The Carbon Footprint of Bitcoin

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Abstract
Blockchain began with Bitcoin, which was the first successful attempt to validate transactions via a decentralized data protocol. Participation in its validation process requires specialized hardware and vast amounts of electricity, which translate into a significant carbon footprint. Here we demonstrate a methodology for estimating the power consumption associated with Bitcoin’s blockchain based on IPO filings of major hardware manufacturers, insights on mining facility operations, and mining pool compositions. We then translate our power consumption estimate into carbon emissions, using the localization of IP addresses. We determine the annual electricity consumption of Bitcoin, as of November 2018, to be 48.2 TWh, and estimate that annual carbon emissions range from 21.5 to 53.6 MtCO₂. The means that the level of emissions produced by Bitcoin sits between the levels produced by the nations of Bolivia and Portugal. With this article, we aim to gauge the external costs of Bitcoin, and inform the broader debate on the costs and benefits of cryptocurrencies. The externalities we discuss here may help policy-makers in setting the right rules as the adoption journey of blockchain has just started.

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Introduction

In 2008, Satoshi, the pseudonymous founder of Bitcoin, published a vision of a digital currency which, only a decade later, reached a peak market capitalization of over $800 billion. The revolutionary element of Bitcoin was not the idea of a digital currency in itself, but the underlying blockchain technology. Instead of a trusted third party, incentivized network participants validate transactions and ensure the integrity of the network via the decentralized administration of a data protocol. The distributed ledger protocol created by Satoshi has since been referred to as the ‘first blockchain’.

Bitcoin’s blockchain uses a Proof-of-Work consensus mechanism to avoid double-spending and manipulation. The validation of ownership and transactions is based on search puzzles of hash-functions, as first introduced by a spam-protection mechanism called Hashcash. These search puzzles have to be solved by network participants in order to add valid blocks to the chain. The difficulty of these puzzles adjusts regularly in order to account for changes in connected computing power and to maintain approximately ten minutes between the addition of each block.

During 2018, the computing power required to solve a Bitcoin puzzle increased more than threefold, and heightened electricity consumption accordingly. Speculations about the Bitcoin network’s source of fuel have suggested, among other things, Chinese coal, Icelandic geothermal power, and Venezuelan subsidies. In order to keep global warming below 2°C – as internationally agreed in Paris COP21 – net-zero carbon emissions during the second half of the century are crucial. To take the right measures, policy makers need to understand the carbon footprint of cryptocurrencies.

We present a techno-economic model for determining electricity consumption in order to provide an accurate estimate of the carbon footprint of Bitcoin. Firstly, we narrow down the power consumption, based on mining hardware, facilities, and pools. Secondly, we develop three scenarios representing the geographic footprint of Bitcoin mining, based on pool server IP, miners’ IP, and device IP addresses. Thirdly, we calculate the carbon footprint, based on the regional carbon intensity of electricity consumption.

In comparison to previous work, our analysis is based on empirical insides. We use hardware data derived from recent IPO filings, which are key to a reliable estimate of power consumption as the
efficiency of the hardware in use is an essential parameter in this calculation. Furthermore, we include assumptions about auxiliary factors which determine the power usage effectiveness (PUE). Losses from cooling and IT-equipment have a significant impact, but have been largely neglected in prior studies. Besides estimating the total power consumption, we determine the geographical footprint of mining activity based on IP addresses. This geographical footprint allows for more accurate estimation of carbon emissions compared to earlier work.

Previous academic studies, such as predictions of future carbon emissions, or comparisons of cryptocurrency and metal mining, are based on vague estimates of power consumption, and lack empirical foundations. Consequently, the estimates produced vary significantly among studies, as listed in Table 1.

<table>
<thead>
<tr>
<th>Study</th>
<th>Power consumption [MW]</th>
<th>Carbon emissions [Mt CO₂]</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>2017</td>
<td>2018</td>
</tr>
<tr>
<td>Vranken</td>
<td>100-500</td>
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<tr>
<td>Bevand</td>
<td>470-540</td>
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<td>Mora</td>
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<td>Foteinis</td>
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<tr>
<td>De Vries</td>
<td>2,550^b</td>
<td>3,441^c</td>
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<tr>
<td>Krause</td>
<td>948</td>
<td>12,080^d</td>
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<tr>
<td>McCook</td>
<td></td>
<td>7,744^e</td>
</tr>
<tr>
<td>Digiconomist</td>
<td>364-1,727^a</td>
<td>5,501^f</td>
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</tbody>
</table>

Table 1 | Power consumption and carbon emission estimates in previous studies. a. power consumption range in 2017, b. power consumption as of 03/2018, c. as of 06/2018, d. as of 07/2018, e. as of 11/2018, f. as of 11/2018, g. as of 2017, h. 02/2018 including Ethereum, i. as of 11/30/2018, j. lower and upper limit of minimal and maximal marginal life-cycle carbon emissions factors, based on best-guess power consumption.

We show that, as of November 2018, the annual electricity consumption of Bitcoin ranges between 35.0 TWh and 72.7 TWh, with a realistic magnitude of 48.2 TWh. We further calculate that the resulting annual carbon emissions range between 21.5 and 53.6 MtCO₂; a ratio which sits between the levels produced by Bolivia and Portugal. The magnitude of these carbon emissions, combined with the risk of collusion and concerns about control over the monetary system, might justify regulatory intervention to protect individuals from themselves and others from their actions.
Mining hardware

Bitcoin prices for 2017 chart a curve shaped like an upturned hockey stick, and boosted the investment made by network participants in mining hardware. First-generation miners used central processing units (CPU) in conventional personal computers with computing power of less than 0.01 gigahashes per second (GH/s). Over time, miners switched to graphic processing units (GPU), with 0.2-2 GH/s in 2010 and, starting in 2011, moved to field-programmable gate arrays (FPGA) with 0.1-25 GH/s. Since 2012, application-specific integrated circuit (ASIC) devices, with up to 18,000 GH/s have prevailed. Figure 1 charts the market price, network hash rate, and resulting profitability threshold, where miners’ income equals cost. Comparing this profitability threshold to the efficiencies of ASIC models shows that only ASICs operate profitably nowadays.

![Market Price vs. Hash Rate vs. Profitable Efficiency](image)

**Fig. 1 | Bitcoin market price [BTC/USD], network hash rate [PH/s], profitable efficiency [J/GH] and hardware efficiencies of ASICs released by major producers [J/GH].** Hash rate and market price were retrieved from Blockchain.com (https://www.blockchain.com/charts). Calculations of the profitable hardware efficiency are reported in Supplementary Notes Sheet 3.6. We assume an average electricity price of USD 0.05/kWh as argued in previous estimates. A detailed overview of ASIC models released can be found in Supplementary Notes Sheet 4.1.

From IPO filings disclosed in 2018, we determine the distribution of market share held by the three major ASIC producers; Bitmain, Canaan, and Ebang. The hardware in use and its efficiency are key to a reliable estimate of power consumption. Based on the IPO filings, we conclude that, as of November 2018, Bitmain’s hardware provides 76% of the network’s computing power, and the hardware of each of Canaan and Ebang provides 12% (see Supplementary Notes Sheet 3.4).
Mining facilities

There is no typical size of cryptocurrency mining operations, but a wide scale ranging from students who do not pay for their electricity (some of whom applied to support this research),23 to gamers who leverage their graphics cards whenever they are not playing (as reflected in Nvidia’s volatile sales allocated to crypto),24 all the way up to dedicated, large-scale crypto-mining farms (for instance, in abandoned olivine mines in Norway).25

Depending on the scale of mining operation, auxiliary efficiency losses may occur in addition to hardware losses. The two main categories of auxiliary losses are cooling and IT-equipment. We classify miners into three groups according to the scale of their operation: small (S) miners provide less than 0.1 PH/s (equal to seven of the most efficient ASICs), medium (M) miners provide less than 10 PH/s, and large (L) miners provide more than 10 PH/s. This classification is based on our personal communications with miners.

For large-scale miners, we use the power usage effectiveness (PUE) of Google’s most efficient data center of 1.09.26 For medium-scale miners, we use a PUE of 1.15, based on personal communication with mining companies in Germany. For small-scale miners, we assume a moderate efficiency of 1.12, as higher losses from dust and cable inefficiencies are more than offset by the lack of a need for cooling.

We determine the distribution among these three categories using Slushpool data, displayed in Figure 2. Slushpool is a mining pool with an 11% market share, which provides live statistics on the computing power of connected users.27 By assuming that distribution is the same in the rest of the network, we determine that 8% are small, 27% are medium, and 65% are large-scale miners, resulting in an overall PUE of 1.11 (see Supplementary Notes Sheet 2 for a sensitivity analysis of this assumption).
Fig. 2 | Hash rate distribution of Slushpool grouped by individual miners' computing power. Data generated in web scrawling of Slushpool pool statistics (https://slushpool.com/stats/?c=btc), ten-minute intervals reported in Supplementary Notes Sheet 3.7.

Mining pools

Miners combine their computing power and share the block rewards and transaction fees in order to reduce the time and variance of finding a new block. Back in 2011, a miner with an up-to-date GPU (2 GH/s) could expect to find a block roughly once a month. In November 2018, due to the increasing difficulty, the same miner could expect to find a block every 472,331 years. Even today’s most powerful ASIC (18,000 GH/s) yields an expected discovery rate of one block every 52 years.

The average time it takes to find a new block depends on the network’s current level of difficulty and computing power of the hardware in use. As of November 2018, the difficulty was 6,936,230,051,963. As each block has about $2^{32}$ hashes, and one block is solved every 10 minutes, the network’s hash rate was 49,651,468 TH/s (6,936,230,051,963 x $2^{32}$ H / 600 seconds).

Solving a block is rewarded with new Bitcoins and the fees of all newly-included transactions. The reward per block in new Bitcoins started at 50 for the first blocks and halves every 210,000 blocks. At the current number of blocks in November 2018 (552,100), the block reward equals 12.5 BTC per block and as a result, 1,800 (=12.5 x 24h x 6/h) new Bitcoins are currently mined every day. As the time to solve one block remains constant and the reward continues to halve, the last of about 21 million Bitcoins will be mined in 121 years from now.
Nowadays, nearly all network participants are organized in public pools or self-organized private pools. Thereby, more than two-thirds of the current computing power is grouped by Chinese pools, followed by the 11% of pools registered in the EU, as depicted in the chart in Figure 3.

**Fig. 3 | Hash rate distribution among mining pools as of November 2018.** Data pulled from btc.com (https://btc.com/stats/pool?percent_mode=latest#pool-history) and reported in Supplementary Notes Sheet 4.2.
**Power consumption**

We narrow down the solution range by calculating a lower and an upper limit prior to estimating a realistic level of electricity consumption by Bitcoin. The lower limit is defined by a scenario in which all miners use the most efficient hardware. The upper limit is defined as the break-even point of mining revenues and electricity costs. Figure 4 charts the range including our best-guess estimate, which follows the approach of the lower limit, but includes the anticipated energy efficiency of the network, based on hardware sales and auxiliary losses (see Methods for details).

![Electricity load [MW]](image)

**Fig. 4 | Power consumption corridor.** Values are charted at daily intervals. Data are reported in Supplementary Notes Sheet 3.2-3.3. Sensitivities are shown in Supplementary Notes Sheet 2.

Figure 4 shows that the upper limit of power consumption is more volatile as it follows the market price of Bitcoin. The lower limit is more stable as it is defined by hardware efficiency and hash rate. We estimate a power consumption of 364 MW at the end of 2016, 1,727 MW at the end of 2017, and 5,501 MW in November 2018, based on auxiliary losses and ASIC sales.
Mining locations

Below, we develop three scenarios examining the regional footprint of Bitcoin, which are based on the localization of pool IP, miners’ IP, and device IP addresses. Some miners may use services like TOR or VPN to disguise their locations, for instance, for legal reasons. However, as a good overall network connection increases the probability of having a new block accepted in the network, it is generally advantageous to propagate blocks through the fastest connection.

Based on analyzing pool IPs on BTC.com and Slushpool, we find evidence that miners tend to allocate their computing power to local pools. With 17% of total hash power, BTC.com is the largest mining pool administrated in China. Slushpool is its European analogue with 11%. In both pools, regional miners comprise the vast majority of participants. U.S-based miners tend to join the European pool as the operation of mining pools is prohibited inside the U.S. Combining these insights from pool server IPs with pool shares in terms of their regional origin, we determine that there is 68% Asian, 17% European, and 15% North American computing power in the network (see Supplementary Notes Sheet 4.5).

Based on Miner IPs, we find a stronger U.S. presence. The full nodes and miners in the network communicate via a loosely connected P2P-network. Information (such as new transactions or blocks) are sent to connected peers via a gossip-protocol, reaching all nodes in a timely manner. Therefore, we monitor the origins of new blocks by connecting to all nodes, which are publicly available. We detect different patterns in the data: In some cases, single IP-addresses are responsible for many blocks, while, in other cases, many addresses are only responsible for a small portion of blocks. As for the location of our server, our data set is biased towards the U.S., as over 95% of the mined blocks are on U.S. soil. If we assume a share of 15% for U.S.-based mining devices, we find 34% of all blocks originate from Asia, 24% from Europe, and 24% from Canada, while the rest of the world (South America, Africa, and Australia) are each responsible for less than 1% of the blocks created. Uncertainties are introduced by the server location, the decentralized nature of the network, and the resolution from IP addresses to location by ipinfo.io. Figure 5 displays the origins of blocks on a world map.
Based on Device IPs, we can confirm the U.S. concentration. We identify the location of ASICs via the IoT-search engine Shodan. By searching for connected ASICs, we can view the distribution on a national level. We are able to localize 2,260 ASICs of Bitmain, and the query results support the U.S.-concentration (19%). Venezuela (16%), Russia (11%), Korea (7%), Ukraine (5%), and China (4%) appear next on the list, and Figure 6 charts all the locations of internet nodes with connected Antminers.

Comparing Bitmain’s eleven mining farms in China – which total about 300 MW capacity – to our estimated total network load of more than 6 GW leaves enough space for the unexpected North America concentration. Bitmain’s current construction projects in Texas, Tennessee, Washington State, and Quebec support these findings.
Carbon footprint

We calculate Bitcoin’s carbon footprint based on its total power consumption and geographic footprint. To determine the amount of carbon emitted in each country, we multiply the power consumption by average and marginal emission factors of power generation. Average emission factors represent the carbon intensity of the power generation resource mix, while marginal emission factors account for the carbon intensity of incremental load change.

Unless there is excess zero-carbon power capacity, even the skimming of renewable electricity leads to shortages in surrounding grid areas. These shortages are generally covered by fossil fuel resources. Therefore, we assume that the additional load caused by Bitcoin mining has to be covered by the additional consumption of fossil fuels such as coal or natural gas. Due to uncertainty about which resource technology is covering the additional load accredited to Bitcoin, we estimate a range by using gas as minimal and coal as maximal marginal emission factors.

We assume the hardware runs continuously throughout the year. A comparison of break-even electricity prices for ASIC models shows that this assumption is valid for most fixed retail tariff rates and especially for regions with high mining activity (see Supplementary Notes Sheet 3.5). The steadiness of hash rate distribution in Figure 2 supports this assumption. Therefore, we do not consider potential additional sources of revenue from price volatility in the wholesale market or from the provision of load-balancing services. Figure 7 shows our estimates of carbon emissions for the Bitcoin network in the aforementioned scenarios.

![Figure 7 | Global carbon emissions from Bitcoin mining](image)

Carbon emission factors from IEA\(^3\)0 are listed in Supplementary Notes Sheet 4.4. Calculation of the three scenarios can be found in Sheet 3.1.
Social cost and benefit

Our approximation of Bitcoin’s carbon footprint underlines the need to tackle the environmental externalities that result from cryptocurrencies,\textsuperscript{31} and highlights the necessity of cost/benefit trade-offs for blockchain applications in general. We do not question the efficiency gains that blockchain technology could, in certain cases, provide. However, the current debate is focused on anticipated benefits, and more attention needs to be given to costs. For cryptocurrencies with proof-of-work protocols, policy-makers should not ignore the following aspects:

*Carbon.* As global electricity prices do not reflect the future damage caused by today’s emissions, economic theory calls for government intervention to correct this market failure in order to enhance social welfare. The issue of the social cost of carbon is of course not specific to cryptocurrency. Nonetheless, regulating this gambling-driven source of carbon emissions appears to be a simple means to decarbonize the economy.\textsuperscript{32}

*Concentration.* The case of Bitcoin shows that the risk of concentration must not be ignored. Irrespective of the decentralized nature of Bitcoin’s blockchain, the four largest Chinese pools now provide more than 50\% of the total hash rate, and Bitmain operates three of these four pools. If one player controls the majority of computing power, it could start reversing new transactions, double-spend coins, and systematically destroy trust in the cryptocurrency.

*Control.* With his idea, Satoshi intended for Bitcoin to increase privacy and reduce dependency on trusted third parties.\textsuperscript{2} However, protecting individuals from themselves and others from their actions might justify the downsides of central control, as the potential benefit of anonymity spurs illegal conduct such as buying drugs, weapons, or child pornography. Therefore, a use-case specific degree of central governance is essential. Today, most intermediate parties serve useful functions, and a decentralized socio-economic construct like blockchain should only replace them if it can ensure the same functionality.
Beyond Bitcoin

Bitcoin’s power consumption may only be the tip of the iceberg. Including estimates for three other cryptocurrencies adds 30 TWh to our annual estimate for Bitcoin alone.\textsuperscript{33,34} If we assume correlation to market capitalization, and only consider mineable currencies (unlike second layer tokens or coins with other consensus mechanisms), the remaining 618 currencies could potentially add a power demand over 40 TWh.\textsuperscript{1} This than nearly triples the power consumption we estimate for Bitcoin.

While other blockchain platforms (e.g., the second largest cryptocurrency, Ethereum) work on switching protocols from Proof-of-Work to other, less energy-consuming consensus mechanisms, such as Proof-of-Stake, it is likely that Bitcoin will continue to use the established algorithm. Miners, who have a large influence on the development of Bitcoin, are not interested in removing the algorithm, which is central to their own business. Therefore, it is likely that Bitcoin will remain the largest energy consumer among public blockchain systems.

Besides cryptocurrencies, there are other uses for blockchain. Bitcoin has managed to establish a global, decentralized monetary system, but fails as a general purpose blockchain platform. For instance, Smart Contracts are seen to disrupt traditional business models in finance, trade, and logistics. Like many earlier disruptive technologies, blockchain is merely the foundation and enabler of novel applications.\textsuperscript{35} Alternative protocols will help to reduce the power requirements of future blockchain applications. Notwithstanding, our findings for the first stage of blockchain diffusion underline the need for further research on externalities, in order to support policy-makers in setting the right rules for the adoption of these technologies.
References


Methods

This section provides the methodology for calculating the range of power consumption, and the approach to derive a best-guess estimate.

(1) Lower limit

The lower limit is defined by a scenario in which all miners use the most efficient hardware. We calculate the lower limit of the range by multiplying the required computing power – indicated by the hash rate – by the energy efficiency of the most efficient hardware:

\[ E_{LL} = H \times e_{ef}, \] (1)

with:
- \( H = \text{hash rate [H/s]} \)
- \( e_{ef} = \text{energy efficiency of most efficient hardware [J/H]} \)

(2) Upper limit

The upper limit is defined by the break-even point of revenues and electricity cost. Rational behavior would lead miners to disconnect their hardware from the network as soon as their costs exceed their revenues from mining and validation.

\[ E_{UL} = \frac{(R_B + R_T) \times M}{P_N} \times \frac{1}{t}, \] (2)

with:
- \( R_B = \text{block reward [BTC]} \)
- \( R_T = \text{transaction fees [BTC]} \)
- \( M = \text{market price [USD/BTC]} \)
- \( P_N = \text{electricity price [USD/kWh]} \)
- \( t = \text{time period [h]} \)

(3) Best-guess

The best-guess estimate follows the approach of the lower limit, but includes the anticipated energy efficiency of the network, as well as further losses from cooling and IT components.

\[ E_{BG} = H \times e_N \times PUE_N, \] (3)
The realistic energy efficiency of the network can be determined using the market shares of ASIC producers and the energy efficiency of the hardware in operation.

\[ e_N = \left[ \sum_{i=1}^{n} S_{API} \times e_{API} \right] + \left[ 1 - (\sum_{i=1}^{n} S_{API}) \right] \times e_P, \]  

(4)

with

- \( i = ASIC \) Producer \((1, ..., n)\)
- \( e_N = \) realistic energy efficiency of hardware \([J/H]\)
- \( S_{API} = \) share of ASIC producer \( i \) [%]
- \( e_{API} = \) energy efficiency of ASIC producer \( i \) \([J/H]\)
- \( e_P = \) energy efficiency for zero profit \([J/H]\)

If some of the computing power cannot be assigned to one of the major ASIC producers, we assume this computing power originates from hardware, which generates zero profit. By equalizing \( E_{UB} \) and \( E_{RM} \), we derive

\[ e_P = \frac{(R_B + R_T) \times M}{P_N \times H \times PUE_N} \times \frac{1}{t}. \]  

(5)

In terms of the average losses from cooling and equipment, we differentiate between three types of mining facilities according to size, and weight them by their share in terms of computing power

\[ PUE_N = S_S \times PUE_S + S_M \times PUE_M + S_L \times PUE_L. \]

- \( j = \) facility type \((Small, Medium, Large)\)
- \( S_j = \) share of facility type \( j \) [%]
- \( PUE_j = \) losses from cooling and IT equipment of facility type \( j \) [%]

The resulting carbon footprint of the Bitcoin network depends on the carbon intensity \( I_N \) of the power mix:

\[ F = E \times I_N. \]

In order to incorporate local differences in the carbon intensity of the power mix, we differentiate among regions and weight them by computing power share:

\[ I_N = \sum_{i=Reg}^{n} S_{Reg \_i} \times I_{Reg \_i} + \cdots + S_{Reg \_n} \times I_{Reg \_n}. \]
Data availability

All data used in this analysis are included in the Supplementary Notes file [Link when published], or publicly available online under the noted sources.

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Author contributions

C.S. conceived of the study. All authors contributed to the design of the study and data acquisition. L.K. and C.S. aggregated and analyzed the data. C.S. drafted the manuscript. L.K. and U.G. reviewed several drafts, made substantial revisions, and provided additions.

Competing interests

The authors declare no competing financial or non-financial interests.
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