$

subject to the constraints (1)-(4). The solution to this problem gives the short run equilibrium in period t. This equivalence between a planner's problem and the short run equilibrium assumes that the battery charges and discharges in a profit maximizing way given the short run prices for electricity. Because we want to calculate profits for each technology, we also calculate auxiliary dynamic equations as follows. Using the solution to the Bellman Equation for period t we can calculate the price p_t in the short run equilibrium.[8] Using this we define π_{it} as the expected short-run profits for each technology per unit of capacity.[9]

$$\pi_{it}(S_t, \sigma_t) = (p_t - c_i) f_{it}(\sigma_i) + E_t[\pi_{i,t+1}(S_{t+1}, \sigma_{t+1})]. \tag{6}$$

For the battery, expected short run profits are given by:

$$\pi_{s,t}(S_t, \sigma_t) = -p_t{}^* b_t / \bar{S} + E_t[\pi_{b,t+1}(S_{t+1}, \sigma_{t+1})].$$

The outer step starts with an initial guess for the equilibrium values of K_i and $\bar{S}$. Given these values, we determine the solution to the inner step and determine the functions $\pi_{i,t}$ and $\pi_{s,t}$. We then do a numerical search for the values for the K_i such that for each technology i we have:

$$E_0[\pi_{i1}(0, \sigma_1)] - r_i = 0,$$

and for the battery we have:

$$E_0[\pi_{s,t}(0, \sigma_1] - r_s = 0.$$

Notice we assume the battery starts at empty going into the first period.

Our application of the HMY (2022) model considers four generation technologies: two renewable, wind and solar, and two fossil fuel, natural gas combined cycle and natural gas peaker.[10] The marginal production costs and capital costs for these technologies are given in Table A1 in the Appendix. Comparing the two natural gas technologies, we see that combined cycle gas plants have lower marginal but higher capital costs than peaker plants. As in HMY (2022), we assume the benefit function U_t is quadratic in Q_t, so that marginal benefit (i.e. the demand for electricity) is linear. We augment this with an additional linear demand curve for electricity for Bitcoin mining, as described in the next section.

3. Bitcoin demand for electricity

We present two ways of thinking about Bitcoin demand for electricity: one, an engineering-based approach; and two, a revealed preference approach based on the available data. We start with the engineering-based approach as it is instructive for understanding the factors that impact Bitcoin profitability.

3.1. Bottom-up approach to estimating Bitcoin electricity demand

The profitability of Bitcoin mining is the total revenue from the effort spent mining less the costs of that effort. Total revenue is a product of computational effort, the inverse difficulty of finding new blocks in the blockchain, the conversion of new blocks to Bitcoin reward, and the price of Bitcoin, p^b. Computational effort in this setting is measured by the number of hashes per second, where a *hash* can be thought of as one guess of the cryptographic puzzle that miners attempt to solve to find new blocks b. The number of hashes needed to solve a blockchain block b is the product of a known parameter in the Bitcoin network called Bitcoin Difficulty denoted D multiplied by a constant denoted γ that comes from Bitcoin source code.[11] The Bitcoin algorithm was designed to modulate Bitcoin Difficulty up and down so that blocks are consistently rewarded every 10 min, regardless of the amount of hashing effort on the network. This means when more mining effort is present on the Bitcoin network, the difficulty measure increases, and when less mining effort is on the network, the difficulty measure decreases.[12] When miners

[7] We cannot use a one step planner's problem to find the long-run competitive equilibrium because we will allow the miner's demand to depend on the realization of the capacity factor uncertainty. This creates an externality since the miner's utility depends on the capacity of solar and wind, and so the one step long-run planner's problem does not correspond to the long-run competitive equilibrium.

[8] Given M_t or Q_t, the price is determined by the inverse demand curve from miners or consumers.

[9] Because the supply curve is a step function, for any technology that is producing in period t we have either $p_t - c_i = 0$ or $q_{it} = f_{it} K_i$.

[10] HMY (2022) also include a nuclear technology, but this technology is not used unless capital costs are significantly reduced. Coal is not included because it is unlikely that any new coal plants will be built in the U.S. in the future, and thus coal would not be part of the long-run generation portfolio.

[11] γ is referred to as the "the constant of proportionality" in Bitcoin parlance.

find a new block, they are rewarded in Bitcoin based on the network's Bitcoin Block Award, which is the amount of Bitcoin c that is created and awarded to the miner when a block is solved (CoinWarz, 2022). While going forward fewer blocks will be rewarded per effort, the system is designed to continue to incentivize Bitcoin mining, which serves the dual purpose of creating new coin and verifying the digital ledger.

The costs of effort are calculated as the amount of electricity W used per hash per second s, which is based on the efficiency of the hardware used for mining times the price of electricity p^e.[13] Bitcoin profits π in an hour can be expressed:

$$\pi = \textit{mining effort}\{\textit{constant}^*\textit{coin reward}^*\textit{value} - \textit{electricity costs}\}$$
$$= \frac{h}{s}\left\{\left(\frac{1}{D}\gamma s\right)\left(\frac{c}{b}\right)\left(\frac{\$}{c}\right) - \left(\frac{W}{h/s}\right)\left(\frac{\$}{W}\right)\right\}, \tag{7}$$

where the second line shows the units associated with the variables in the first line. Here $s = \frac{3600}{10}$ as the Bitcoin network is set up such that it consistently takes 10 min to solve a block, and the numerator reflects seconds per hour. For a given set of parameters governing Bitcoin Difficulty, Block Award, and machine efficiency, we can find the electricity price for which mining is profitable conditional on the Bitcoin price. The Difficulty and Block Award parameters are easily observed from the Bitcoin network: we use the current Difficulty measure of 29.57 trillion hashes per winning block, and the current Block Award of 6.25 coins per block (CoinWarz, 2022). Finally, we use the current frontier technology for mining hardware efficiency.[14] We estimate the electricity price for which miner profits are greater than zero conditional on a Bitcoin price using this frontier technology. We find that for the maximum and minimum Bitcoin prices observed over the period August 3, 2021—August 3, 2022, of \$68,990 and \$17,602 per coin respectively, mining is profitable when electricity prices are below \$607 and \$155 per MWh. In the data used for simulation described below, the reference price is below \$155 per MWh in 98.4 % of hours in a year and below \$607 per MWh in 99.4 % of hours.

3.2. Revealed preference approach to estimating Bitcoin electricity demand

To estimate an electricity demand curve for miners in a revealed preference approach, we use publicly available Bitcoin energy consumption data from the Cambridge Bitcoin Electricity Consumption Index (Cambridge, 2021), which we will refer to as CBECI.[15] For this paper, we use CBECI's central estimate of daily energy use associated with daily Bitcoin mining, which assumes that miners use the most energy-efficient bundle of hardware available to mine.[16] CBECI estimates a global hashrate as well as country specific shares of the global hashrate, attributing energy demand for mining to miners based on IP addresses and find that mining is predominantly located in nine countries—Canada, China, Germany, Iran, Ireland, Kazakhstan, Malaysia, Russia, and the U.S. Miners in China initially occupy the largest share, around 65 % over the period 4th quarter 2019 through 1st quarter 2021, while starting in July 2021 the U.S. takes over as the country with the largest global mining share. Fig. A.1 in the Appendix shows the country hashrate shares over this time period. We map the country-specific hashrate shares into energy estimates by using CBECI's time-varying estimate of total global energy use from mining.

We match the time-varying estimates of country-specific electricity demand for mining with information about electricity and natural gas prices by country, purchased from Global Petrol Prices (Global, 2022), shown together with consumption data in Fig. 1(a). Since the electricity and natural gas price data are only available by calendar quarter, we sum daily country-level electricity consumption over each quarter. Given the potential for Bitcoin demand to impact electricity prices, we use a two-stage least squares instrumental variables approach, using a country's natural gas prices as an instrument for their electricity prices. We estimate the parameters of the following regression:

$$E_{ct} = \alpha + \beta\widehat{Z_{ct}} + \mu_t + \epsilon_{ct}, \tag{8}$$

[12] The algorithm is programmed such that the Bitcoin difficulty measure endogenously updates every two weeks, with limits on the size of the update up and down, set at 300 % up and 75 % down (Coin Metrics, 2022a).

[13] In this paper we view the costs of mining hardware as previously incurred lump sum costs, and mining decisions here are conditional on owning hardware. We leave future research to study the hardware investment decision.

[14] The energy efficiency of Bitcoin hardware evolves over time. The current frontier technology, Bitmain Antminer S19 XP, can produce 140 trillion hashes per second consuming 3250 watts (Software Testing Help, 2022).

[15] As energy consumed by Bitcoin miners is not easily observed, CBECI develops a model that estimates energy consumption based on several data sources and assumptions about hardware used for mining. A key input to the model is the daily network hashrate, which refers to the average rate at which miners solve hash puzzles per day, measured in Exahases per second (Eh/s). These inputs to CBECI's model come from dynamically updated data from Coin Metrics (Coin Metrics, 2022b). Next, CBECI evaluates the set of hardware potentially used by miners and their associated technical specifications, which inform CBECI's estimate of the energy efficiency of alternative hardware, measured in Joules per Gigahash (J/Gh).

[16] CBECI also develops a lower and upper bound estimate of energy consumption assuming that miners use the most and least efficient hardware available, respectively. Given this paper seeks to estimate price elasticity of mining, it is worthwhile to note that CBECI also includes a static electricity cost assumption of 0.05 USD per KWh in their model, which is used to inform their estimate the type of hardware used for mining at any point in time. Their central estimate of energy use assumes that miners use the lowest cost equipment available up to the profitable threshold based on the assumed electricity cost. When no mining hardware is profitable at 0.05 USD per KWh, miners continue to mine in their model and use the last hardware that was used profitably. CBECI's use of an electricity cost to partially inform their model's selection of hardware used for mining highlights an opportunity for further research; namely, allowing hardware to be an endogenous function of the country-specific electricity prices that we use for the price elasticity estimation.

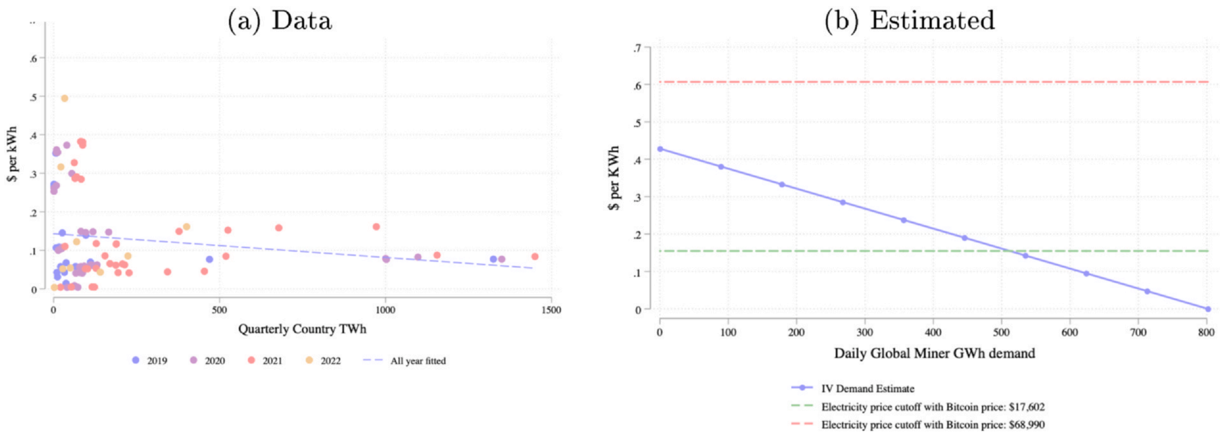

Fig. 1. Engineering and Revealed Preference Approaches to Demand *Notes:* Fig. 1(a) plots quarterly TWh consumed by Bitcoin miners at the country level on the x-axis, by quarterly country electricity price on the y-axis. Fig. 1(b) shows a predicted linear demand curve—solid blue line—based on the parameters estimated from the data using Equation 8 in Section 3. The dashed green line shows the electricity price above which mining is no longer profitable based on Equation 7 using the lowest Bitcoin price observed over the period 8/3/2021—8/3/2022. The dashed red line shows the electricity price above which mining is no longer profitable using the highest Bitcoin price observed over the same period.

where E_{ct} is country c's electricity demand from Bitcoin miners in quarter-year t and $\widehat{Z_{ct}}$ is the electricity price instrumented by country-quarter natural gas price. We include year by quarter fixed effects, μ_t, to control for changes in factors impacting Bitcoin profitability, notably including changes in Bitcoin prices. We exclude country fixed effects as we do not think of energy demand for mining as contained within one country and do not want to focus on within-country responses to variation in electricity price changes. For example, high prices in one country could induce miners to relocate to another lower-electricity price country. The parameter estimates from 8 are shown in Table A2 in the Appendix. We use these parameter estimates to construct the Bitcoin electricity demand curve in Fig. 1(b). This figure also includes the electricity price cutoffs above which mining is no longer profitable from the engineering-based approach discussed above. Overall we take Fig. 1(b) to illustrate that the revealed preference-based demand curve estimation is in the general range of the two electricity price cutoffs at recently observed minimum and maximum Bitcoin prices.

A potential drawback of both of our approaches to understanding Bitcoin's electricity demand is that neither considers changes in mining hardware efficiencies over time. Innovation in computing hardware will increase miners' hashrate per unit of electricity consumed, which would decrease the marginal electricity costs of mining and, all else equal, increase mining profitability. However, hardware innovation that reduces computing costs could also induce more miner entry, increasing the difficulty parameter in Equation 7 and thereby decreasing mining profitability. Further, the block to coin ratio has decreased over time—specifically, it has been reduced by one half three times since 2009—and its next decrease by one half is expected as early as 2024 (Conway, 2021). Bitcoin prices are also notoriously volatile, which could impact both hardware innovation and miner entry. Thus, while mining hardware may be expected to increase in efficiency over time, given the uncertainty of other factors impacting future Bitcoin profitability and their impact on hardware innovation, the overall trend in Bitcoin profitability going forward is uncertain. Prat and Benjamin (2021) develop a structural model of miner entry and the evolution on computing power on the Bitcoin network and find that a significant portion of mining revenue is invested in mining hardware. Charles et al. (2021) also develop a structural model of the Bitcoin industry and find that innovation spending is proportional miner rewards. Future research would do well to further investigate the factors influencing each variable in Equation 7, in particular to consider endogenous technological efficiency improvements as a function of Bitcoin price.

4. Simulation

We study long-run electricity market outcomes under three different experiments: without Bitcoin electricity demand, with Bitcoin electricity demand, and with Bitcoin electricity demand where miners provide demand response whenever there is an unexpected shortfall in generation from renewable resources.[17] To do so we extend HWY (2022) to include demand from Bitcoin miners and introduce uncertainty in renewable energy generation. For our set of experiments, we assume that the entire global demand for Bitcoin electricity takes place in the Texas interconnection region. Our results will thus be effected to some extent by the particular features of the Texas electricity sector. For example, the wind and solar availability in Texas will have a key role in the long-run equilibrium, and other states may be more or less endowed with these natural resources.[18]

[17] In particular, if generation from renewables in a given hour is less than the expected value, then Bitcoin demand is decreased by the same amount to exactly offset the renewable shortfall.

[18] Overall, is not obvious whether this modeling choice will yield an overly optimistic assessment of the ability of Bitcoin to increase renewable generation and

For the experiments we need values for all of the exogenous variables and functions delineated in Section 2. We then find the long-run equilibrium by applying the two step algorithm described in that section. The simulation is based on all 8760 h in a year. For each hour, we have a reference level of demand, a reference price, and Texas-specific capacity factors for wind and solar generation. The values for these variables, averaged across each hour, are shown in Fig. A.2 in the Appendix. Reference prices and reference demand peak around 5 p.m., while solar capacity factors are the largest around 1 p.m., and wind capacity factors are the largest around midnight. To construct consumers' linear demand curves for electricity in each hour, we use the reference demand and prices in conjunction with HMY (2022)'s baseline assumption that the demand elasticity is −0.15. Integrating the demand curves gives us the benefit functions U_t for consumers' electricity consumption. The miners' hourly demand curve comes from dividing the quarterly linear Bitcoin demand function into hours. Integrating these hourly demand curves yields the benefit functions W_t. The capital and marginal costs for the production technologies are given in Table A1 in the Appendix.

We determine the parameters of the distributions for the capacity factors as follows. We first calculate hourly capacity factors by technology using the observed wind and solar generation data in Texas from 2016—2020.[19] Solar and wind generation data come from publicly available ERCOT reports and capacity data from the U.S. Energy Information Administration Form-860. We partition time into hours of the day ($i = 1 \dots 24$) and days ($k = 1 \dots 365 * 5$). For a given hour of the day i, we estimate a Seemingly Unrelated Regression (SUR) using the system of equations:

$$\begin{aligned} s_{i,k} &= c_{s,i} + \beta_{s,i} d + \varepsilon_{s,i} \\ w_{i,k} &= c_{w,i} + \beta_{w,i} d + \varepsilon_{w,k}, \end{aligned} \tag{9}$$

where $s_{i,k}$ is the set of all solar capacity factors for hour i over all days in 2016–2020 and d is a month-level fixed effect.[20] Residuals from these regressions for several specific hours are shown in Fig. A.5. Using the residuals, we determine the variance/covariance matrix for a joint normal random variable. Uncertainty about capacity factor in hour i in month j is modeled as the sum of the predicted capacity factor from the SUR plus a random component from the joint random variable. We discretize this joint random variable into a three point equal probability marginal distribution for the solar capacity factors. For each value in this three point distribution, we discretize the resulting conditional normal random variable into a three point equal probability conditional distribution for wind capacity factors. This procedure allows the wind and solar shocks to be correlated, with the degree of correlation determined by the residuals in the SUR. In the end, we have a set of 288 nine-point joint distributions for uncertainty about capacity factors. An element of this set represents the distribution for a given hour i in a given month j. So, for example, hour 12 for each day in January has the same distribution.

5. Results

Our results from several simulated experiments are provided in Table 1. The baseline results in this Table do not include battery storage. Without storage, the planner's dynamic program is separable across periods, and we can directly calculate expected prices and electricity generation by technology. With storage, one needs to use Monte Carlo methods to study these quantities. After discussing the baseline results, we present the results for a model with storage and compare to our baseline results to illustrate the interaction between Bitcoin demand and storage.

The first two rows in Table 1 compare the long-run technology capacity and carbon emissions outcomes with and without Bitcoin electricity demand. [21] We see that wind capacity substantially increases in the experiment with Bitcoin demand, around double the wind capacity as without. Solar capacity marginally increases with Bitcoin demand, while combined cycle natural gas also increases and gas peaker capacity decreases. Carbon emissions with Bitcoin increase substantially, by around 1.6 times the experiment without Bitcoin, or 30 milion metric tons (mil mt). The last row shows the investment outcomes when Bitcoin miners are being used as demand response. In this experiment, the grid operator can turn the miners' demand off whenever there is an unexpected shortfall in renewable energy generation. Allowing miners to provide demand response modestly increases wind and solar, but more substantially decreases the amount of investment in combined cycle gas. This experiment lowers emissions compared to Bitcoin without demand response, with Bitcoin increasing emissions now by only 2 mil mt annually relative to baseline. Overall, we find that integrating Bitcoin onto the Texas interconnection can occur without large increases in carbon emissions when miners are providing demand response. Finally, we calculate the share of generation provided by renewable resources by dividing total wind and solar generation over total generation and find that both Bitcoin experiments increase the share of generation provided by renewables, with shares of 0.63 and 0.74 with demand response, compared to 0.61 without Bitcoin.

(*footnote continued*)
impact on carbon emissions. Spreading Bitcoin demand over a larger geographic area may increase or decrease renewable generation depending on how these other areas have characteristics that differ from Texas.

[19] We use the HMY (2022) procedure to calculate capacity factors, which measure production per MW of installed capacity.

[20] This procedure is similar to Gautam et al. (2016) where they include load and solar energy as dependent variables, and also Jie et al. (2015), though they use a non-parametric estimation rather than a SUR.

[21] Our baseline has considerably more solar capacity than what is currently installed in Texas. There are two reasons for this. First, in our long run model, solar is exploited to its full economic potential. This is not yet true in Texas, although solar is expanding quickly. Second, nuclear and coal are not used in the long run equilibrium, and these sources currently represent about 15 % of Texas capacity.

Table 1
Generation capacity with and without Bitcoin.

Experiment	Solar	Wind	Gas CC	Gas Peaker	Carbon
Baseline	48.68	34.24	27.47	5.62	46.43
Bitcoin	58.39	75.39	42.60	0.00	75.07
Bitcoin with Demand Response	58.48	82.92	29.42	0.00	48.67

Notes: This table shows the optimal long-run technology capacity across alternative experiments, as well as the resulting total annual carbon emissions. Capacities are in GW and carbon emissions are in millions of metric tons.

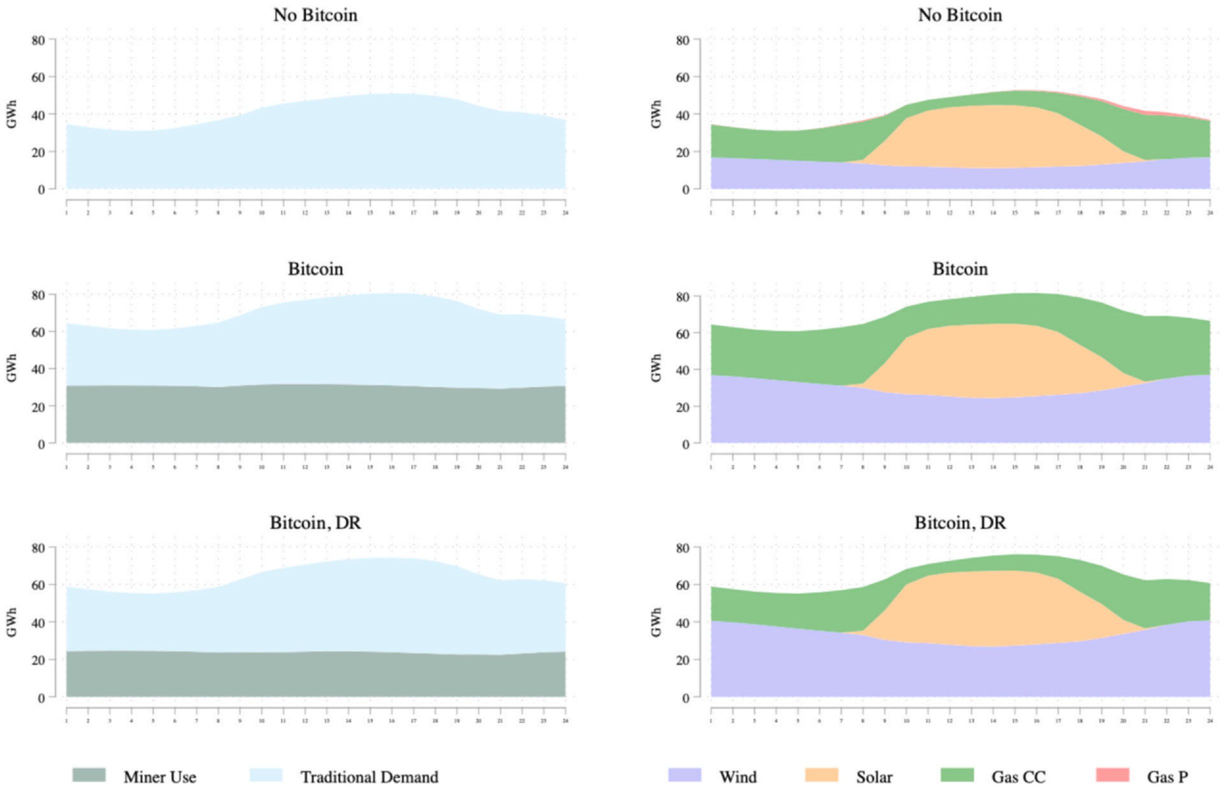

Fig. 2. Average Hourly Consumption and Generation across Experiments *Notes:* Each row in this figure corresponds to a unique experiment, with hour of the day on the x-axis. The figures on the left hand side plot GWh consumption from traditional consumers and Bitcoin miners, averaged at the hourly level. The right hand side figures plot the average hourly generation by technology for the corresponding experiments.

We use the long-run investment outcomes from the planner's problem to simulate one representative year's worth of electricity outcomes, average these outcomes by hour, and plot them in Fig. 2. The left hand side shows average hourly consumption from the two sources of electricity demand, traditional consumers and miners, and the right hand side shows the average hourly generation by technology. A notable result is that Bitcoin demand is relatively flat throughout the hours of the day, especially compared to the more lumpy shape of traditional demand. As we see on the right hand side, wind generation (blue) is also relatively flat throughout the day. Comparing the top right panel to the middle and bottom right panels, we see that most of the increase in Bitcoin demand is met with an increase in wind generation. Further, the gas peakers (red) that were required without Bitcoin are no longer needed. In the middle-right panel, we seen an increase in generation from combined cycle gas plants (green) in all hours compared to the top panel, the experiment without Bitcoin. When allowing Bitcoin to provide demand response, we see in the bottom panel a reduction in combined cycle gas, which provides the emissions attenuating effect we find in Table 1.

Although Bitcoin proponents have not generally included the effects on prices in their arguments for the benefits of Bitcoin on the electricity grid, price variation is an important metric for grid operations. Larger price volatility indicates more switching costs throughout the day as marginal generators turn off and on. Large price changes would also indicate larger peaks and troughs in electricity demand throughout the day, and demand profiles with larger changes in demand are generally harder to manage than smoother hourly consumption profiles. Table 2 compares daily price variation across the experiments by

Table 2
Summary statistics for price and price variance by experiment.

Experiment	Median	Mean	Max	Std. Dev.
Price:				
No Bitcoin	26.68	32.46	1781.29	55.39
Bitcoin, No Demand Response	29.91	33.84	404.28	19.73
Bitcoin, Demand Response	26.68	32.81	809.77	33.74
Price Variance:				
No Bitcoin	1.81	123.83	117577.05	1953.21
Bitcoin, No Demand Response	2.20	15.89	5285.39	106.33
Bitcoin, Demand Response	3.07	46.18	23202.77	503.30

Notes: This table shows summary statistics for price and price variance across alternative experiments. Variance is calculated as the squared difference of average daily price less hourly prices, divided by 24 hourly observations within each day.

Table 3
Generation capacity with and without Bitcoin including storage.

Experiment	Solar	Wind	Gas CC	Gas Peaker	Carbon	Storage
Baseline	52.58	44.38	19.88	0.00	30.15	32.54
Bitcoin	61.45	93.75	29.90	0.00	51.52	30.89
Bitcoin with Demand Response	58.02	94.22	20.30	0.00	33.01	21.66

Notes: This table shows the optimal long-run technology capacity across alternative experiments include storage, as well as the resulting total annual carbon emissions. Capacities are in GW (GWh for storage) and carbon emissions are in millions of metric tons.

Table 4
Summary statistics for price and price variance by experiment with storage.

Experiment	Median	Mean	Max	Std. Dev.
Price:				
No Bitcoin	26.69	31.70	1010.90	48.16
Bitcoin, No Demand Response	28.32	32.99	244.15	19.29
Bitcoin, Demand Response	26.67	32.02	492.02	29.76
Price Variance:				
No Bitcoin, No Demand Response	2.06	94.00	37306.35	1284.60
Bitcoin, No Demand Response	2.18	15.28	1738.02	78.13
Bitcoin, Demand Response	2.77	36.17	8212.74	314.11

Notes: This table shows summary statistics for price and price variance across alternative experiments with storage. Variance is calculated as the squared difference of average daily price less hourly prices, divided by 24 hourly observations within each day.

constructing a measure of within day price variation as the sum of the squared deviations of hourly prices less average daily price divided by 24 hourly price observations.

Bitcoin demand increases mean electricity prices with and without demand response, which is as expected given Bitcoin increases demand overall, which increases prices. While adding Bitcoin demand increases the median daily price variance, it decreases the mean daily variance and substantially decreases the maximum daily price variance as well as the standard deviation in daily price variance. Daily variance across experiments is shown in Fig. A.3 in the Appendix. This figure plots daily variance with Bitcoin (blue) and without Bitcoin (green). Median daily electricity prices are consistently higher with Bitcoin demand, as reflected in the medians in Table 2. Yet, the mean daily variance with Bitcoin is lower than without. This is because Bitcoin demand leads to fewer days with very high price variance. To review why Bitcoin decreases the occurrence of high price variation days, recall that Fig. 2 illustrates that Bitcoin adds demand that is relatively flat throughout the day, which flattens the relative variation in hourly demand. As shown in Table 1, with Bitcoin gas peaker plants are no longer needed to address hours with large increases in demand relative to demand in other hours. Gas peakers are more expensive on a marginal cost basis, creating steepness in the right end of the supply curve. Thus, removing gas peakers and larger variation in hour to hour demand decreases days with large price variation, even while mean prices are higher from an increase in total demand.

We now consider several modifications to our baseline results. First we include battery storage. The amount of storage is determined in the long-run equilibrium in the manner described in Section 2, and the results are provided in Table 3. The results show that in all experiments battery storage increases the amount of wind and solar capacity compared to the corresponding experiments without storage. But storage does not qualitatively change the way Bitcoin demand interacts with investment outcomes and grid operations. As in baseline results, adding Bitcoin demand increases renewables and carbon emissions, but demand response almost entirely eliminates the carbon emissions. Including demand response in both cases yields smaller changes in wind and solar, but decreases emissions substantially. We also find that storage and demand response are substitutes. Adding demand response lowers the amount of storage by about 30 %. Summary statistics for prices and price variance in the experiments with storage are provided Table 4, and the daily variance with storage is illustrated in Fig. A.4. Both the table and figure show that storage reduces the maximum daily price variance in all experiments compared to without storage in Table 2, and as a result, storage generally lowers mean daily variance.

Second, we conduct a bounding exercise on the amount of Bitcoin demand. Our experiments placed the entire demand for Bitcoin in Texas, which we did to highlight the effect of large scale Bitcoin mining on an electricity grid. To see the sensitivity of our results to this assumption, we consider two other cases in which we scale the Bitcoin demand to recent estimates from the CBECI of, one, the share of global Bitcoin demand coming from miners located in the U.S., two, the share of global Bitcoin demand coming from miners located in Texas, and then we place each demand in the Texas electricity grid. In the demand scaling experiments we find that adding Bitcoin consistently increases optimal long-run wind and solar capacities, though as expected, with attenuated effects. For example, in the U.S. and Texas demand scaling experiments without demand response we see an increase in wind by around 11 and 2 GW respectively, compared to an increase of around 40 GW in our main results. Consistent with our main results, allowing miners to provide demand response in both demand scaling experiments mitigates Bitcoin's impact on carbon emissions. In summary, while we find that demand scaling changes the magnitude of the renewable capacity effects of Bitcoin, the directions of effects are consistent across the different demand scenarios.

6. Conclusion

We have evaluated several claims about Bitcoin mining and the electricity grid. Notably, we find that Bitcoin mining comes with an increase in the total amount of renewable capacity and generation, from increases in wind capacity in Texas as well as a modest increase in the share of generation provided by renewable resources. Yet, if the reason we want to increase renewable generation is to reduce carbon emissions, then the positive externalities of Bitcoin mining are attenuated, as carbon emissions can increase. On the other hand, there may be other positive externalities to increasing renewable energy capacity such as cost reductions from economies of scale and learning-by-doing, which we have not evaluated here. It is important to emphasize that these results are particular to the Texas electricity grid, which is endowed with high potential for solar and wind resources, and are not necessarily applicable to other interconnection regions with differing wind and solar resource availability and costs.

We also find that when Bitcoin miners provide grid management support in the form of making up for unexpected shortfalls in renewable generation (i.e. demand response), their overall emissions impact is moderated, yielding only a modest increase in carbon emissions as compared to the experiment without Bitcoin demand. Yet, very high Bitcoin prices could also have the effect of making miners unwilling to shut off. Future research would do well to study the incentives on both the grid operator and miners side in terms of both interconnection agreements and demand response commitments.

In our model we have abstracted away from the details of the miners' operational decisions to purchase computer equipment and select mining locations. Rather, we have used the estimated demand curve for electricity use for Bitcoin mining as an aggregate measure of the benefits of Bitcoin mining. We have also considered only one electricity region in a single country. It may be fruitful in future research to consider a more detailed model in which Bitcoin mining capacity is an endogenous variable along with the capacities of the various electricity generating technologies, and Bitcoin miners select locations in which to mine based on electricity prices.

Data Availability

Non-proprietary data will be made available upon request.

Declaration of Competing Interest

None.

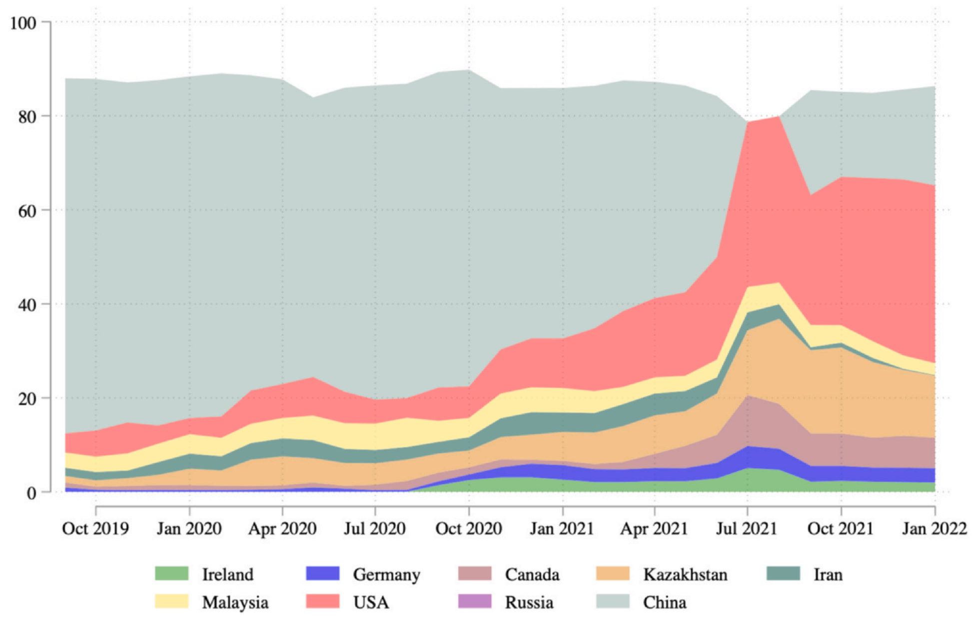

Fig. A.1. Country Share of Global Bitcoin Hashrate (CBECI) *Notes:* This figure shows daily country-specific shares of global Bitcoin hashrate using data from CBECI. These data are then used to estimate country-specific energy consumption from Bitcoin by multiplying country hashrate shares by CBECI's estimate of global Bitcoin energy consumption.

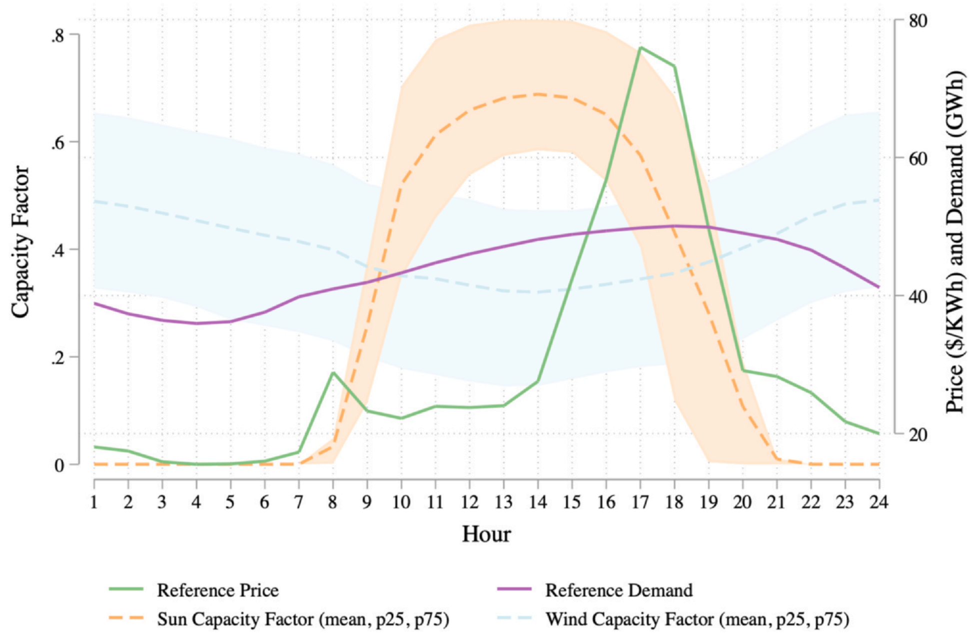

Fig. A.2. Data for Texas Interconnection, Averaged over Each Hour *Notes:* This figure shows the reference price and demand used in HMY (2022). Wind and sun capacity factors are constructed using the method in HMY (2022), extended to include additional data years, 2016–2019, using data from the Electric Reliability Council of Texas (ERCOT), the Energy Information Administration (EIA) Form-860, EIA Form-923, and EIA Form-930. The dashed lines show the mean capacity factor in each hour, with shading representing capacity factors contained in the 25th to 75th percentiles of hourly capacity factor distributions.

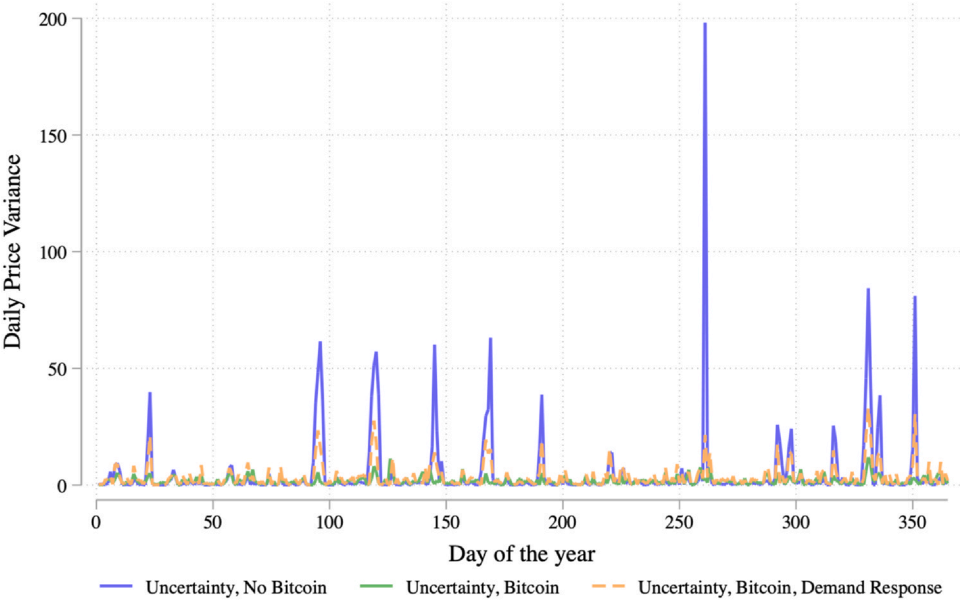

Fig. A.3. Daily price variance across experiments *Notes:* This figure shows the daily price variance across alternative experiments. Variance is calculated as the squared difference of average daily price less hourly prices, divided by 24 hourly observations within each day.

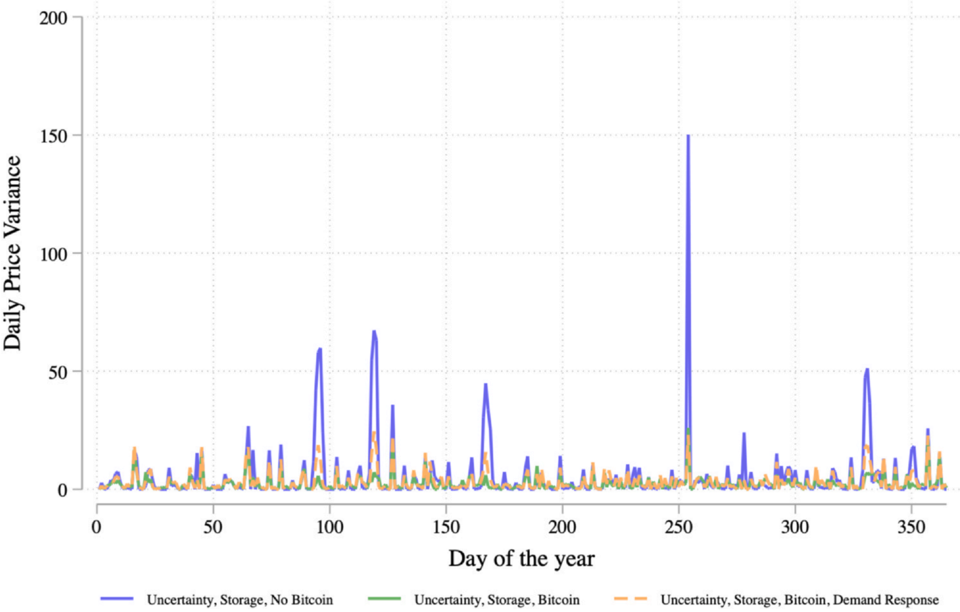

Fig. A.4. Daily price variance across experiments with storage *Notes:* This figure shows the daily price variance across alternative experiments including storage. Variance is calculated as the squared difference of average daily price less hourly prices, divided by 24 hourly observations within each day.

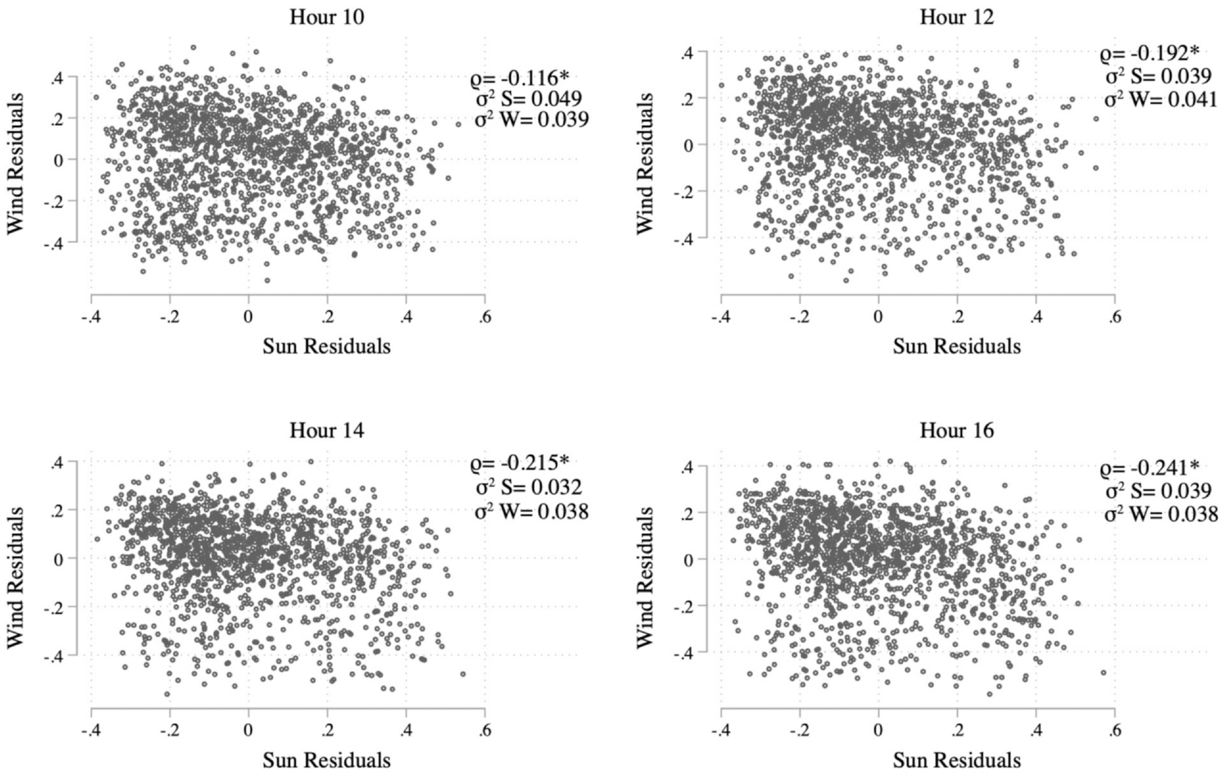

Fig. A.5. Joint distributions of solar and wind residuals in the seemingly un-related regressions *Notes:* These figures shows the wind and sun residuals for illustrative hours from the estimating equations in 9. ρ denotes the correlation coefficient between the residuals, (*) indicates a p-value < 0.05, and σ^2 denotes the variance for the wind and solar residuals respectively.

Table A1
Capital and marginal production costs.

	Annual Capital Cost $ per MW	Marginal Cost $ per MWh	Carbon Emissions tons/MWh
Gas Peaker	54,741	44.13	0.526
Gas Combined Cycle	79,489	26.68	0.338
Wind (onshore)	99,452	0	0
Solar PV	62,456	0	0

Notes: Data correspond to the renewable innovation/subidy case in HMY (2022), which has capital cost for solar and wind equal to 75 % of their baseline values. This case is used to approximate the existing subsidies for solar and wind. Battery capital costs are $18,935 per MWh. All costs are for new resources entering service in 2026.

Table A2
Demand estimation.

	(1) OLS	(2) 2SLS
USD per GWh	-0.456	
	(−1.63)	
USD per GWH, instrumented		-0.170
		(−0.90)
Constant	123383.045	72951.308
	(1.08)	(0.90)
Year by Quarter FE	Yes	Yes
Observations	99	59

Notes: This table shows the coefficient estimates from estimating Equation 8. Column (1) is an ordinary least squares estimations, and column (2) is an instrumental variables specification using natural gas prices as an instrument for electricity price. Natural gas and electricity price observations are at the country-quarter level.

Appendix A. Tables and figures

Fig. A.1, A.2, A.3, A.4, A.5, A1, A2.

References

Menati Ali, Le Xie.2021.Preliminary Study of Utilizing Cryptocurrency Mining for Demand Flexibility in Electric Energy Systems. Working Paper.
Badea, Liana, Mungiu-Pupazan, Mariana Claudia, 2021. The economic and environmental impact of bitcoin. IEEE Access 9, 48091–48104.
Belizaire John.2022.Hearing on Cleaning up Cryptocurrency: The Energy Impacts of Blockchain.United States Congress: House Committee on Energy and Commerce.
Brooks Brian, P., 2022. Hearing on cleaning up cryptocurrency: the energy impacts of blockchain. U. S. Congr.: House Comm. Energy Commer.
Bruno, Biais, Bisiere, Christophe, Bouvard, Matthieu, Casamatta, Catherine, 2019. The blockchain folk theorem. Rev. Financ. Stud. 32 (5), 1662–1715.
Cambridge.2021.Cambridge Bitcoin Electricity Consumption Index.
Bertucci Charles, Louis Bertucci, Jean-Michel Lasry, and Pierre-Louis Lions.2021.Economic Modelling of the Bitcoin Mining Industry.
Coin Metrics.2022a.Coin Metrics, Bitcoin.⟨https://www.coindesk.com/learn/bitcoin-mining-difficulty-everything-you-need-to-know/#::text=Bitcoins%20mining%20difficulty%20is%20updated,to%20mine%20a%20new%20block⟩.
Coin Metrics.2022b.Coin Metrics, HashRate.
Coinbase.n.d.What is proof of work or proof of stake? ⟨https://www.coinbase.com/learn/crypto-basics/what-is-proof-of-work-or-proof-of-stake⟩.2023.
CoinWarz.2022.Bitcoin Mining Calculator.⟨https://www.coinwarz.com/mining/bitcoin/calculator⟩.
Conway Luke.2021. ⟨https://www.investopedia.com/bitcoin-halving-4843769#::text=These%20fees%20ensure%20that%20miners,and%20keep%20the%20network%20going.&text=In%202009%2C%20the%20reward%20for,as%20of%20May%2011%2C%202020⟩.
Council Texas Blockchain.2022.Texas Bitcoin Miners Turn Off to Conserve Power for the Grid.
Digiconomist.2022.Ethereum Energy Consumption Index.⟨https://digiconomist.net/ethereum-energy-consumption⟩.
Dirk, Baur, Hong, KiHoon, Lee, Adrian, 2018. Bitcoin: medium of exchange or speculative assets? J. Inst. Financ. Mark. Inst. Money 54, 177–189.
Fernández-Villaverde, Jesus, 2018. Cryptocurrencies: a crash course in digital and monetary economics. Austral Econ. Rev. 51 (4), 514–526.
Findijs Alex.2021.Texas power grid remains unprepared for severe winter storms.⟨https://www.wsws.org/en/articles/2022/01/05/grid-j05.html⟩.
Gautam, Gowrisankaran, Reynolds, StanleyS, Samano, Mario, 2016. Intermittency and the value of renewable energy. J. Political Econ. 124 (4), 1187–1234.
Global.2022.Global Petrol Prices.
Halaburda, Hanna, David, Yermack, 2023. Bitcoin mining meets Wall Street: a study of publicly traded crypto mining companies. NBER Work. Pap. 30932.
Halaburda Hanna, Guillaume Haeringer, JoshuaS Gans, and Neil Gandal.2022.The microeconomics of cryptocurrencies.Journal of Economic Literature, forthcoming.
Holland Stephen P., Erin T. Mansur, and Andrew J. Yates.2022.Electrification in the Long Run. NBER Working Paper 30082.
Initiative Bitcoin Clean Energy.2021.Memorandum: Bitcoin is Key to an Abundant, Clean Energy Future.⟨https://assets.ctfassets.net/2d5q1td6cyxq/5mRjc9×5LTXFFihIlTt7QK/e7bcba47217b60423a01a357e036105e/BCEI_White_Paper.pdf⟩.
Intergovernmental Panel on Climate Change.2022.IPCC Sixth Assessment Report: Cliamate Change 2022: Impacts, Adaptation and Vulnerability.
Cochran Jaquelin, Paul Denhom, Bethany Speer, Mackay Miller.2015Grid Integration and the Carrying Capacity of the U.S. Grid to Incorporate Renewable Energy. NREL Technical Report.
Jie, Zhang, Hodge, Bri-Mathias, Florita, Anthony, 2015. Joint probability distribution and correlation analysis of wind and solar power forecast errors in the western interconnection. J. Energy Eng. 141, 1.
Li J., N. Li, J. Peng, H. Cui, and Z. Wu.2019.The political geography and environmental impacts of cryptocurrency mining. Henry M. Jackson School Int. Stud., Univ. Washington, Washington, DC, USA, Tech. Rep.
HQ Lunie.2019.Why Is Proof of Stake Better for the Environment?⟨https://medium.com/luniehq/why-is-proof-of-stake-better-for-the-environment-8ac074721930⟩.
Prat, Julien, Benjamin, Walter, 2021. An equilibrium model of the market for bitcoin mining. J. Political Econ. 129 (8), 2415–2452.
Software Testing Help.2022.Top 10 bitcoin mining hardware 2022 updated list.⟨https://www.softwaretestinghelp.com/bitcoin-mining-hardware/#::text=at%20a%20power%20efficiency%20of,power%20at%20your%20mining%20location⟩.
Statista.2022.Market capitalization of Bitcoin from April 2013 to January 16, 2022.
Smith Sean Stein.2022.Crypto Power Usage Is Helping To Spur Renewable Energy Investments.⟨https://www.forbes.com/sites/seansteinsmith/2022/06/05/crypto-power-usage-is-helping-to-spur-renewable-energy-investments/?sh=3010f6452cb6⟩.
U.S. Department of Energy.2022.Demand Response.⟨https://www.energy.gov/oe/activities/technology-development/grid-modernization-and-smart-grid/demand-response⟩.
de Vries, Alex, 2018. Bitcoinas growing energy problem. Joule 2 (5), 801–805.
William, CongLin, He, Zhiguo, Li, Jiasun, 2021. Decentralized mining in centralized pools. Rev. Financ. Stud. 34 (3), 1191–1235.