Inferring Electricity Demand from the Bitcoin Mining Boom: Case Study in Washington, US

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Abstract

While many scholars have raised concerns about Bitcoin's global energy requirements, very few have econometrically quantified the effects of Bitcoin on a large scale in major Bitcoin operating countries like the United States. Here, I use a recently developed Bitcoin energy consumption index from the University of Cambridge to investigate the relationship between energy demands and Bitcoin mining in a case study of Washington State. I do this by first creating a series of panel data regressions to capture differing marginal effects by region in Washington State, and then generating pooled OLS models with differing controls on time and other factors to observe a state-wide effect. The regressions demonstrated consistent results of a unit change in CBECI affecting energy demand by up to 1-2% in some balancing authorities, but also contained mixed results that illustrate close to no effect. Though Bitcoin does not seem to be a major concern for electricity demand at a regional and state level over the past five years, Bitcoin mining operations in the US are just getting started. As more individuals participate on the Bitcoin blockchain, further studies will be needed to investigate how Bitcoin mining operations will interact with the U.S. electric grid.

I. Introduction

Considerable concerns about Bitcoin's energy demand pose a threat to the global climate agenda (De Vries, 2018; Mora et al., 2018). In January of 2018, each Bitcoin mined required 60,461kWh of electricity compared to 1005kWh of electricity two years prior--approximately a 60-fold increase (Krause & Tolaymat, 2018; Goodkind et al., 2020). Given the current dependence on non-renewable energy in the total electricity supply, the scenarios in which Bitcoin and other cryptocurrencies continue to experience widespread adoption similar to the growth rate of other technologies implies enormous social and environmental implications that cannot be ignored.

Currently, the United States holds the second largest share, approximately 7-8% of the global average monthly hashrate or the total computing power of the Bitcoin network (CCAF publications, 2021). Despite holding only a 7-8% recorded hashrate, the amount of energy Bitcoin operations consume from the combination of individual residential miners and large concentrated mining farms or pools in the United States is bound to considerably affect the energy demand in certain areas. Counties in the United States like Chelan County, Washington, for instance, have experienced multiple energy consumption booms from the rise in cryptocurrency's popularity going back to 2010 (Greenberg & Bugden, 2019). Furthermore, foreign and domestic institutions are increasingly trying to scale up mining operations that repurpose underused power and cheap renewable energy sources in the United States (Harper, 2021; Allison, 2020).

With the United States trending towards significant involvement with cryptocurrency mining operations, it raises concerns about how Bitcoin's high energy requirement will affect the U.S. electricity carbon footprint through its consumption of non-renewable energy. To explore the extent of this concern, this paper investigates the relationship between Bitcoin mining, or the solving of complex computation intensive processes for verifying blockchain transactions and energy demand in Washington State, an area where major crypto mining activities are believed to exist.

To explore this relationship, the Cambridge Bitcoin Electricity Consumption Index (CBECI) is used as an indicator for Bitcoin mining. The CBECI constructs a lower-bound, upper-bound, and prediction estimate of Bitcoin's total electricity consumption based on a thorough review of acclaimed literature in this space and the most comprehensive publicly available information on the following: the Bitcoin market price, Bitcoin network hashrate, Bitcoin miner fees, Bitcoin issuance, Bitcoin difficulty of finding a new block for the Bitcoin network, mining equipment efficiency, average electricity cost incurred by miners, and data centre efficiency. These factors influence the financial feasibility of certain mining operations and willingness to operate. For example, if fees given to miners to process transactions are too low in combination with higher difficulty in finding blocks, revenue decreases, and will disincentivize mining. The use of this index captures the main factors that incentivize bitcoin mining operations and will capture the energy consumption effects attributed to bitcoin mining globally.

Other variables such as temperature, GDP, and electricity price of Washington State are also considered. The relationship between Bitcoin mining and energy demand, while controlling for these variables at a regional level, may further isolate how global Bitcoin energy consumption impacts U.S. energy demand in Washington State. Multiple regression models are employed to capture the differential marginal effects of different regions in Washington. Additional pooled

OLS regressions are utilized to observe the impact of CBECI on Washington State while controlling for variances in time and location.

The final results of the regression models show consistent results of a unit change in CBECI affecting energy demand by up to 1.04% in the North Central region surrounding the Balancing Authority, DOPD, and up to 2.08% in the energy demand surrounding the Balancing Authority near Seattle, SCL. On the state-wide level, results were inconclusive and showed close to no effect. The paper will continue in the following format: II. Background, III. Literature Review, IV. Conceptual Framework, V. Data, VI. Methodology, VII. Results, VIII. Conclusion, IX. References, X. Appendix.

II. Background

Cryptocurrencies--digital currencies that use a cryptographic verification process for anonymous, decentralized, and secure transactions contain transformative technology that can disrupt traditional financial services and the global economy. This technology, called blockchain, is usually a public ledger that records digital information about transactions in blocks that have a unique digital signature over a large peer-to-peer network of computers. To add a new block to the chain, participants called "miners" compete to solve an algorithm that provides the identifier for the new block. Units of the cryptocurrency are then given in exchange for successfully solving the algorithm, or contributing to the validation process.

Although the cutting edge technology of blockchain has the potential to provide tremendous value to all aspects of the global economy, such as a store of value or logistics tracking, the algorithm currently implemented to validate new blocks in cryptocurrencies is predominantly an energy intensive, proof-of-work process. In a proof-of-work algorithm, miners who provide more computational resources are proportionally likely to solve the complex compute-intensive problem (Satoshi, 2008; Goodkind et al., 2020). As a result of competition in the most distinguished cryptocurrencies like Bitcoin, dedicated large-scale mining pools and mining farms have formed in areas of cheap electricity for the sole purpose of solving these algorithms (Goodkind et al., 2020).

Bitcoin is currently the largest cryptocurrency by market capitalization. As Bitcoin continues to garner acceptance from the public as a digital asset, more computing power is needed to validate transactions from new participants. Therefore, new mining pools and farms form and existing mining pools and farms scale up their operations in the Bitcoin. The aggregate energy consumption makes Bitcoin a huge target for reducing carbon emissions from coal, natural gas, and other dirty energy sources associated with its electricity consumption.

III. Literature Review

Previous literatures that have employed environmental economic analysis start with quantifying the energy and carbon costs of cryptocurrency mining. Since blockchain technology is relatively new, studies like Krause & Tolaymat (2018) enable some environmental economic assessments of cryptocurrencies by quantifying energy and carbon emissions of cryptocurrencies through a bottom-up approach. Using available cryptocurrency price data, hash rate data, and hardware power efficiency data, Krause and Tolaymat (2018) provide a methodology that derives energy and carbon costs from multiplying the hash rate with the energy consumption of a typical mining hardware. Other studies like Li. et al. (2019) establish experiments by setting up their own mining algorithms, consensus mechanisms, and computer GPUs to mine cryptocurrencies for determining mining energy efficiencies and associated carbon emissions. The CBECI used in this study carefully reviews Krause and Tolaymat (2018)'s research and other similar sources to develop its methodology to predict energy consumption.

Goodkind et al. (2020) also apply Krause and Tolaymat methodology for quantifying carbon emissions and calculate estimates of the economic damages of air pollution emissions per coin. Using the value of statistical life estimates, their results indicate that $1 of Bitcoin value in 2018 is responsible for $0.49 in cryptodamages (mortality and climate costs of cryptomining) in the United States and $0.37 in China respectively (Goodkind et al., 2020). Similarly, this paper aims to build on this literature by analyzing the energy demand, and associated carbon emissions attributed to mining operations in the United States.

The bulk of the literature highlights concerns about Bitcoin's future carbon footprint. Mora et al. (2018), Qin et al. (2020), and many other studies use meta-analysis and projection models to demonstrate that Bitcoin's energy consumption will continue to surpass major nations like Sri Lanka, Hong Kong, and Argentina. Moreover, Mora et al. (2018)'s study claims that Bitcoin alone could potentially be responsible for enough CO2 emissions to push global temperatures more than 2 °C within three decades, assuming that there are no constraints on expanding low-cost electricity supply for mining, no Bitcoin transaction limitations, and other important factors such as future energy mixes (Dittmar & Praktiknjo, 2019).

Others argue that Bitcoin incentivizes society to transition and deploy more renewable energy capacity. They believe that Bitcoin serves as a complementary technology for clean energy production and storage by being a flexible load option for alleviating renewable energy curtailment (Bitcoin Clean Energy Initiative, 2021; Shan & Sun, 2019). Shan & Sun (2019)'s case study created a simulation in the California Independent System operator and finds that the system can earn a range of 5.6 to 48.1 million dollars while reducing renewable curtailment by 50,8% to 79.9%. A shift in mining activities to the generation side in California would have reduced 50,000 tons of CO_2 emissions and 200,000 tons of CO_2 emissions respectively.

Rather than focus on projections or engage in investigating energy consumption of Bitcoin through mathematical models, my study aims to utilize recently recorded data on energy demand in the United States and Cambridge's Bitcoin energy consumption index from 2015-2020 to be one of the first studies to investigate a causal relationship between Bitcoin mining and U.S. energy demand using econometric regressions.

IV. Conceptual Framework

Exploring the causal relationship between electricity demand and Bitcoin operations requires understanding that there are other real factors in the error term that influence this relationship. Correlations between many factors and electricity demand may be captured in the relationship between Bitcoin mining and electricity demanded. To mitigate the risk in attributing the relationship of electricity demand to some other factors outside of what I want to estimate, I attempt to first narrow down the areas analyzed to regions that appeal to cryptocurrency miners.

I exploit the fact that certain regions with cheap renewable energy costs are being utilized for cryptocurrency mining activity. This approach navigates around the anonymity limitation due to the encryption of Bitcoin's peer-to-peer network. Since data on geolocation and the real number of miners are anonymous given the encryption protocols of the peer-to-peer networks of cryptocurrencies, information about the location of IP addresses may reflect inaccurate information because miners can connect to mining pools in other countries or redirect their IP addresses with virtual private networks (Li et al., 2019). The area I focus on in this study is Washington State.

Many sources point to Washington State, especially the North Western region, attracting dozens of cryptocurrency miners due to cheap hydroelectric power from the Columbia River. Chelan County in Washington State, for instance, charged residential customers 2.7 cents per kilowatt hour in 2018, one of the lowest rates for electricity in the United States (Greenberg & Bugden, 2019). Greenberg & Bugden (2019)'s also note that Chelan county has been home to dozens of permitted crypto mining operations and unauthorized miners over the years. Moreover, Washington State has active news articles, press releases, and public comments about cryptocurrency mining operations dating back to 2010. Therefore, it is an ideal candidate for investigating the relationship between bitcoin mining and electricity consumption.

Regions in Washington State all have a Balancing Authority that is responsible for maintaining the electricity balance within its region (*Appendix, Figure 1*). Effects are separated out by Balancing Authority in Washington State to observe the effects attributed to each region.

Some other important factors affecting the dependent variable energy demand in Washington State could be temperature, GDP, and electricity price. Therefore, to avoid omitted variable bias in the conceptual framework, we consider controlling for these variables alongside our main explanatory variable.

$$Energy\ Demand = {}_0 + \beta_1 CBECI + \beta_2 Balancing\ Authority + \beta_3\ Temperature + \beta_4 GDP + \beta_5 Electricity\ Price$$

The conceptual framework assumes that an electricity requirement of Bitcoin's magnitude should be reflected in the electricity demand in Washington State where there exists active expansion of crypto mining operations.

V. Data

Data on electricity demand is provided by the U.S. Energy Information Administration (EIA). The EIA tracks hourly electricity data by balancing authority back to 2015.The hourly EIA data based on balancing authority also contains data on the net generation of electricity from non-renewable and renewable sources starting from July 2018. Since renewable energy sources are generally the cheapest energy sources in the world, observing balancing authorities with high levels of renewable energy generation provides valuable insights about whether bitcoin mining is happening more at locations with high levels of renewable energy generation. The hourly data is collapsed aggregately to the daily level for analyzing relationships with Bitcoin energy use. Only data from balancing authorities in Washington State from October 10, 2015 to December 31, 2020 are considered given data limitations. Average yearly electricity price in Washington State is also provided by the EIA.

Daily data on temperature is provided from the National Oceanic and Atmospheric Administration (NOAA). The daily data provided is based on temperature collecting stations all over Washington State. I average the daily data to construct an average daily temperature data of Washington State from 2015-2020. This includes the average minimum temperature of the day, average maximum temperature of the day, and average observed temperature of the day in Washington State. These temperature variables should control for any significant macro thermodynamic changes that might affect energy demand.

Lastly, data for Washington State GDP is from the Bureau of Economic Analysis, U.S. Department of Commerce. Quarterly data on GDP is provided by the State. Here, I use real GDP dollars in reference to the 2012 dollar to control for any significant economic changes in Washington State. *Tables 2, 4, 5, 6, 7* and *Figure 3* in the appendix summarize the data from the EIA, NOAA, and the Bureau of Economic Analysis.

Cambridge Bitcoin Energy Consumption Index

The Cambridge Bitcoin Electricity Consumption Index is available from the University of Cambridge Centre for Alternative Finance in real time. This index constructs a lower bound estimate, upper bound, and best-guess estimate of Bitcoin's electricity consumption based on model parameters that use the most comprehensive publicly available information (*Appendix, Table 8a and Figure 8b*). The table below contains the descriptions, units of measurement and sources for the model parameters taken from the University of Cambridge Centre for Alternative Finance website.

Parameters	Description	Units of Measurement	Source
Network Hashrate, mean daily	The mean rate at which miners are solving hashes that day	Exahashes per second (Eh/s)	Coinmetrics
Bitcoin Issuance Value, daily	The sum USD value of all bitcoins issued that day	USD	Coinmetrics
Miner fees, daily	The sum USD value of all fees paid to miners that day	USD	Coinmetrics
Difficulty, mean daily	The mean difficulty of finding a new block that day	Dimensionless	Coinmetrics
Bitcoin market price	The fixed closing price of the asset as of 00:00 UTC that day	USD	Coinmetrics
Network hashrate, real-time estimate	The real-time estimate of the rate at which miners are solving hashes	Exashahses per second (Eh/s)	https://blockchain.com/
Mining equipment efficiency	The energy efficiency of a given mining hardware type	Joules per Gigahash (J/Gh)	Static: hardware specs from 60+ equipment types, taken from various sources
Electricity cost	Average electricity cost incurred by miners	USD per kilowatt-hour ($/kWh)	Static: estimate (assumption)
Data centre efficiency	Measures how efficiently energy is used in a data centre: expressed via power usage effectiveness	Dimensionless	Static: estimate (assumption)

Table 8c: CBECI model parameters. Taken from: https://cbeci.org/cbeci/methodology

The Bitcoin metrics are important factors to consider for mining. The hashrate parameters provide information about the total computing power of all miners, and thus informs miners about the global competition. Since Bitcoin miners earn rewards for validating transactions in Bitcoin and collect fees for processing and securing transactions for users, miner fees, and the Bitcoin market price all affect a mining operation's revenue. Bitcoin issuance and difficulty add scarcity to the profitability equation.

The CBECI variable in this study uses the default electricity price of $0.05/kWh. Contributors to CBECI find this value to be the most consistent based on previous research and in-depth conversations with miners worldwide (CCAF publications, 2021). The electricity price is important because it is one of the main inputs that determines the costs of a mining operation and whether mining will be profitable.

Data of the mining equipment efficiency is from a compiled list of 60 various Bitcoin application-specific integrated circuits (ASICs) models specifically designed for SHA-256 operations, the encryption protocol used for verifying transactions in Bitcoin. The Cambridge Centre for Alternative Finance describes ASICs as "specialized hardware specifically optimized for Bitcoin mining" (CCAF publications, 2021).

The regressions use the lower bound estimate, the assumption that miners always use the most efficient hardware available, upper bound estimate, the assumption that miners always use the least efficient hardware that is still profitable at a given point in time, and the prediction estimate, which assumes that the miners use an equally-weighted basket of all hardware types that are profitable.

Below are the mathematical expressions used to calculate the three different energy consumption estimates provided on the Cambridge Centre for Alternative Finance Methodology page (CCAF publications, 2021).

$$E_{lower}\left(P_{el}\right) = min\left(Eq_{prof}\left(P_{el}\right)\right) * H * PUE * 3.16 * 10^{7},$$

$$\begin{gathered} with \\ E_{lower} \ - \ lower\ bound\ power\ consumption\ [W] \\ min\left(Eq_{prof}\left(P_{el}\right)\right) \ - \ energy\ efficiency\ of\ the\ most\ efficient\ hardware\ [J/h] \\ H \ - \ hashrate\ [h/s] \\ PUE \ - \ power\ usage\ effectiveness \end{gathered}$$

Figure 9a: Mathematical model of lower bound estimate. Taken from: https://cbeci.org/cbeci/methodology

$$E_{upper}\left(P_{el}\right) = max\left(Eq_{prof}\left(P_{el}\right)\right) * H * PUE * 3.16 * 10^{7},$$

$$\begin{gathered} with \\ E_{upper} \ - \ upper\ bound\ power\ consumption\ [W] \\ max\left(Eq_{prof}\left(P_{el}\right)\right) \ - \ energy\ efficiency\ of\ the\ least\ efficient \\ but\ still\ profitable\ hardware\ [J/h] \\ H \ - \ hashrate\ [h/s] \\ PUE \ - \ power\ usage\ effectiveness \end{gathered}$$

Figure 9b: Mathematical model of upper bound estimate. Taken from: https://cbeci.org/cbeci/methodology

$$E_{estimated}\left(P_{el}\right) = \frac{\sum_{i=1}^{N} \vartheta_i}{N} * H * PUE * 3.16 * 10^{7},$$

$$\begin{gathered} with \\ E_{estimated} \ - \ best\ guess\ power\ consumption\ [W] \\ \frac{\sum_{i=1}^{N} \vartheta_i}{N} \ - \ average\ energy\ efficiency\ of\ profitable\ hardware\ [J/h] \\ H \ - \ hashrate\ [h/s] \\ PUE \ - \ power\ usage\ effectiveness \end{gathered}$$

Figure 9c: Mathematical model of best-guess estimate. Taken from: https://cbeci.org/cbeci/methodology

Limitations

The CBECI has a strong dependence on the electricity cost estimate. Electricity costs can vary widely depending on country, region and even provider. In addition, other potential cost factors such as maintenance, cooling costs, and property costs are ignored in the model. Further explanations and discussions about the data can be found on the website (CCAF publications, 2021).

(Summary Statistics for all the variables used in the regression in *Appendix, Table 10*)

VI. Methodology

I aim to create an empirical strategy that can trace out the response of energy demand to changes in the Cambridge Bitcoin Energy Consumption Index. This estimate needs to account for individual heterogeneity so it is imperative to have a strategy that will take heterogeneity into consideration and avoid bias. Regression with select controls that directly affect energy demand or might be correlated with the CBECI should be included. Multiple variations of the following OLS models are used on the lower-bound, upper-bound and predicted values of the CBECI to observe the effect of Bitcoin mining through the CBECI. Part 1 (*Equations 1, 2, 3*) of the empirical strategy investigates the relationship between the main explanatory variable on electricity demand at the regional level. Part 2 (*Equation 4*) investigates the relationship as a State.

Eq1: $\log(demand_t) = \beta_1 CBECI_t * BA + \delta_{BA}$

The variable *demand* is the total electricity demand in megawatts for the day *t*. The β_1 coefficient represents the variable of interest, which is the interaction between the CBECI, our Bitcoin mining indicator, and balancing authority, the entity responsible for maintaining the electricity balance for its region. The interaction term enables us to analyze the differential marginal effect among balancing authorities in Washington. The term δ is a dummy variable for balancing authority that accounts for specific regional characteristics.

Eq2: $\boldsymbol{log(demand_t) = \beta_1 CBECI_t * BA + \delta_{BA} + \tau}$

The factor regression in Equation 2, additionally includes a dummy variable τ to control for any variance due to trends over time. This dummy variable accounts for the day of the week, month, and year. Energy demand requirements can change over the seasons and the day of the week. The time dummies should hold any significant time effects constant and help isolate the relationship between CBECI and electricity demand by Balancing Authority.

Eq3: $\boldsymbol{log(demand_t) = \beta_1 CBECI_t * BA + \delta_{BA} + \beta_4 temp_t + X + \tau}$

The final regression for analyzing regional differences is Equation 3. I include temperature and economic controls too. Though these additional controls may not affect regression results significantly, they still may correlate with the relationship between CBECI and demand. Temperature is included as an independent control to account for thermodynamic effects. Temperature directly affects mining hardware cooling needs and efficiency when the temperatures are higher. Including a GDP economic control considers any shocks due to economic conditions. An electricity price considers any additional demand shocks on electricity that may occur.

Eq4: $\boldsymbol{log(demand_t) = \beta_1 CBECI_t + \beta_4 temp_t + X + \tau}$

Lastly, Equation 4 tests for any state-wide effects of CBECI on total electricity demand of Washington State. Here, multiple variations and similar controls are included for consideration of endogeneity and robustness.

VII. Results

The estimated effects of CBECI on energy demand in each region are shown in *Tables 11a, 11b, and 11c* in the Appendix. Estimated effects of CBECI on energy demand in Washington State are shown in *Tables 12a, 12b, and 12c* in the Appendix.

CBECI prediction estimate regional results

The results using predicted estimates of CBECI show mixed results. Balancing Authorities with natural gas generation and other fuel generations (AVA and PSEI) show that the predicted estimate of CBECI negatively affects energy demand by about 1.4% and 0.11% to 0.169% per unit change in terawatt hour respectively. The interaction between Balancing Authority, AVA, and the CBECI reflects 1.37% to 1.43% decrease in energy demand per unit change in CBECI predicted value and is statistically significant at the p-value < 0.001 level. The interactions attributed to DOPD and GCPD, show positive effects on electricity demand ranging from .08% to 0.42%. These Balancing Authorities are near the North Central region where Chelan County is. The interaction between DOPD and CBECI predicted values indicate that a unit increase in predicted CBECI causes a 0.356% to 0.42% increase in energy demand and is significant at the p-value < 0.001 level for all regional effects models. The last statistically significant interaction variable is with SCL, which manages electricity for a major city, Seattle. A unit change in CBECI for predicted values explains about 0.88% to 0.94% of the electricity demand in the region SCL covers. Interestingly, only the three Balancing Authorities responsible for the smallest magnitudes of energy showed statistically significant results.

CBECI lower-bound estimate regional results

Regressions using the CBECI lower-bound estimate also show statistically significant results for the same three Balancing Authorities (AVA, DOPD, SCL) previously. The interaction with AVA explains that a unit change in terawatt hour for CBECI causes about a 2.65% to 2.98% decrease in energy demand. The DOPD CBECI interaction estimates a range from 0.696% to 1.04% is attributed to a unit increase in CBECI. Lastly, the SCL CBECI interaction reflects a 1.74% to 2.08% increase in energy demand per unit change in CBECI. The CBECI lower-bound estimate seems to cause stronger effects to electricity demand than that of the CBECI predicted estimate.

CBECI upper-bound estimate regional results

The opposite is true for the CBECI upper-bound estimate results. The AVA interaction shows a statistically significant effect of approximately -0.813% to -0.876% across all the regressions. The DOPD interaction reflects a 0.124% to 0.183% change in energy demand per unit change in CBECI and the SCL interaction shows about a 0.243% to 0.306% change in energy demand across the regression outputs. Furthermore, CHPD, and PSEI also have statistically significant results of approximately -0.1% at the 1% level.

Washington Statewide Effects

Using prediction CBECI estimates with no time controls, a unit increase in CBECI caused 0.0392-.0532% change in energy demand. With time controls, a unit increase in CBECI caused -0.0598% change in energy demand. Results for minimum and maximum CBECI estimates were very similar. (*Appendix, Table 12d*)

Further Analysis

The small coefficient values for our main explanatory variable may not seem that impactful on energy demand. On a regional level, however, affecting 1% of energy demand is a considerable amount. For instance, 1% of DOPD's total electricity demand totals to about 2,416 megawatts. Using EIA's statistics on the average annual electricity consumption of about 877 kWh per month for a U.S. residential customer in 2019, 2,416 megawatts is roughly equal to the electricity use of 230 residential customers over one year.

Observing close to no effect on energy demand could also be interpreted a few ways. One interpretation is that Bitcoin mining does not affect Energy Demand of the area in question significantly enough to be reflected in the results. Another reason could be omitted variable bias and that something affecting energy demand of the state isn't accounted for.

VIII. Conclusion

To conclude, the research finds that the relationship between CBECI and energy demand vary. At the regional level, results show support for Greenberg and Bugden (2019)'s findings about Chelan County and the North Central Region. Interaction variables with DOPD, a balancing authority close to this area showed statistically significant results of a unit increase in the prediction CBECI affecting energy demand by 0.356% to 0.42% and a unit increase in the lower-bound CBECI affecting energy demand by 0.696% to 1.04%. Another takeaway was the results that the region surrounding the Balancing Authority SCL also showing consistent results of CBECI affecting energy demand positively. A unit increase in prediction CBECI resulted in 0.88% to 0.94%

increase in energy demand across all regressions and a unit increase in lower-bound CBECI caused 1.74%-2.08% increase in energy demand.

An interesting finding was that Balancing Authorities that had net generation of natural gas and other gases had consistently negative effects on energy demand. This result could imply that large-scale Bitcoin pools or farms don't necessarily operate in locations with significant non-renewable energy consumption, which isn't surprising given that the cheapest forms of electricity are now from renewable sources (Bitcoin Clean Energy Initiative, 2021).

Lastly, the study also found no conclusive evidence on Bitcoin mining significantly impacting energy demand at a statewide level. There was mixed results and close to no effect on the relationship between CBECI and energy demand at the state level. However, this might just be because Bitcoin is still in its early stages, and mining operations currently expanding in the U.S. do not affect a significant portion of the share of all electricity demanded in the State.

As Bitcoin and other cryptocurrencies become increasingly prevalent, quantifying the potential effects will be crucial. Future studies need to find strategies to effectively capture the effects of blockchain technology at a large-scale. Currently, the results show that bitcoin mining operations do not considerably affect the energy demand at a regional and state-level. This, however, should not dismiss the effects of cryptocurrency miners heavily impacting energy consumption at a county or town level and at the global level. Further investigation on a sub region to local-level could provide additional insights on how electricity demand is being affected in the United States given that the statistically significant results mainly came from the smallest energy demanding Balancing Authorities over the time period October 10, 2015 to December 31, 2020 in Washington State.

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X. Appendix

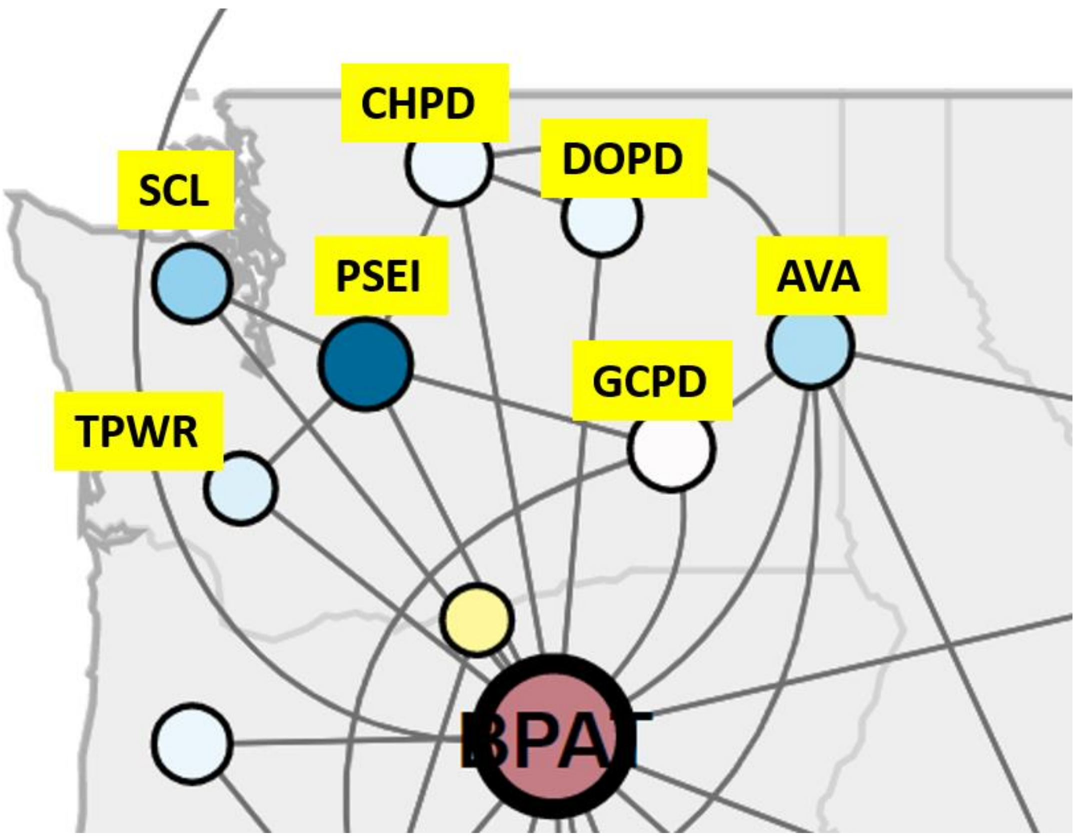

Figure 1: Geographical Locations of Balancing Authorities in Washington State

-> year = 2015

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	48474.54	0	0	0	0	0	0	0
CHPD	592250	0	0	0	0	0	0	0
DOPD	241605.3	0	0	0	0	0	0	0
GCPD	647858	0	0	0	0	0	0	0
PSEI	479276	0	0	0	0	0	0	0
SCL	161191.5	0	0	0	0	0	0	0
TPWR	715355.4	0	0	0	0	0	0	0
Total	412287.2	0	0	0	0	0	0	0

-> year = 2016

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	140049.8	0	0	0	0	0	0	0
CHPD	261758.6	0	0	0	0	0	0	0
DOPD	211335.5	0	0	0	0	0	0	0
GCPD	675499.7	0	0	0	0	0	0	0
PSEI	434906.4	0	0	0	0	0	0	0
SCL	259172.2	0	0	0	0	0	0	0
TPWR	678743.8	0	0	0	0	0	0	0
Total	380209.4	0	0	0	0	0	0	0

-> year = 2017

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	111768.3	0	0	0	0	0	0	0
CHPD	287737.5	0	0	0	0	0	0	0
DOPD	234835.5	0	0	0	0	0	0	0
GCPD	678617.7	0	0	0	0	0	0	0
PSEI	437711.7	0	0	0	0	0	0	0
SCL	226149.7	0	0	0	0	0	0	0
TPWR	678426.7	0	0	0	0	0	0	0
Total	379321	0	0	0	0	0	0	0

-> year = 2018

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	114414.7	0	148859.1	0	13992.09	55060.99	1415.104	49697.41
CHPD	279312.2	0	0	0	0	59842.3	0	22972.05
DOPD	247796.5	0	0	0	0	60099.54	0	0
GCPD	709859.4	0	0	0	0	53552.54	0	0
PSEI	430831	28308.78	22951.38	45.10411	2066.726	10870.19	0	6838.718
SCL	283939.7	0	0	0	0	71112.04	0	0
TPWR	680794.7	0	0	0	0	56608.46	0	0
Total	392421.2	4044.111	24544.35	6.443444	2294.117	52449.44	202.1577	11358.31

-> year = 2019

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	18902.86	0	262663.6	0	34254.21	117799.1	15220.51	128335.1
CHPD	287472.7	0	0	0	0	123964.2	0	59899.22
DOPD	288071.4	0	0	0	0	129643.9	0	0
GCPD	704685.9	0	0	0	0	112801.8	0	0
PSEI	423773.6	342945.4	241983.3	538.8575	39791.93	131957.8	0	128414.8
SCL	298399.1	0	0	0	0	139523.6	0	0
TPWR	671728.6	0	0	0	0	113150.4	0	0
Total	384719.2	48992.21	72092.41	76.97965	10578.02	124120.1	2174.359	45235.59

-> year = 2020

Summary statistics: mean
  by categories of: ba (group(balancingauthority))

ba	demand~w	ng_coal	ng_nat~s	ng_pet~m	ng_oth~l	ng_hydro	ng_solar	ng_wind
AVA	57953.77	0	252051.3	0	37058.54	141488.4	18758.14	143229.4
CHPD	269282	0	0	0	0	93579.47	0	92817.73
DOPD	265897.6	0	0	0	0	127994.4	0	0
GCPD	699509	0	0	0	0	84473.74	0	0
PSEI	371764.2	210597.1	222792.3	539.9454	38009.18	156063	0	145738.2
SCL	420608.8	0	0	0	0	139192.2	0	0
TPWR	663409.1	0	0	0	0	117792	0	0
Total	392632.1	30085.29	67834.81	77.13505	10723.96	122940.5	2679.735	54540.75

Table 2: Summary Statistics by Balancing Authorities in Washington State and by Year. The ng is an abbreviation for net generation. Variables (left to right): demand, ng coal, ng natural gas, ng petroleum, ng other fuels, ng hydro, ng solar, and ng wind. All values are recorded in megawatts (MW).

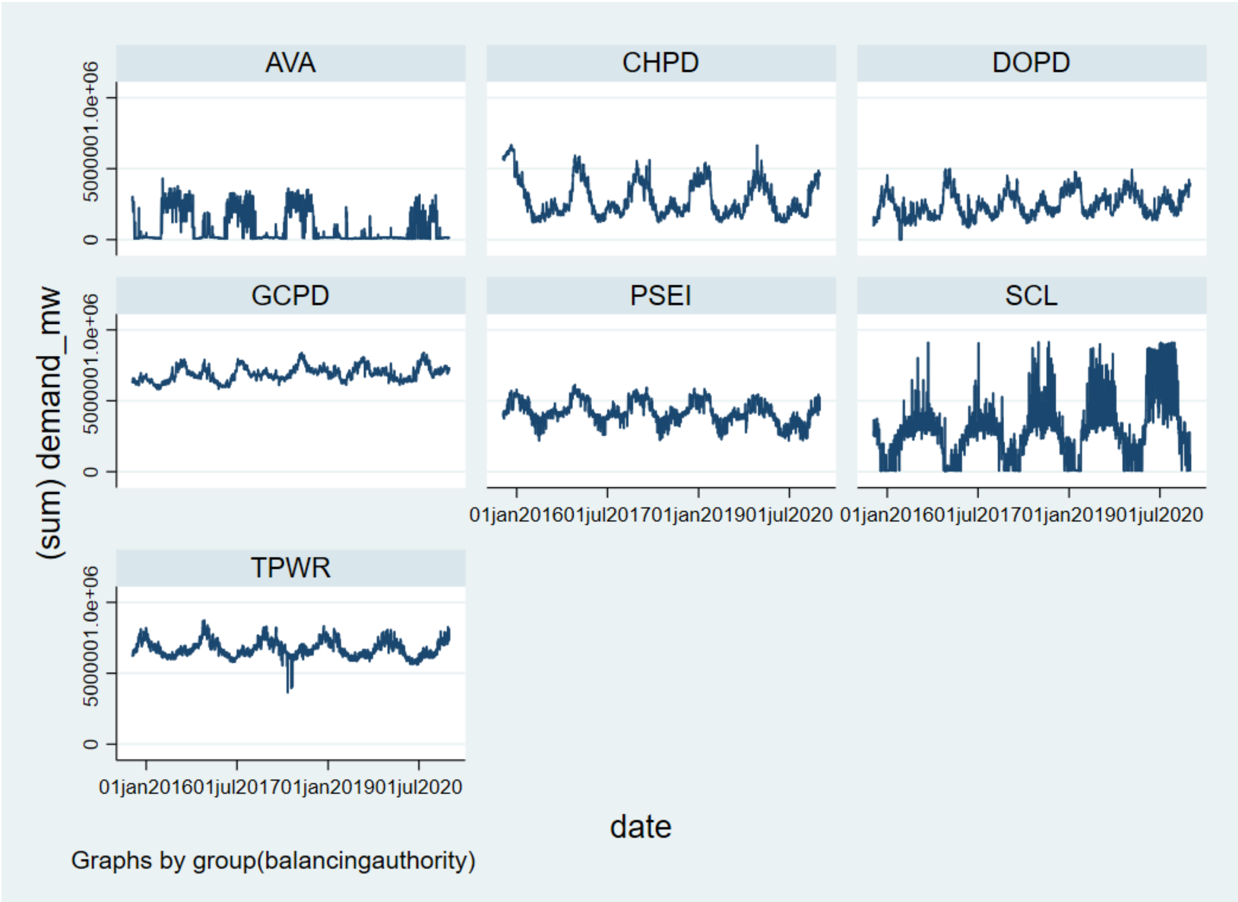

Figure 3: Line graphs of Energy Demand over October 2015-December 2020, by Balancing Authority in Washington State

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
demand mw	13370	387009.54	237398.57	0	915633
ng coal	13370	15900.248	69108.082	0	413799
ng natgas	13370	31465.945	100346.23	0	596854
ng petroleum	13370	30.723	348.238	0	20760
ng otherfuel	13370	4514.816	12494.922	0	63398
ng hydro	13370	57300.568	67623.918	0	217876
ng solar	13370	967.65	4118.242	0	33445
ng wind	13370	21266.329	51587.526	0	283437

Table 4: EIA Summary Statistics for Washington State (not separated by region)

Summary statistics: N mean sd min max by(year)
year: 2015

	N	mean	sd	min	max
tavg	581	35.848	8.493	19.398	57.355
tmin	581	32.603	7.879	15.048	47.469
tmax	581	45.22	9.915	29.306	69.296
tobs	581	36.483	8.202	20.121	52.741
2016					
tavg	2562	44.267	11.844	13.346	72.073
tmin	2562	39.566	9.731	7.711	58.526
tmax	2562	56.863	14.787	22.852	88.359
tobs	2562	44.393	10.725	14	66.162
2017					
tavg	2555	43.341	14.196	10.806	74.396
tmin	2555	37.805	11.544	7.674	61.358
tmax	2555	55.557	17.269	22.595	91.145
tobs	2555	42.682	12.658	12.65	67.961
2018					
tavg	2555	44.225	12.523	14.955	74.387
tmin	2555	38.963	10.058	10.987	61.228
tmax	2555	56.739	15.279	27.231	91.317
tobs	2555	43.649	11.02	15.817	69.312
2019					
tavg	2555	43.034	12.331	15.532	69.165
tmin	2555	37.89	11.21	10.053	57.827
tmax	2555	55.209	15.113	25.401	86.1
tobs	2555	42.541	11.652	15.594	64.312
2020					
tavg	2562	43.857	12.427	16.028	74.303
tmin	2562	38.651	10.165	14.756	60.905
tmax	2562	56.349	14.953	24.311	91.681
tobs	2562	43.424	11.025	17.869	69.31

Table 5: Summary Statistics of Average Temperature Data in Washington State by Year. (T represents Temperature; avg = average; min = minimum; max= maximum; obs = observed)

Average Washington State Electricity Price

year	mean
2015	7.4
2016	7.68
2017	7.94
2018	8
2019	8.04
2020	8.16

Table 6: Average Electricity Price in Washington State by Year

Washington State GDP Average

year	mean
2015	450691.81
2016	463995.81
2017	489503.83
2018	524547.5
2019	548737.61
2020	544695.98

Table 7: Average Real Gross Domestic Product in Washington State by Year

Summary statistics: CBECI N mean sd min max by year

year: 2015	N	mean	sd	min	max
max	84	4.425	.852	3.402	6.292
min	84	1.33	.256	1.022	1.891
pred	84	2.737	.527	2.104	3.892
2016					
max	366	10.01	1.626	5.955	13.007
min	366	2.085	.728	1.194	3.636
pred	366	5.458	.864	3.683	7.484
2017					
max	364	45.611	28.4	12.862	116.032
min	364	5.363	2.661	2.077	12.389
pred	364	13.308	5.923	6.369	28.292
2018					
max	366	102.215	28.516	47.874	177.546
min	366	18.919	3.177	12.387	25.515
pred	366	41.804	7.329	28.042	55.357
2019					
max	364	112.302	39.642	55.611	195.031
min	364	23.598	6.755	15.552	35.368
pred	364	54.414	14.217	34.314	77.105
2020					
max	366	115.333	29.71	71.073	218.492
min	366	34.332	3.853	23.623	43.116
pred	366	70.398	12.386	46.879	100.667
2021					
max	90	350.577	93.362	223.715	479.451
min	90	40.26	1.574	37.497	43.622
pred	90	120.792	10.498	101.596	139.384

Table 8a: CBECI Summary Statistics by Year. Upper-bound (max), lower-bound (min), and predicted (pred) are the three estimates summarized.

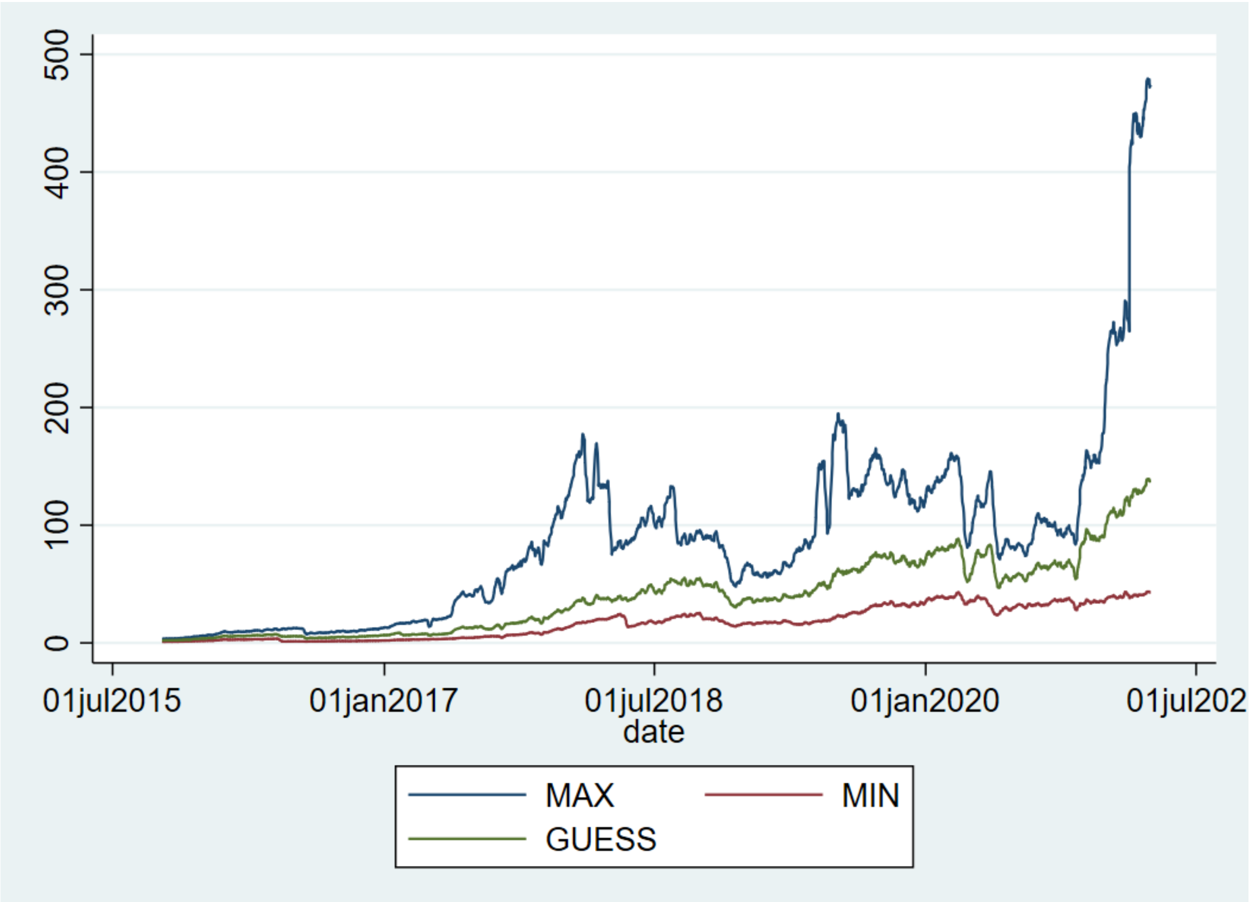

Figure 8b: CBECI Estimates October 2015-April 2020. Upper-bound estimate (MAX), Lower-bound estimate (MIN), and predicted estimate (GUESS).

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
demand mw	1337 0	387009.54	237398.57	0	915633
guess	1337 0	35.573	26.609	2.104	100.667
max	1337 0	73.894	51.84	3.402	218.492
min	1337 0	16.181	12.65	1.022	43.116
tavg	1337 0	43.402	12.646	10.806	74.396
tmin	1337 0	38.316	10.551	7.674	61.358
tmax	1337 0	55.669	15.477	22.595	91.681
eprice	1337	7.939	.194	7.4	8.16

	0				
GDP	1337	511521.77	35921.857	450691.81	557527.63
	0				

Table 10: Summary Statistics for all variables considered in the regressions

	(1) log_demand	(2) log_demand	(3) log_demand
1.ba#c.guess	-0.0143***	-0.0137***	-0.0140***
	(-22.01)	(-13.72)	(-13.74)
2.ba#c.guess	-0.00120	-0.000610	-0.000841
	(-1.84)	(-0.61)	(-0.83)
3.ba#c.guess	0.00356***	0.00420***	0.00397***
	(5.44)	(4.19)	(3.90)
4.ba#c.guess	0.000828	0.00142	0.00119
	(1.27)	(1.41)	(1.17)
5.ba#c.guess	-0.00169**	-0.00110	-0.00133
	(-2.60)	(-1.10)	(-1.31)
6.ba#c.guess	0.00882***	0.00940***	0.00917***
	(13.54)	(9.38)	(9.02)
7.ba#c.guess	-0.000204	0.000384	0.000153
	(-0.31)	(0.38)	(0.15)
1.ba	0	0	0
	(.)	(.)	(.)
2.ba	1.618***	1.618***	1.618***
	(39.54)	(40.49)	(40.52)
3.ba	1.335***	1.332***	1.332***
	(32.51)	(33.21)	(33.23)
4.ba	2.501***	2.501***	2.501***
	(61.12)	(62.60)	(62.64)
5.ba	2.081***	2.081***	2.081***
	(50.87)	(52.10)	(52.13)
6.ba	0.869***	0.869***	0.869***
	(21.24)	(21.76)	(21.77)

7.ba	2.514***	2.514***	2.514***
	(61.45)	(62.94)	(62.98)
Time controls		Yes	Yes
Other controls			Yes
_cons	10.91***	10.79***	11.09***
	(377.23)	(211.26)	(13.14)
N	13357	13357	13357

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
1=AVA 2=CHPD 3=DOPD 4=GCPD 5=PSEI 6=SCL 7=TPWR
Time Controls: Month, Year, Day of Week Dummies
Other Controls: Temperature, GDP, electricity price

Table 11a: Regression Outputs for CBECI prediction estimate on Electricity Demand by Balancing Authority. Control variables included in the regression are listed at the bottom. If included, notated with "Yes".

	(1)	(2)	(3)
	log_demand	log_demand	log_demand
1.ba#c.min	-0.0298***	-0.0265***	-0.0269***
	(-21.74)	(-11.55)	(-11.57)
2.ba#c.min	-0.00231	0.00104	0.000577
	(-1.68)	(0.45)	(0.25)
3.ba#c.min	0.00696***	0.0104***	0.00995***
	(5.05)	(4.54)	(4.27)
4.ba#c.min	0.00147	0.00481*	0.00435
	(1.07)	(2.10)	(1.87)
5.ba#c.min	-0.00368**	-0.000334	-0.000799
	(-2.68)	(-0.15)	(-0.34)
6.ba#c.min	0.0174***	0.0208***	0.0203***
	(12.69)	(9.06)	(8.72)
7.ba#c.min	-0.000449	0.00290	0.00243
	(-0.33)	(1.26)	(1.05)
1.ba	0	0	0
	(.)	(.)	(.)
2.ba	1.640***	1.640***	1.640***
	(41.15)	(42.14)	(42.17)
3.ba	1.377***	1.373***	1.374***

	(34.42)	(35.17)	(35.19)
4.ba	2.534***	2.534***	2.534***
	(63.60)	(65.13)	(65.17)
5.ba	2.108***	2.108***	2.108***
	(52.91)	(54.18)	(54.21)
6.ba	0.928***	0.928***	0.928***
	(23.30)	(23.86)	(23.87)
7.ba	2.542***	2.542***	2.542***
	(63.79)	(65.33)	(65.37)
Time controls		Yes	Yes
Other controls			Yes
_cons	10.89***	10.77***	11.61***
	(386.38)	(213.00)	(13.05)
N	13357	13357	13357

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
1=AVA 2=CHPD 3=DOPD 4=GCPD 5=PSEI 6=SCL 7=TPWR
Time Controls: Month, Year, Day of Week Dummies
Other Controls: Temperature, GDP, electricity price

Table 11b: Regression Outputs for CBECI lower-bound estimate on Electricity Demand by Balancing Authority. Control variables included in the regression are listed at the bottom. If included, notated with "Yes".

	(1) log_demand	(2) log_demand	(3) log_demand
1.ba#c.max	-0.00813***	-0.00866***	-0.00876***
	(-24.31)	(-22.45)	(-22.57)
2.ba#c.max	-0.000413	-0.000952*	-0.00105**
	(-1.24)	(-2.47)	(-2.70)
3.ba#c.max	0.00183***	0.00133***	0.00124**
	(5.46)	(3.44)	(3.18)
4.ba#c.max	0.000434	-0.000104	-0.000198
	(1.30)	(-0.27)	(-0.51)
5.ba#c.max	-0.000469	-0.00101**	-0.00110**
	(-1.40)	(-2.61)	(-2.84)
6.ba#c.max	0.00306***	0.00253***	0.00243***
	(9.17)	(6.55)	(6.27)

7.ba#c.max	-0.0000558	-0.000594	-0.000688
	(-0.17)	(-1.54)	(-1.77)
1.ba	0	0	0
	(.)	(.)	(.)
2.ba	1.515***	1.515***	1.515***
	(35.51)	(36.38)	(36.40)
3.ba	1.236***	1.231***	1.232***
	(28.83)	(29.43)	(29.46)
4.ba	2.408***	2.408***	2.408***
	(56.42)	(57.81)	(57.85)
5.ba	1.965***	1.965***	1.965***
	(46.06)	(47.18)	(47.22)
6.ba	0.866***	0.866***	0.866***
	(20.29)	(20.79)	(20.80)
7.ba	2.421***	2.421***	2.421***
	(56.73)	(58.12)	(58.16)
Time controls		Yes	Yes
Other controls			Yes
_cons	11.00***	10.85***	10.23***
	(364.70)	(212.26)	(14.23)
N	13357	13357	13357

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
1=AVA 2=CHPD 3=DOPD 4=GCPD 5=PSEI 6=SCL 7=TPWR
Time Controls: Month, Year, Day of Week Dummies
Other Controls: Temperature, GDP, electricity price

Table 11c: Regression Outputs for CBECI upper-bound estimate on Electricity Demand by Balancing Authority. Control variables included in the regression are listed at the bottom. If included, notated with "Yes".

	(1) log_demand	(2) log_demand	(3) log_demand
guess	0.000392***	0.000532**	-0.000598***
	(5.35)	(3.25)	(-3.98)
tavg		0.00213***	0.000988***
		(13.34)	(7.61)
tmin		-0.000918***	-0.00114***

	(1)	(2)	(3)
		(-10.14)	(-17.83)
tmax		-0.00116***	-0.000408***
		(-10.66)	(-4.02)
eprice		-0.0239***	0.0297***
		(-8.59)	(7.59)
GDP		9.68e-08***	-0.000000187***
		(4.65)	(-7.24)
Time controls			Yes
_cons	14.79***	15.82***	14.04***
	(4553.65)	(125.66)	(91.93)
N	1910	1910	1910

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Time Controls: Month, Year, Day of Week Dummies

Table 12a: Regression Outputs for CBECI prediction estimate on Electricity Demand in Washington State.

	(1) log_demand	(2) log_demand	(3) log_demand
min	0.000694***	0.000645*	-0.00119***
	(4.50)	(2.00)	(-3.34)
tavg		0.00212***	0.000998***
		(13.26)	(7.68)
tmin		-0.000904***	-0.00114***
		(-9.98)	(-17.93)
tmax		-0.00116***	-0.000413***
		(-10.65)	(-4.06)
eprice		-0.0240***	0.0296***
		(-8.51)	(7.39)
GDP		0.000000119***	-0.000000190***
		(6.15)	(-7.34)
Time controls			Yes

_cons	14.80***	15.75***	14.06***
	(4673.06)	(123.54)	(87.35)
N	1910	1910	1910

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Time Controls: Month, Year, Day of Week Dummies

Table 12b: Regression Outputs for CBECI lower-bound estimate on Electricity Demand in Washington State.

	(1) log_demand	(2) log_demand	(3) log_demand
max	0.000144***	0.0000280	-0.000263***
	(3.81)	(0.43)	(-5.99)
tavg		0.00210***	0.000947***
		(13.15)	(7.32)
tmin		-0.000898***	-0.00111***
		(-9.88)	(-17.34)
tmax		-0.00115***	-0.000386***
		(-10.56)	(-3.81)
eprice		-0.0232***	0.0276***
		(-8.29)	(7.50)
GDP		0.000000140***	-0.000000189***
		(7.76)	(-7.45)
Time controls			Yes
_cons	14.80***	15.65***	14.16***
	(4351.08)	(130.11)	(109.40)
N	1910	1910	1910

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Time Controls: Month, Year, Day of Week Dummies

Table 12c: Regression Outputs for CBECI upper-bound estimate on Electricity Demand in Washington State.

	(1)	(2)	(3)
	log_demand	log_demand	log_demand
guess	0.000392***	0.000532**	-0.000598***
	(5.35)	(3.25)	(-3.98)
min	0.000694***	0.000645*	-0.00119***
	(4.50)	(2.00)	(-3.34)
max	0.000144***	0.0000280	-0.000263***
	(3.81)	(0.43)	(-5.99)
Temperature And Economic controls		Yes	Yes
Time controls			Yes
N	1910	1910	1910

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Time Controls: Month, Year, Day of Week Dummies

Table 12d: Summary Regression Outputs for CBECI on Electricity Demand in Washington State.