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# Implausible projections overestimate near-term Bitcoin $CO_2$ emissions

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**Author contributions**

All authors contributed equally to the conception and design of this critique, and to the preparation and review of the manuscript. Masanet, Shehabi, Lei, and Vranken led the analytical components of this critique.

**Competing interests**

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

**Data availability**

The authors declare that all data supporting the findings of this critique are available within the article, its Supplementary Information file and at https://github.com/emasanet/Bitcoin-analysis.

Bitcoin mining is becoming an increasingly energy-intensive process[1,2,3] whose future implications for energy use and $CO_2$ emissions remain poorly understood. This is in part because—like many IT systems—its computational efficiencies and service demands have been evolving rapidly. Therefore, scenario analyses that explore these implications can fill pressing knowledge gaps, but they must be approached with care. History has shown that poorly constructed scenarios of future IT energy use—often due to overly-simplistic extrapolations of early rapid growth trends—can do more harm than good by spreading misinformation and driving ill-informed decisions.[4,5,6] Indeed, the utility of an energy demand scenario is directly proportional to its credibility, which is typically demonstrated through careful attention to technology characteristics and evolution, analytical rigor and transparency, and designing scenarios that align with plausible future outcomes.

Regrettably, the Bitcoin $CO_2$ emissions scenarios presented in the recent Mora et al. article[7] lack such credibility and should not be taken seriously by the research and policy communities. We arrived at this conclusion by replicating in detail Mora et al.'s methods, which revealed numerous flaws in the design and execution of their analysis as documented in the Supplementary Information. We describe the five most significant issues below.

First, the use of transactions as the driver of future Bitcoin emissions is questionable, given the tenuous correlation between transactions and mining energy use. It is well established that energy use is driven by the computational difficulty of blocks mined[1-3], whereas the number of transactions per block has no effect on block mining difficulty. Indeed, the authors themselves calculate 2017 Bitcoin energy use and emissions based on block difficulty, not number of transactions (Supplementary Eq. 1). Without explanation or justification, the authors switch to transactions as the driver for projecting emissions in all future years, undermining the consistency of their calculations and the integrity of their projections.

Second, all three Bitcoin adoption scenarios designed by Mora et al. represent sudden and highly improbable departures from historical trends in Bitcoin transactions, whose annual growth ranged from 1.3x-2.3x over the preceding five years.[8] Specifically, Mora et al. assume that Bitcoin transactions—which totaled 104 million in 2017, representing a mere 0.03% of global cashless transactions—would abruptly leap to 78 billion by 2019 in the fast scenario (a 750x increase in only 2 years), to 11 billion by 2020 in the median scenario (a 108x increase), and to 8 billion by 2023 in the slow scenario (a 76x increase). All three adoption scenarios follow steep logarithmic growth trajectories thereafter, which are conspicuously inconsistent with historical trends (Supplementary Fig 4), and which mathematically can only lead to large near-term emissions increases. The authors base their scenarios on adoption rates of 40 “broadly used” technologies whose social utilities vary widely and bear little resemblance to that of Bitcoin. The authors never explain why such comparisons are valid, nor do they justify the plausibility of the very abrupt changes in Bitcoin transaction levels and growth trajectories associated with their resulting scenarios. Hence, these scenarios should not be taken seriously.

Third, Mora et al. applied outdated values for mining rig efficiencies and electric power carbon intensities, which inflated their estimated 2017 Bitcoin energy use and $CO_2$ emissions values considerably. When estimating the direct electricity use of Bitcoin mining, the authors erroneously included many old and inefficient rigs in their selection pool that were no longer economically viable in 2017 (Supplementary Fig 5), betraying a lack of understanding of current mining equipment and economics. Furthermore, Mora et al provided equal weighting when selecting a rig from their pool as the sole rig type to mine a block, thus over-representing slower inefficient rigs and creating scenarios that require physically impossible rig counts. When we excluded unprofitable rigs in our replicated analysis, Mora et al.’s model produced an estimate of 28 TWh in 2017 (Supplementary Fig 6), which is one fourth of their original estimate of 114 TWh. Furthermore, they applied 2014 carbon intensities (g $CO_2$/kWh) to calculate 2017 emissions, ignoring non-negligible grid decarbonization improvements in the intervening years (Supplementary Fig 7),[9] even though sufficient data existed at the time of their study for reasonable estimates of 2017 carbon intensities.[10,11] Applying more reasonable 2017 electricity use and carbon intensity values in their model produced an estimate of 15.7 $MtCO_2e$, far lower than their original estimate of 69 $MtCO_2e$.

Fourth, by analytical design, Mora et al. applied 2017 per-transaction energy use and $CO_2$ emissions values in all future years, multiplied by annual transactions (Supplementary Eq 2). This decision effectively held both mining rig efficiency and grid carbon intensities constant for the next 100 years (Supplementary Fig 7). This dubious choice ignores the dynamic natures of mining rig and power grid technologies and violates the widely-followed practice of accounting for technological change in forward-looking energy technology scenarios. In acknowledging their static grid intensity assumption, they point to at least one reference containing credible grid intensity outlooks[10] but failed to utilize them. Estimating the future energy efficiency of mining is certainly difficult, but the authors never explain why they simply ignored this important scenario consideration, nor do they justify how assuming static mining efficiency for 100 years—when mining rigs have evolved monthly[1]— can lead to any useful insights.

Fifth, in constructing their slow, median, and fast adoption scenarios, Mora et al. committed key errors when analyzing adoption rates within their 40-product comparison pool.[12] Namely, when replicating their analysis, we discovered that, for many comparison products, they designated the first available data point as the first year of product usage. For example, the authors designate the first year of usage for electric power as 1908, at which point U.S. household adoption had climbed to 10% (Mora et al. Fig. 1b). Yet Thomas Edison began offering electric power to (far fewer) U.S. households in Manhattan in 1882, over two decades earlier.[13] By omitting the initial low-adoption years of US market availability for numerous technologies, their scenarios were biased toward inaccurately steep near-term adoption trajectories in all three cases. When we replicated their analysis using more reasonable estimates of the first year of technology usage, their own methods produced slower adoption curves, particularly in the median and slow growth scenarios (Supplementary Fig 8).

To assess how these last three analytical flaws affected Mora et al.'s projections, we replicated their original scenario analysis (Fig 1a), and then applied reasonable corrections in stepwise fashion. We first applied the 2017 per-transaction Bitcoin carbon intensity we obtained by excluding unprofitable rigs (Fig 1b). We then utilized weighted-average grid intensities based on mining locations assumed by the authors, including grid intensity evolution based on IEA outlooks that reflect current and announced national power policies in mining locations (Supplementary Fig 7) (Fig 1c). Finally, we applied our calculated adoption curves in all three scenarios (Fig 1d).

The results show that, had the authors avoided the key errors we described above, their own study design would have yielded much different, and far less alarming, projections of future Bitcoin carbon emissions. That said, we find the study design itself sufficiently flawed—e.g., use of transactions as driver, comparisons to 40 unrelated technologies, ignoring rig evolution—that such corrections alone are not enough to salvage the authors' approach. On these bases, we argue that the Mora et al. scenarios are fundamentally flawed and should not be taken seriously by researchers, policymakers, or the public.

Given the highly dynamic and unpredictable nature of Bitcoin markets and mining demand—e.g., Bitcoin transactions and exchange values dropped steeply in 2018—developing credible scenarios of cryptocurrency emissions remains an important challenge for the research community. While Mora et al. likely had the right motivations, to be useful, such scenarios must be approached with more rigor and greater analytical care.

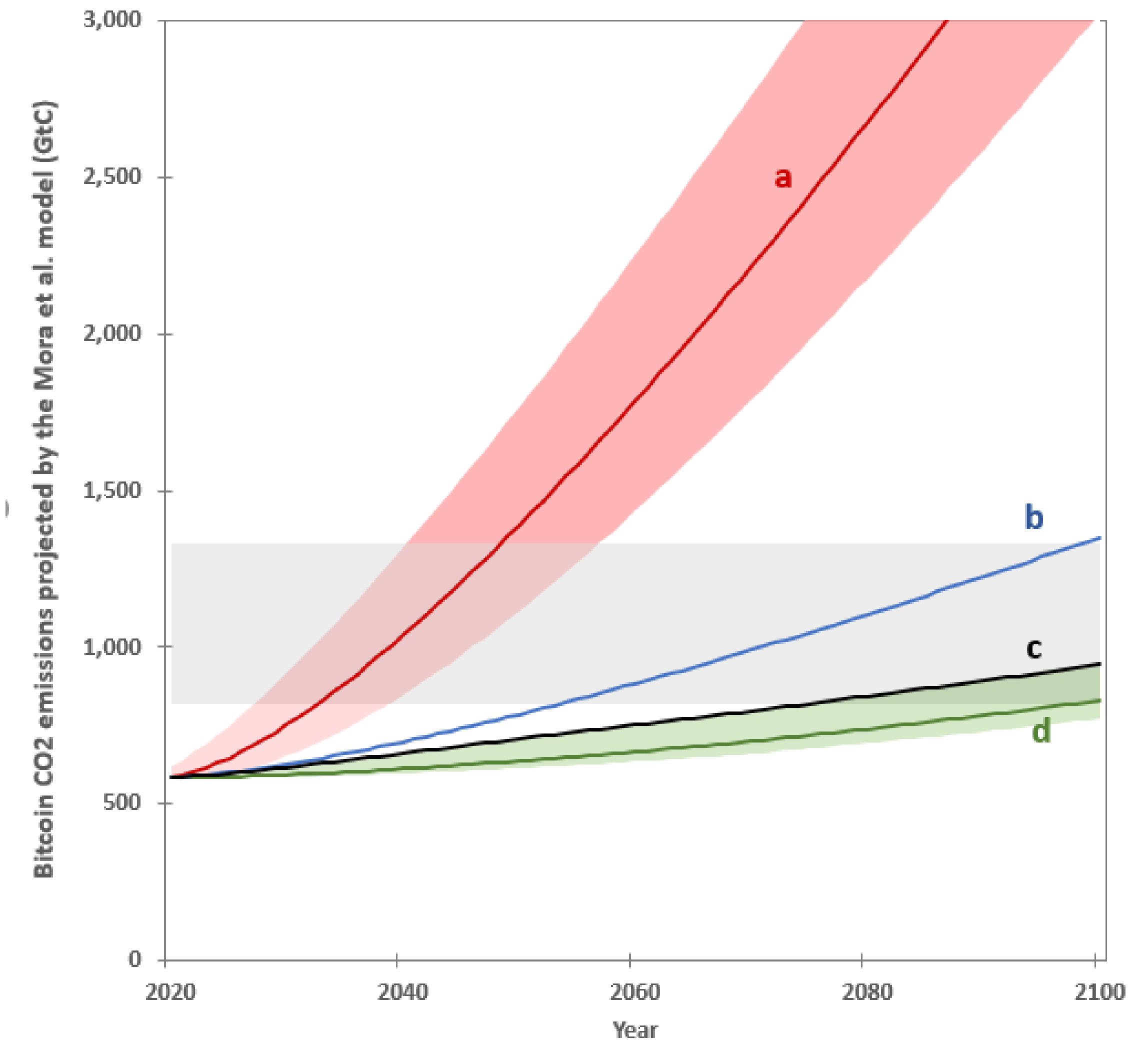


**Figure 1: Comparison of Bitcoin $CO_2$ emissions projected by the Mora et al. model: (a) our replicated analysis showing close agreement with the authors' results; and the model's projections after first (b) removing unprofitable rigs in the base year (median scenario only), then (c) accounting for evolution of the electric power grid in mining locations (median scenario only), and finally (d) correcting errors in their stated adoption scenario approach.**

**References**

[1] Vranken, H. Sustainability of bitcoin and blockchains. Current Opinion in Environmental Sustainability 28, 1-9, doi:https://doi.org/10.1016/j.cosust.2017.04.011 (2017).

[2] Krause, M. J. & Tolaymat, T. Quantification of energy and carbon costs for mining cryptocurrencies. Nature Sustainability 1, 711-718, doi:10.1038/s41893-018-0152-7 (2018).

[3] Bevand, M. Op Ed: Bitcoin Miners Consume A Reasonable Amount of Energy — And It's All Worth It, <https://bitcoinmagazine.com/articles/op-ed-bitcoin-miners-consumereasonable- amount-energy-and-its-all-worth-it/> (2017).

[4] Koomey, Jonathan G, Chris  Calwell, John A Laitner, Jane  Thornton, Richard E Brown, Joseph H Eto, Carrie A Webber, and Cathy  Cullicott. "Sorry, wrong number:  The use and misuse of numerical facts in analysis and media reporting of energy issues." Ed. Socolow, Robert H, Dennis Anderson, and John Harte. Annual Review of Energy and the Environment 2002 27 (2002) 119-158. LBNL-50499.

[5] Koomey, Jonathan, Huimin Chong, Woonsien Loh, Bruce Nordman, and Michele Blazek. 2004. "Network electricity use associated with wireless personal digital assistants." The ASCE Journal of Infrastructure Systems (also LBNL-54105). vol. 10, no. 3. September. pp. 131-137. [http://ascelibrary.org/doi/abs/10.1061/(ASCE)1076-0342(2004)10%3A3(130)]

[6] Koomey, J. Turning Numbers into Knowledge: Mastering the Art of Problem Solving. (Analytics Press, 2017).

[7] Camilo Mora, Randi L. Rollins, Katie Taladay, Michael B. Kantar, Mason K. Chock, Mio Shimada & Erik C. Franklin. Bitcoin emissions alone could push global warming above 2°C. Nature Climate Changevolume 8, pages931–933 (2018)

[8] Bitcoinity. Number of transactions - Bitcoinity.org. (2019). http://data.bitcoinity.org/bitcoin/tx_count/5y?t=l

[9] International Energy Agency. Power - Tracking Clean Energy Progress. (IEA, 2019). https://www.iea.org/tcep/power/

[10] International Energy Agency. Energy Technology Perspectives 2017. (IEA, 2017).

[11] International Energy Agency. World Energy Outlook 2017. (IEA, 2017).

[12] Our World in Data. Technology adoption by households in the United States. (2019). https://ourworldindata.org/grapher/technology-adoption-by-households-in-the-united-states?time=1903..2016

[13] Ania Monaco. Edison's Pearl Street Station Recognized With Milestone: IEEE honors the world's first central power station. 27 July 2011. (2011). http://theinstitute.ieee.org/tech-history/technology-history/edisons-pearl-street-station-recognized-with-milestone810

# Supplementary Information

## Implausible projections overestimate near-term Bitcoin $CO_2$ emissions

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In this document we show that the analysis by Mora et al., which predicts that Bitcoin mining alone can increase global warming by more than 2° C in 11 to 22 years, is fundamentally flawed and should not be taken seriously by researchers, policymakers, or the general public.

Hereafter we refer to Mora et al. as "the authors." We first document our replication of the authors' original methods and results in Sections I, II, and III, elaborating on several methodological problems we encountered during the process. Next, in Sections IV-VIII, we discuss in depth five major flaws related to the authors' study design and execution. As part of these discussions, we apply our replicated model to demonstrate that, had the authors avoided some key analytical errors, their own model would have produced significantly lower carbon emissions trajectories that invalidate their original alarmist predictions.

### I. Replication of 2017 $CO_2$ emissions estimate

We first replicated the authors' 2017 Bitcoin $CO_2$ emissions estimate, based on the R script they provided as their model. We generalize their calculation approach as follows (using our own notation):

$$C_{2017} = \sum_{i=1}^{n} \frac{E_i H_i G_i}{3.6*10^6} \quad (1)$$

The variable $C_{2017}$ is Bitcoin's global carbon emissions quantity in 2017, expressed in units of grams of $CO_2$ equivalents (g $CO_2$e). $E_i$ is the energy efficiency of the mining rig assigned to solve block $i$, expressed in units of joules of direct electricity use per hash (J/H). The authors assign rigs randomly (i.e., with equal probability) to each block from a list they provide in their Supplementary Information (SI) Table 1. $H_i$ is the expected number of hashes required to solve block $i$, which is calculated by multiplying its difficulty by $2^{32}$. $G_i$ is the regional $CO_2$ intensity of grid electricity generation (g $CO_2$e/kWh), which the authors assign depending on which pool solved block *I* as documented in their SI Table 2. The denominator converts direct electricity use from joules into kWh (1 kWh = $3.6*10^6$ joules). The results are summed over $n$ = 55,864 blocks, the total number solved in 2017.

Our replication of the authors' code generated an expected 2017 global Bitcoin $CO_2$ emissions value ($C_{2017}$) of 69 Mt $CO_2e$ (18.8 Mt C), which is identical to the authors' result, and an expected 2017 global Bitcoin direct electricity use value of 114 TWh. The latter value was not reported by the authors.

## II. Replication of future $CO_2$ emissions projections

Next we attempted to replicate the authors' future projections of Bitcoin $CO_2$ emissions. The authors did not provide code or explicit formulae for replicating their projections. Therefore, we had to rely on the authors' qualitative methodological descriptions and their results graphs to generalize their projection approach mathematically as follows (using our own notation):

$$C_j = T_{2017} f_j \hat{C}_{2017} \quad (2)$$

The variable $C_j$ is Bitcoin's global $CO_2$ emissions quantity in future year $j$ (g $CO_2e$). $T_{2017}$ is the total number of global cashless transactions in 2017 (314.2 billion), which the authors assume will remain constant for all future years $j$. The variable $f_j$ is the authors' assumed fraction of global cashless transactions attributable to Bitcoin in year $j$. $\hat{C}_{2017}$ is Bitcoin's average per-transaction carbon emissions intensity (g $CO_2e$/transaction) associated with solving all blocks in 2017.

We note that the authors calculate $C_j$ each year by randomly selecting combinations of blocks that had already been solved in their estimation of 2017 Bitcoin $CO_2$ emissions (as described in Section I) until total Bitcoin transactions in year $j$ are fulfilled. This procedure is repeated 1,000 times. This approach effectively delivers an expected per-transaction $CO_2$ intensity in each year $j$ that is very similar to the simple quotient of 2017 expected carbon emissions (69 Mt CO2e) and 2017 total Bitcoin transactions (103.7 million). This quotient has a value of $\hat{C}_{2017}$ = 665 kg CO2e/trans (181 kg C/trans).

Therefore, we use this constant $\hat{C}_{2017}$ value for analytical efficiency in our results replication, given that the authors use transactions as their future emissions driver (i.e., activity variable) in Eq. 2. In doing so, we arrive at very similar $CO_2$ emission projections to those of the authors, as discussed below.

The authors construct three different scenarios for $f_j$, which they provide over a 100-year projection period, based on their adoption rate analysis of 40 different "broadly adopted" technologies. Our replication of the authors' Bitcoin $CO_2$ emissions projections, which were generated using Eqs. (1) and (2) and the authors' values for $f_j$, are shown in Supplementary Fig. 1.

Before comparing our replicated results to those of the authors, three caveats are required:

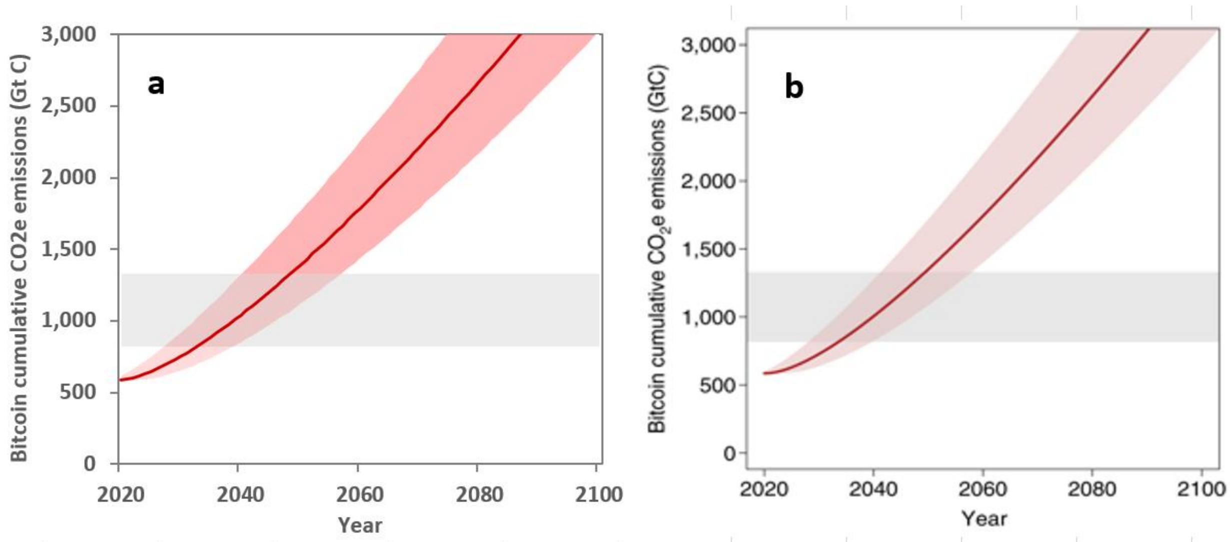
1. The authors' lack of transparency prevents precise comparisons. The authors did not provide their numerical projection results; instead, they only provided one projection results figure with coarse axis scales (their Fig. 1c). This lack of transparency makes exact replication impossible. Therefore, we checked the general accuracy of our replication by comparing our results to their Figure 1c and to the number of years stated by the authors until cumulative Bitcoin $CO_2$ emissions would exceed 231.4 Gt C (the authors' lower 2° C warming threshold).

2. The authors' base year, and its associated cumulative $CO_2$ emissions, are unclear. Without explanation or explicit acknowledgement, the authors appear to have chosen 2020 as the base

year for projections in their Fig. 1c, even though they had earlier estimated 2017 Bitcoin $CO_2$ emissions. Furthermore, and again without explanation, the authors appear to have assumed a cumulative global anthropogenic $CO_2$ emissions value of around 585 Gt C in 2020 (which we estimated via direct measurement of Fig. 1c), to which they cumulatively add projected Bitcoin $CO_2$ emissions over time in each scenario. Yet, in their paper, the authors also state that cumulative global anthropogenic carbon emissions had already reached 584.4 Gt C in 2014, six years earlier. This is a glaring analytical inconsistency that we could not reconcile when replicating the authors' projections.

3. <u>The authors' Bitcoin adoption values are opaquely labeled and incongruous.</u> We encountered several difficulties interpreting the authors' data for Bitcoin adoption ($f_j$), which they provided in a downloadable file for three different scenarios: median, lower25, and upper75. These three scenarios are represented in the paper as typical, slow, and fast adoption pathways, respectively. The authors label the year of each adoption value ($f_j$) ordinally, starting with a value of 2, while their emissions projection results are labeled by calendar year starting in 2020. They do not explain which ordinal year corresponds to which calendar year in their results, nor do they provide an ordinal year 1. Furthermore, the authors provide several negative values of Bitcoin adoption ($f_j$)—specifically, for ordinal year 2 in the median scenario and for ordinal years 2-5 in the lower25 scenario—which are physical impossibilities and incongruous with current (albeit small) Bitcoin adoption levels. They do not explain these negative adoption values, which are also clearly visible in their Fig 1b, which appears to start in ordinal year 2. In light of these documentation deficiencies, we attempted to establish correspondence between their Figs 1b and 1c (via Eqs 1 and 2) and concluded that the authors most likely assigned ordinal year 3 to calendar year 2020 in their analysis and simply ignored years with negative Bitcoin adoption values in each scenario, even though Bitcoin currently has a positive (albeit small) market penetration and will continue emitting $CO_2$ until 2020 in any scenario. The authors' failure to provide numerical results and explanations of ordinal years and negative values make it impossible to verify our conclusions about the authors' intentions in these figures. However, these conclusions do enable us to replicate the authors' results quite accurately.

With these caveats in mind, our replicated results in Supplementary Fig. 1 show similar carbon emissions trajectories for all three scenarios compared to the authors' Fig 1c. Our results also replicate the authors' calculations indicating that cumulative Bitcoin $CO_2$ emissions cross the 231.4 Gt C threshold in 2028, 2033, and 2039 in the Upper75, median, and Lower25 scenarios, respectively. However, the aforementioned methodological issues already raise serious questions about the credibility of the authors' analysis.



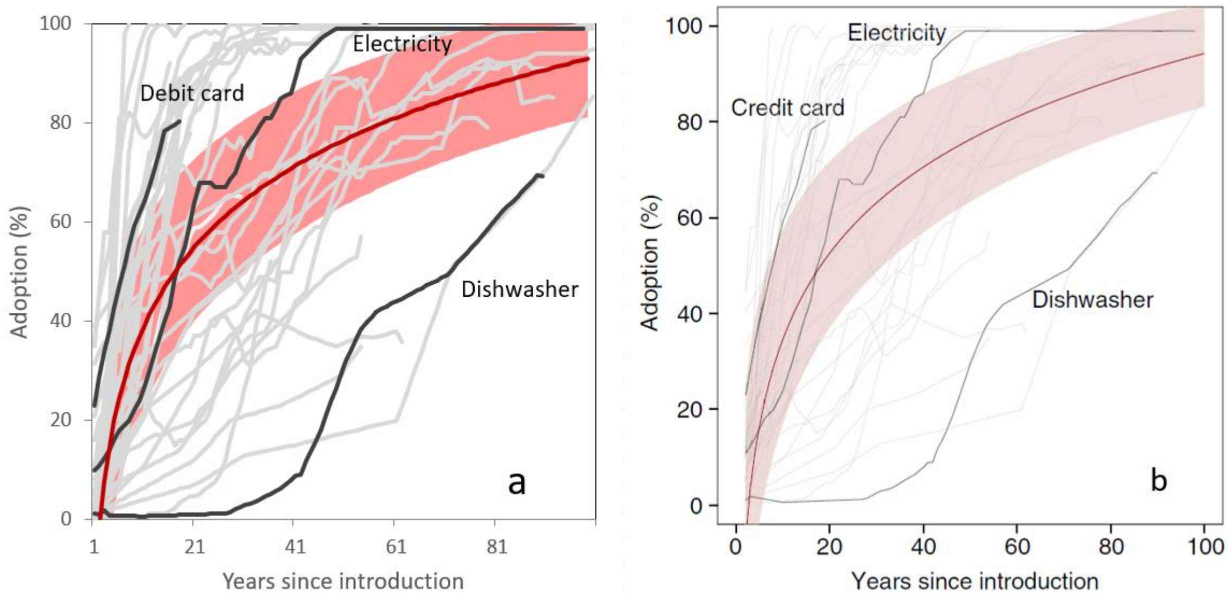

**Supplementary Figure 1. (a) Our replicated Bitcoin $CO_2$ emissions projections using the authors' data and model; (b) the authors' Bitcoin $CO_2$ emissions projections, as shown in their Figure 1c.**

### III. Replication of Bitcoin adoption scenarios

To better understand the basis for the authors' steep growth trajectories in all three scenarios they considered, we also replicated their derivation of Bitcoin adoption values in each scenario based on their stated comparison to 40 "broadly adopted" technologies. To do so, we obtained the same source data used by the authors[1,2] and replicated their comparative analysis, first by normalizing all adoption data in the same manner as the authors, then by constructing regression curves for the median, 25$^{th}$ percentile, and 75$^{th}$ percentile of the technology adoption ranges each year. Our replicated median, lower25, and upper75 adoption curves are shown in Supplementary Fig. 2, which are in close agreement with those of the authors in their Fig 1b (repeated below for convenience).

Our replication also revealed a likely error in the authors' representation of data contained in their Fig. 1b. Namely, the rapidly rising trendline labeled "credit card" appears to be based on adoption data for debit cards in the original source[2], not credit cards.

This error is notable, in that many readers of the Mora et al. paper may look to credit cards as the most appealing comparison product among the 40 in the authors' pool—given that early credit cards represented a disruptive new transaction technology—and form opinions about Bitcoin's future adoption potential on this basis. However, credit card usage in the United States followed a more gradual adoption path than that shown in the authors' Fig. 1b. Specifically, the first universal U.S. credit card (Diner's Club) was introduced in 1950[3] and by 1970 (20 years later) the fraction of U.S. families holding credit cards had risen to 50%[4], whereas the authors' (mislabeled) adoption curve implies that credit cards grew much faster, penetrating around 80% of U.S. households in a similar time period.




**Supplementary Figure 2. (a) Our replication of the authors' Bitcoin adoption scenarios; (b) the authors' original Bitcoin adoption scenarios as shown in their Figure 1b.**

Next, we discuss two major study design flaws that became apparent to us during the process of replicating Mora et al.'s methods and results.

## IV. The use of transactions as an energy demand driver is questionable

As summarized in Eq. 2, the authors project Bitcoin's future $CO_2$ emissions in each scenario using transactions as the emissions driver—i.e., the activity variable— in all future years. We consider this approach as a fundamental study design flaw, since it is well known that the electricity consumed, and hence the $CO_2$ emitted, by Bitcoin mining does not depend on the number of transactions but, rather, on the difficulty and number of blocks mined. [5,6,7]

The pace at which blocks are mined is kept constant at around 6 blocks per hour. The difficulty parameter in the mining algorithm is adjusted every 14 days to maintain this pace. An increasing number of transactions will therefore not cause an increase in the number of blocks. Instead, this will cause that individual blocks will include more transactions. The effort to mine a block is however independent of the number of transactions in the block.

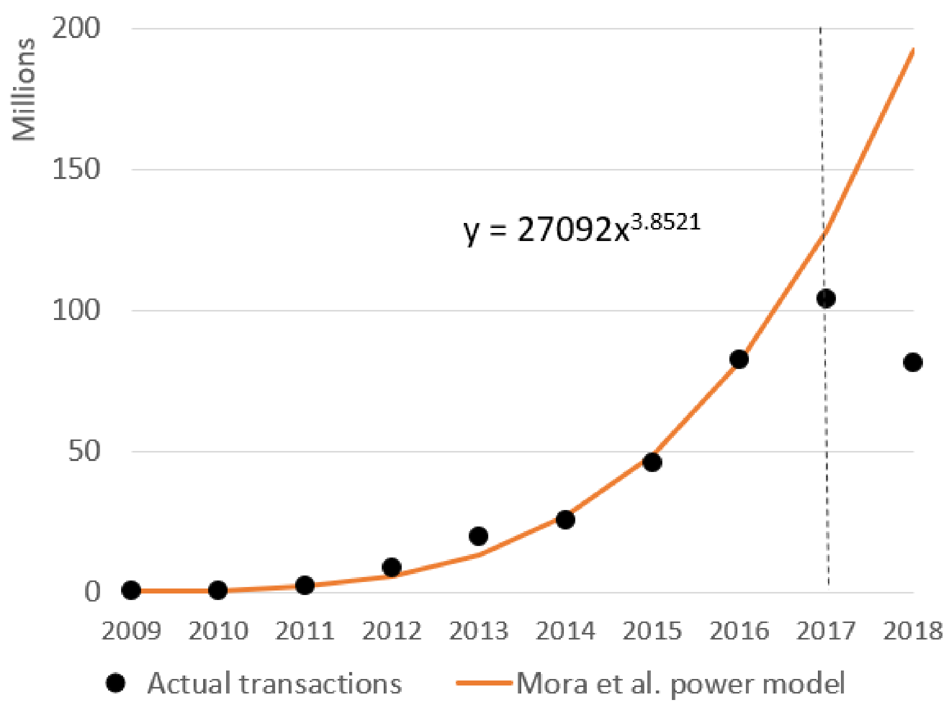
Indeed, the authors themselves calculate 2017 Bitcoin energy use and emissions based on block difficulty, not number of transactions (Eq. 1). Without explanation or justification, the authors switch to transactions as the driver for projecting emissions in all future years, undermining the consistency of their calculations and the integrity of their projections.

To illustrate this flaw, let's assume that all 314.2 billion cashless transactions in 2017 would be Bitcoin transactions. Then in the authors' approach this takes about 159 million blocks (considering that one block contained on average about 1,974 transactions in 2017).[8] This implies mining at a pace of 18,170 blocks per hour—three orders of magnitude greater than the established fixed pace of 6 blocks per hour—which betrays a lack of understanding of how real-world mining works. In contrast, in the above example, transactions would be increased on average to 5,977,930 per block, keeping the pace nearly constant at 6 blocks mined per hour. Hence, blocks will become much larger, which will cause scalability issues, mainly in communication latency, but it would not necessarily increase mining effort.

### V. The authors' Bitcoin adoption scenarios are implausible

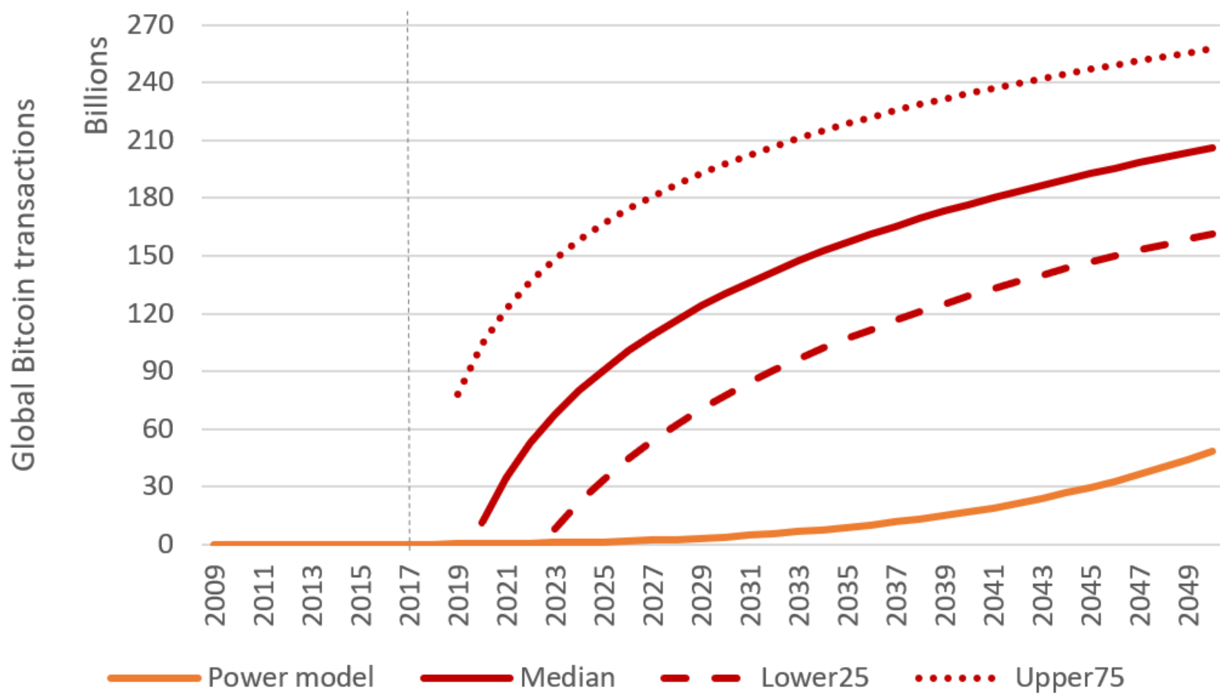
As evident in Eq. (2), the authors' future Bitcoin $CO_2$ emissions estimates are sensitive to their design of adoption scenarios ($f_i$). The authors' typical, slow, and fast adoption scenarios are plotted in Supplementary Fig 1b, which paints a seemingly unavoidable future of sudden and rapid Bitcoin adoption. Mathematically, the authors' use of steep logarithmic growth curves in all scenarios can only result (see Eq. 2) in large near-term increases in Bitcoin's carbon emissions, even in the slowest adoption scenario.

The authors implicitly justify steep future growth by pointing to rapid historical (2009-2017) growth in global Bitcoin transactions (the authors' Supplementary Figure 1), which they model using a power function. However, 2018 data (most of which were available prior to publication of the authors' study) expose the well-documented danger of simply extrapolating past trends into the future: global Bitcoin transactions fell by 22% in 2018[9]. Therefore, in 2018, as shown in Supplementary Fig. 3, the authors' power model already overestimates global Bitcoin transactions by a factor of 2. This discrepancy underscores why readers should be wary of any future energy/carbon emission projections based on simple extrapolation of early rapid growth trends, especially for information technology (IT) systems, whose efficiencies and service demands can evolve quickly.[10,11,12]




**Supplementary Figure 3. Annual global Bitcoin transactions (2009-2018) with the authors' historical (2009-2017) power model extended to 2018.**

Upon initial observation, the steep upward slope of the authors' historical power model (Supplementary Fig. 3) might seem visually coherent with the steep initial upward slopes of the authors' future adoption scenarios (authors' Fig 1b). However, when these data series are plotted together on the same scale—i.e., billions of transactions—major inconsistencies emerge. As shown in Supplementary Fig. 4, the authors' own historical power model follows a much flatter future trajectory in the near-term compared to the Bitcoin transactions assumed by the authors in their scenarios, all three of which abruptly switch to significantly steeper trajectories at their outsets.




**Supplementary Figure 4. Comparison of historical (2009-2017) Bitcoin transactions and the future Bitcoin transactions associated with the authors' power model and their three adoption scenarios. Note: Due to negative initial values and missing data for 2018 (see Section II), the authors' three scenarios have different start years and are represented here with different styles than in previous graphs for clarity.**

Moreover, in the first year of each of the authors' scenarios, implausibly massive jumps in Bitcoin transactions would be required to bridge the gaps compared to present-day totals. In 2017, global Bitcoin transactions totaled 104 million, or a mere 0.03% of global cashless transactions.[13] In the authors' scenarios, however, the following must happen:

- by 2019 (i.e., only 2 years later), Bitcoin adoption must jump to:
    - 78 billion transactions in the fast scenario, which represents a:
        - 750x increase compared to 2017, and a
        - 280x increase compared to their power model extrapolated to 2019
- by 2020 (3 years later), Bitcoin adoption must jump to:
    - 11 billion transactions in the median scenario, which represents a:

        - 108x increase compared to 2017, and a
        - 29x increase compared to their power model extrapolated to 2020
- By 2023 (5 years later), Bitcoin adoption must jump to:
    - 8 billion transactions in the slow scenario, which represents a:
        - 76x increase compared to 2017
        - 9x increase compared to their power model extrapolated to 2023

The authors do not address the above numerical disconnects that exist between present-day Bitcoin transactions, those implied by their power model, and those required in the first years of each future scenario. Nor do the authors justify the plausibility of the very abrupt changes in adoption trajectories and transaction levels associated with their scenarios. Implicitly, the authors require the reader to "suspend disbelief" in accepting scenarios that are numerically inconsistent and historically implausible, yet they provide no evidence why one should do so.

We find these implausible scenarios to be another fundamental study design flaw.

## VI. Use of outdated mining rig efficiency and grid carbon intensity values

When replicating the authors' 2017 Bitcoin energy use and $CO_2$ emissions estimate (see Section I), we found that they applied outdated values for mining rig efficiencies and electric power carbon intensities, which inflated their 2017 energy and emissions results considerably.

When estimating the direct electricity use of Bitcoin mining, the authors erroneously included many old and inefficient rigs in their selection pool that were no longer economically viable in 2017, betraying a lack of understanding of current mining equipment and economics. Supplementary Table 1 lists the pool of mining rigs constructed by the authors, from which they randomly assigned rigs (i.e., with equal probability) to solve blocks in 2017 via Eq. 1. The authors claim they have included "only hardware that is economically profitable by modern standards;"[13] however, they offer no explicit definition of what they mean by "economically profitable" or "modern standards."

Here we demonstrate that the authors included in their pool many old, computationally-slow, and energy-inefficient rigs that had little chance of being "economically profitable" in 2017. To aid in our assessment, we first compiled best available estimates of the release date for each of the 62 models in the authors' mining rig pool.[24-54] Our estimated release dates are shown in Supplementary Table 1, which indicates that the authors included models released as early as January 2013, or five years prior to the end of the authors' reference year (2017).

Next, we compiled historical data on the number of daily blocks solved, their associated difficulty levels, the Bitcoin award per solved block, the transaction fees collected, and the average Bitcoin market value for the period 1-Jan-2013 to 30-Nov-2018.[8,14]

Using these historical data, we then computed the nominal value of daily mined blocks as follows:

$$V_k = N_k(T_k + B_k)M_k \quad (3)$$

The variable $V_k$ is the total value of blocks mined in day $k$ (nominal USD \$), $N_k$ is the number of blocks mined that day, $T_k$ is daily average transaction fee (BTC/block), $B_k$ is the daily mining reward (BTC/block), and $M_k$ is the daily average Bitcoin market value (\$/BTC).

**Supplementary Table 1. The authors' mining rig pool with our best estimates of rig release dates**

| Bitcoin computing hardware | Hashrate (GH/s) | Energy efficiency (GH/J) | Estimated rig release date (mm:dd:yy) |
|---|---|---|---|
| TerraHash Klondike 16 | 5 | 0.156 | 01/01/13 |
| Avalon Batch 1 | 66 | 0.106 | 01/19/13 |
| Avalon Batch 2 | 82 | 0.117 | 01/30/13 |
| Avalon Batch 3 | 82 | 0.117 | 01/30/13 |
| Bitmine Avalon Clone 85 GH | 85 | 0.131 | 05/25/13 |
| Metabank | 120 | 0.706 | 05/31/13 |
| TerraHash DX Mini (full) | 90 | 0.141 | 06/17/13 |
| BFL 500 GH/s Mini Rig SC | 500 | 0.185 | 06/18/13 |
| TerraHash DX Large (full) | 180 | 0.141 | 06/18/13 |
| TerraHash Klondike 64 | 18 | 0.142 | 06/18/13 |
| BFL SC 25Gh/s | 25 | 0.167 | 06/26/13 |
| BFL SC 50 Gh/s | 50 | 0.167 | 06/26/13 |
| HashFast Baby Jet | 400 | 0.909 | 09/13/13 |
| HashFast Sierra | 1200 | 0.909 | 09/13/13 |
| KnCMiner Mercury | 100 | 0.400 | 10/01/13 |
| BFL Single 'SC' | 60 | 0.250 | 10/10/13 |
| KnC Saturn | 250 | 0.833 | 10/11/13 |
| BPMC Red Fury USB | 2.5 | 1.000 | 10/19/13 |
| KnC Jupiter | 500 | 0.833 | 10/26/13 |
| BFL SC 5 Gh/s | 5 | 0.167 | 11/21/13 |
| HashBuster Micro | 20 | 0.870 | 12/08/13 |
| AntMiner S1 | 180 | 0.500 | 12/30/13 |
| KnC Neptune | 3000 | 1.429 | 01/01/14 |
| Spondooliestech SP30 | 4500 | 1.500 | 01/01/14 |
| ROCKMINER R3-BOX | 450 | 1.000 | 01/01/14 |
| CoinTerra TerraMiner IV | 1600 | 0.762 | 01/29/14 |
| HashFast Sierra Evo 3 | 2000 | 0.909 | 03/07/14 |
| NanoFury NF2 | 4 | 0.800 | 03/23/14 |
| AntMiner S2 | 1000 | 0.909 | 05/21/14 |
| BTC Garden AM-V1 310 GH/s | 310 | 0.957 | 05/23/14 |
| ROCKMINER R-BOX | 32 | 0.711 | 05/28/14 |
| ROCKMINER Rocket BOX | 450 | 0.938 | 06/15/14 |
| Spondooliestech SP10 | 1400 | 1.120 | 08/18/14 |
| ROCKMINER R-BOX110G | 110 | 0.917 | 09/09/14 |
| Black Arrow Prospero X-1 | 100 | 1.000 | 09/23/14 |
| BFL Monarch 700 GH/s | 700 | 1.429 | 09/25/14 |
| AntMiner S4 | 2000 | 1.429 | 09/25/14 |

| **Bitcoin computing hardware** | **Hashrate (GH/s)** | **Energy efficiency (GH/J)** | **Estimated rig release date (mm:dd:yy)** |
|---|---|---|---|
| AntMiner S3 | 441 | 1.297 | 09/27/14 |
| Black Arrow Prospero X-3 | 2000 | 1.000 | 10/08/14 |
| Klondike | 5 | 0.156 | 10/15/14 |
| ROCKMINER R4-BOX | 470 | 1.000 | 10/20/14 |
| ROCKMINER T1 800G | 800 | 0.800 | 12/03/14 |
| AntMiner S5 | 1160 | 1.966 | 12/22/14 |
| Spondooliestech SP20 | 1700 | 1.545 | 12/22/14 |
| Spondooliestech SP35 | 5500 | 1.507 | 01/01/15 |
| Twinfury | 5 | 1.305 | 02/19/15 |
| AntMiner S5+ | 7720 | 2.247 | 08/14/15 |
| AntMiner S7 | 4730 | 3.909 | 08/30/15 |
| Avalon6 | 3500 | 3.241 | 02/08/16 |
| Spondooliestech SP31 | 4900 | 1.633 | 04/01/16 |
| Avalon 721 | 6000 | 6.000 | 11/01/16 |
| AntMiner R4 | 8700 | 10.296 | 02/01/17 |
| Avalon741 | 7300 | 6.348 | 03/01/17 |
| Ebit E9+ | 9000 | 6.923 | 09/08/17 |
| Ebit E9 | 6300 | 7.143 | 09/14/17 |
| WhatsMiner M3 | 12500 | 5.682 | 11/14/17 |
| Avalon761 | 8800 | 6.667 | 12/13/17 |
| Avalon821 | 11000 | 9.167 | 12/20/17 |
| Ebit E9++ | 14000 | 10.526 | 01/01/18 |
| AntMiner S9 | 14000 | 10.448 | 11/01/17 |
| Antminer T9+ | 10500 | 7.332 | 01/01/18 |
| Ebit E10 | 18000 | 11.111 | 02/01/18 |

2

Next, for each of the 62 rigs in the authors' selection pool, we calculated the electricity use that would be necessary if that rig were assigned to solve the blocks in each day $k$, following the mathematical approach in Eq. 1. Finally, we divided the nominal mined block value ($V_k$) by the electricity use that would have been required for a given rig to solve those blocks (kWh), and did so for all days in our analysis period.

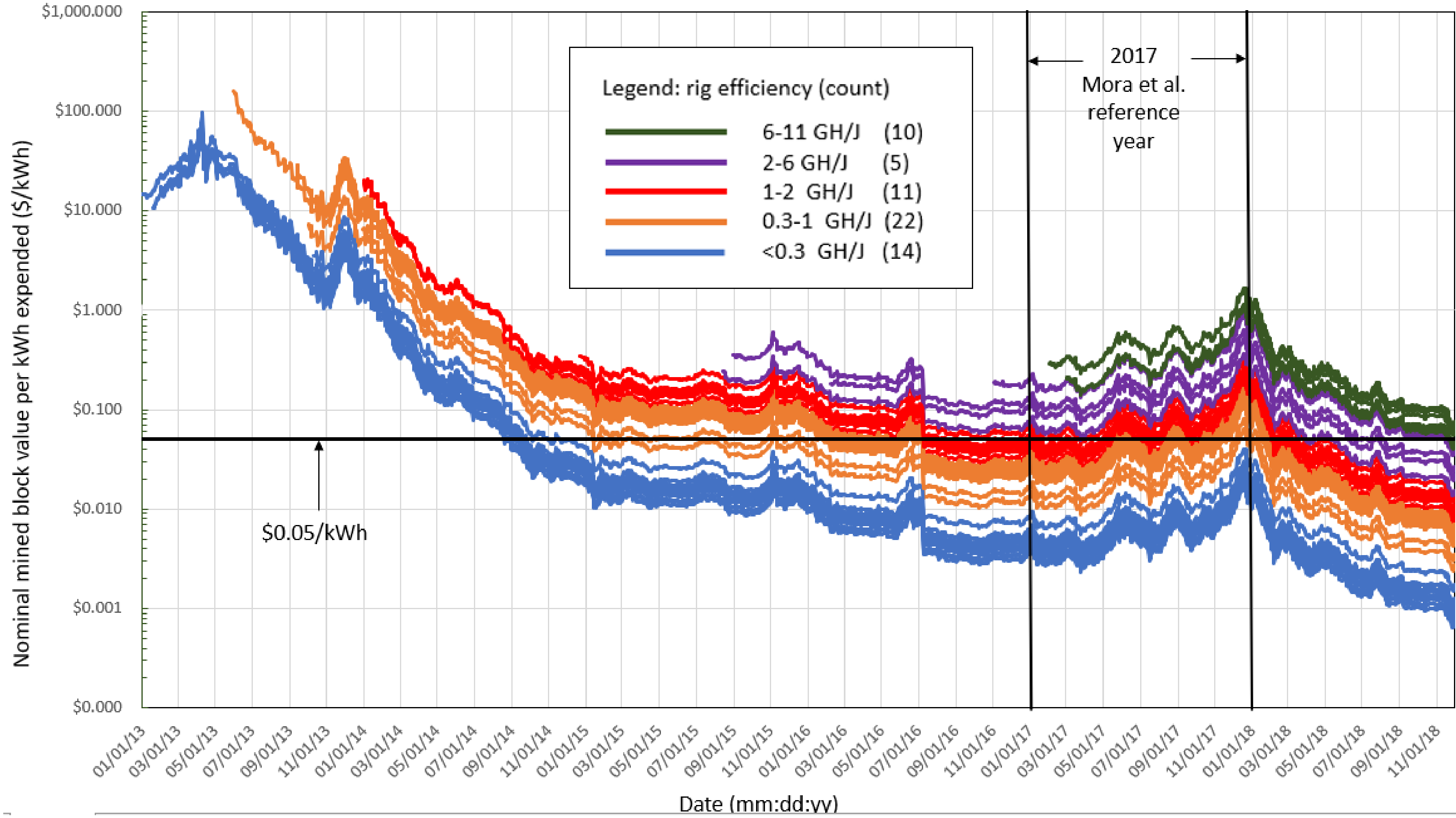
Supplementary Fig. 5 plots our computed nominal mined block value per kWh expended ($/kWh) for all 62 rigs. This metric expresses the maximum mining value that could be extracted per kWh expended during mining; when operating costs per kWh expended ($/kWh) exceed this value, mining cannot be profitable. Operating costs include the costs of electricity, equipment depreciation, labor, and other costs incurred during mining. While empirical data on operating costs are scarce, several published estimates suggest that $0.05/kWh is a reasonable current minimum value, with electricity typically comprising the largest share of operating costs.[7,15]

In Supplementary Fig. 5, we color code rigs of different efficiency classes, indicate the numbers of rigs that fall into each class in the authors' selection pool, and start each rig's data series on its estimated release date. We also indicate the typical $0.05/kWh threshold on the plot; rigs whose data series fall below this threshold in a given time period would not be considered profitable, because nominal mined block value earned per kWh expended would not exceed operating costs.

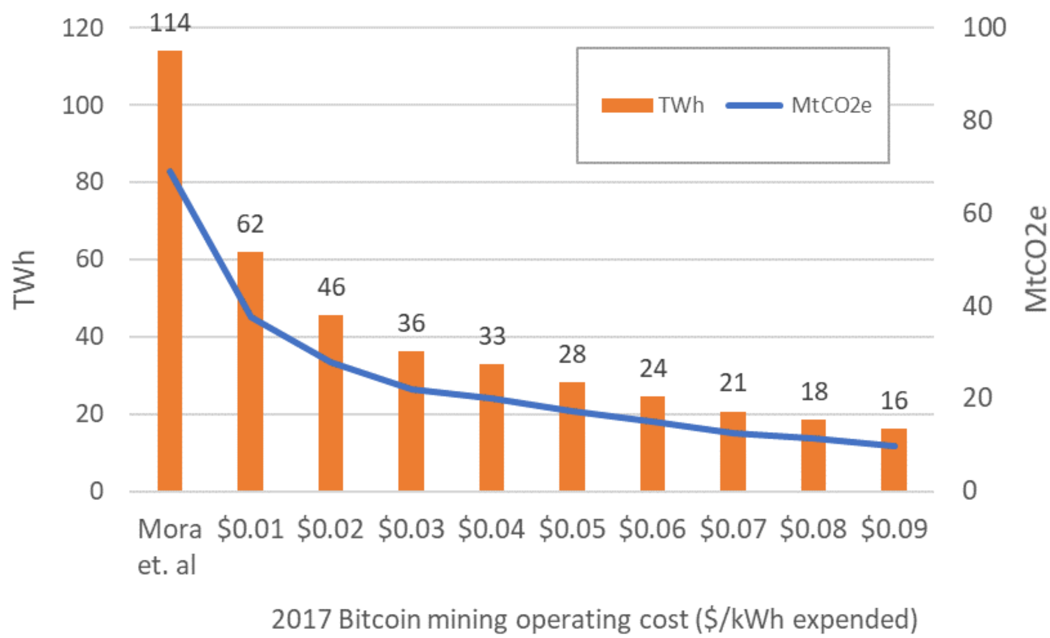
It can be seen that many of the older, less energy-efficient rigs that were included in the authors' selection pool—while profitable when first introduced several years ago—by 2017 would be profitable only at implausibly low operating cost levels. For example, in 2017, many of the lowest efficiency rigs included by the authors (i.e., the blue-shaded rigs with efficiencies less than 0.3 GH/J) could have only been profitable with operating costs less than $0.01/kWh, which is much lower than even the cheapest documented rates for mining electricity costs alone.[15,16,17]

In other words, many of the rigs included in the authors' selection pool were not "economically profitable by modern standards" in the authors' own reference year (2017), and should, therefore, have been excluded from their analysis. In Supplementary Fig. 6, we plot the effects of excluding old, energy-efficient rigs from our replicated analysis at different assumed levels of operating cost. For each monthly period in 2017, we reran our original replication but excluded any rigs from the selection pool that would not have been profitable at various operating cost levels. We summed these monthly results to arrive at total direct Bitcoin electricity use estimates in 2017.

It is clear from Supplementary Fig. 6 that inclusion of old, energy-efficient rigs in the authors' analysis resulted in an inflated 2017 direct electricity use estimate. Even if the authors had excluded rigs that were not profitable at implausibly low operating costs of $0.01/kWh, their 2017 electricity use estimate would have dropped nearly in half, from 114 TWh to 62 TWh, while their 2017 $CO_2$ emissions estimate would have dropped from 69 Mt $CO_2$e to 38 Mt $CO_2$e. At the generally-accepted minimum operating cost level of $0.05/kWh, the authors' 2017 electricity use and $CO_2$ emissions estimates would have dropped much further, to 28 TWh and 17 Mt$CO_2$e, respectively. These latter values are more consistent with other published estimates of Bitcoin's 2017 direct electricity use and related carbon emissions, which include only the newer, faster, and more energy-efficient rigs that were likely to be profitable in 2017.[5-7] Indeed, looking at Supplementary Fig. 6 from left to right, one can clearly see how, as rigs get older, they are invariably pushed out of profitability as newer, more efficient rigs emerge.




**Supplementary Figure 5. Nominal mined block value per kWh expended for the 62 mining rigs included in the authors' selection pool**

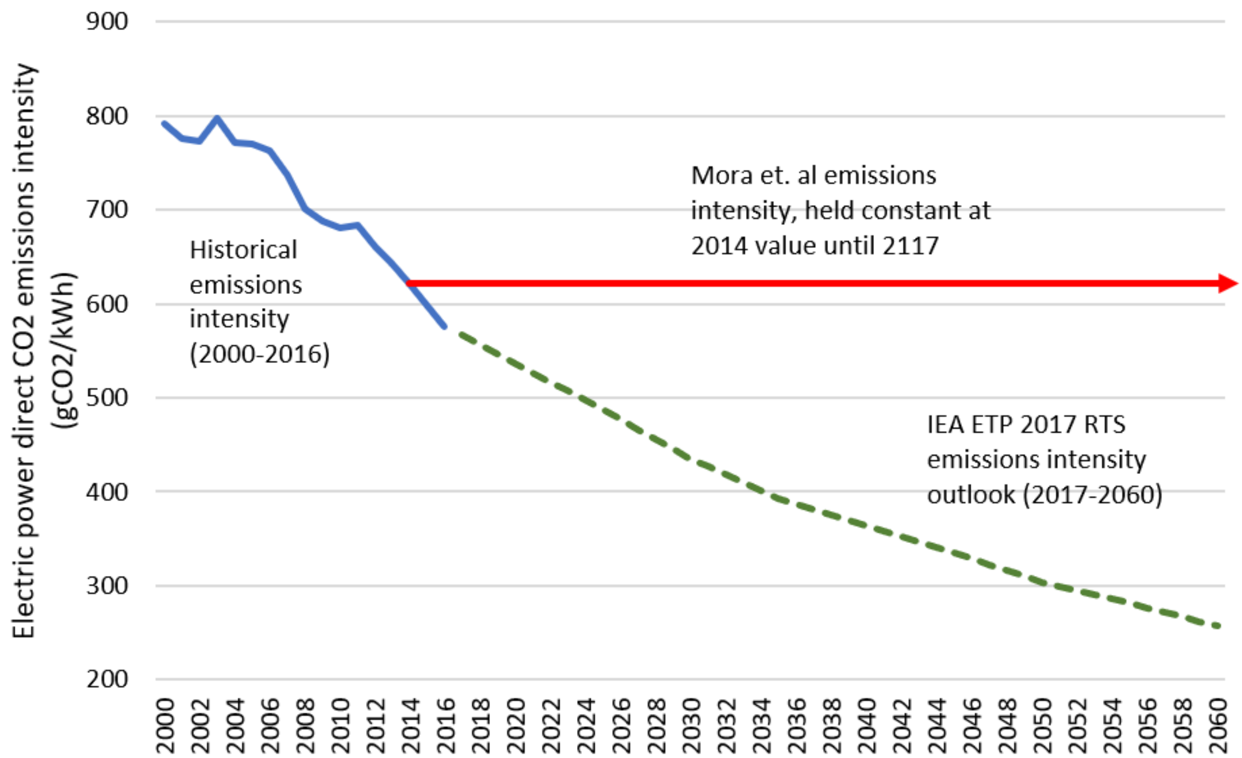



**Supplementary Figure 6. Mora et al. model estimates of 2017 Bitcoin electricity use and $CO_2$ emissions when unprofitable rigs were excluded from their selection pool, at different operating cost assumption levels.**

Furthermore, the authors applied 2014 carbon intensities (g $CO_2$/kWh) to their 2017 electricity use estimates, ignoring non-negligible grid decarbonization improvements in their assumed mining locations during the intervening years (Supplementary Fig 7). This was done even though sufficient data existed at the time of their study for reasonable estimates of 2017 carbon intensities.[18,19,20] Supplementary Fig. 7 plots the location-weighted average grid $CO_2$ emissions intensity from 2000-2016 (historical), with forward-projections from 2017 to 2060 from the IEA's central outlook (based on current and announced national policies in assumed mining locations). From this figure, it's clear that, by using 2014 carbon intensities, the authors arrived at a higher 2017 $CO_2$ emissions value than if they had used available data for 2017 carbon intensities.

To assess the effects of the authors' use of outdated rig efficiencies and grid carbon intensities, we applied our replicated Mora et al. model to estimate 2017 Bitcoin $CO_2$ emissions using more reasonable assumptions. Based on the assumption that $0.05/kWh represents the global average minimum Bitcoin mining operating cost—and excluding rigs that did not yield nominal mining revenues per kWh expended exceeding $0.05/kWh in 2017—the authors' model yielded an estimate of 28 TWh (Supplementary Fig. 6). We then multiplied this value by a location-weighted carbon intensity that was 9% lower than the authors' 2014 value, to capture the technological progress that occurred between 2014 and 2017 (Supplementary Fig. 7). We arrived at a 2017 Bitcoin $CO_2$ emissions estimate of 15.7 $MtCO_2e$, which is far lower than the authors' original estimate of 69 MtCO2e.

Therefore, we determined that, had the authors not erroneously included outdated rig efficiencies and grid carbon intensities, their own model would have estimated substantially lower 2017 energy use and $CO_2$ emissions values, invalidating their original results.




**Supplementary Figure 7. Location-weighted average electric power direct carbon intensity using historical (2000-2016) and projected (2017-2060) data available at the time of the authors' study. Also shown is the level of direct carbon intensity locked into the authors' estimates by assuming static 2014 carbon intensity values. Location-weighted average assumes the following percentages of 2017 Bitcoin electricity use by region, according to the locations assigned by the authors to each solved block: China (62.2%), U.S./China average (9.3%), U.S. (3.9%), global average (17%), Georgia, Finland, and Iceland (5.3%), U.S./E.U. average (0.1%), India (2.3%), and Sweden (0.1%).**

## VII. Holding both mining rig efficiency and grid carbon intensity constant in all future years

As evident in Eq. 2, the authors applied their 2017 per-transaction $CO_2$ emissions values in all future years, multiplying them by annual transactions to obtain future $CO_2$ emissions trajectories for each scenario. This was done by sampling solved blocks from their 2017 analysis until the required transactions in each future year were fulfilled. In other words, they did not vary the mining rig pool options in future years; for example, the pool of rigs they used to solve blocks in 2050 was the same pool of rigs they used to solve blocks in 2017. Moreover, the authors state explicitly that they did not consider any changes over time to the power grids in each assumed mining location. These decisions effectively held both mining rig efficiencies and grid carbon intensities constant for the next 100 years.

This dubious choice ignores the dynamic natures of mining rig and power grid technologies and violates the widely-followed practice of accounting for technological change in forward-looking energy technology scenarios.

Estimating the future energy efficiency of mining is certainly difficult, but the authors never explain why they simply ignored this important scenario consideration, nor do they justify how assuming static mining efficiencies for 100 years—when, historically, mining rigs have evolved monthly with respect to their hashrates and energy efficiencies— can lead to any useful insights. And, in acknowledging their static grid intensities assumption, they point to at least one available reference containing credible grid intensity outlooks,[20] but failed to utilize these data. The fallacy in keeping grid carbon intensities constant at 2014 levels can clearly be seen in Supplementary Fig. 7, which shows a widening gulf over time between the authors' static assumption (in red) and that of the prevailing outlook (the IEA's ETP 2017 Reference Technology Scenario, in green) for the authors' assumed mining locations.

We consider the authors' decisions to hold both mining rig efficiencies and grid carbon intensities constant to be fatal flaws of their analysis, and conspicuously out of step with established best practices for IT energy analysis and long-term energy scenario modeling.[21] And, because the authors significantly overestimated 2017 Bitcoin energy use and $CO_2$ emissions by using outdated rig and carbon intensity data, it follows that their decision to lock in these 2017 values in all future years led to inflated $CO_2$ emissions projections as well.

Therefore, we assessed how the authors' own model would have yielded different results had they: (a) at least excluded unprofitable rigs from their 2017 pool; and (b) used available data sources to account for projected changes in grid carbon intensities in their assumed mining locations. We applied our replicated model to first generate scenarios assuming 2017 CO2 emissions of 15.7 $MtCO_2e$ (based on a global average minimum operating cost of $0.05/kWh, as discussed in Section VI), as shown in Supplementary Fig. 9b. To these results, we then applied changes in the location-weighted grid carbon intensity from 2017 to 2060, using available data from the IEA's central outlook based on current and announced national policies in each mining location (Supplementary Fig. 9c).

The results show that, had the authors applied more reasonable values in their analysis—even maintaining the flawed assumption of holding 2017 mining rig efficiencies constant, but at more economically plausible levels—their own model would have delivered much different projections compared to their original results.

## VIII. Improper execution of the 40-product comparison analysis

Lastly, our replication of the authors' 40 technology comparison (see Section III) revealed errors that biased their results in favor of steep initial growth trajectories. While the scientific community may be justified in questioning the authors' comparison of Bitcoin to a seemingly arbitrary mix of technologies that vary widely in their social utility, here we focus only on errors committed by the authors executing their own stated methods.

In constructing their scenarios, the authors state that "the first year of usage for each technology was set to one, to allow comparison of trends among technologies," which is the approach we followed in our replicated analysis (Supplementary Fig. 2). For each technology, the authors equated "first year of usage" with "first year since introduction," as evident in their Fig 1b. However, in our replicated analysis, we discovered that, for many technologies, the authors erroneously assumed that the first nonzero value available in the source data represented the first year of *actual* technology use.

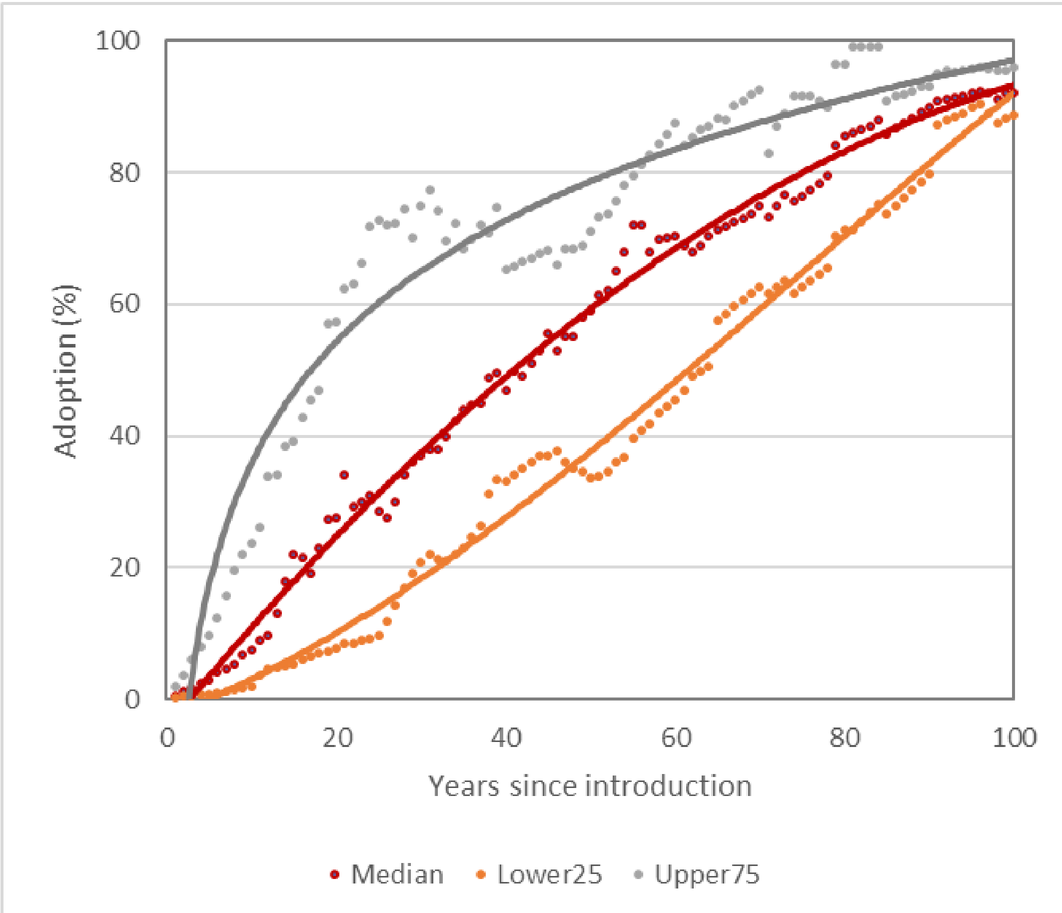
For example, the authors designate the first year of usage for the automobile as 1915, at which point US household adoption was already 10%. However, the modern automobile was invented in the late 1890s, with mass production starting in the United States around 1901.[22] Similarly, the authors designate the first year of usage for electric power as 1908, at which point US household adoption had also climbed to 10%. Yet Thomas Edison began offering electric power to customers in Manhattan over two decades earlier, in 1882.[23] We found similar discrepancies for other technologies in the authors' comparison pool, which are documented in Supplementary Table 2.

By erroneously assuming that the first available adoption number in the source data represented the first year of technology availability, the authors omitted the initial low-adoption years of US market availability for numerous technologies. Mathematically, these omissions biased the authors' scenarios toward inaccurately steep near-term adoption trajectories in all three cases.

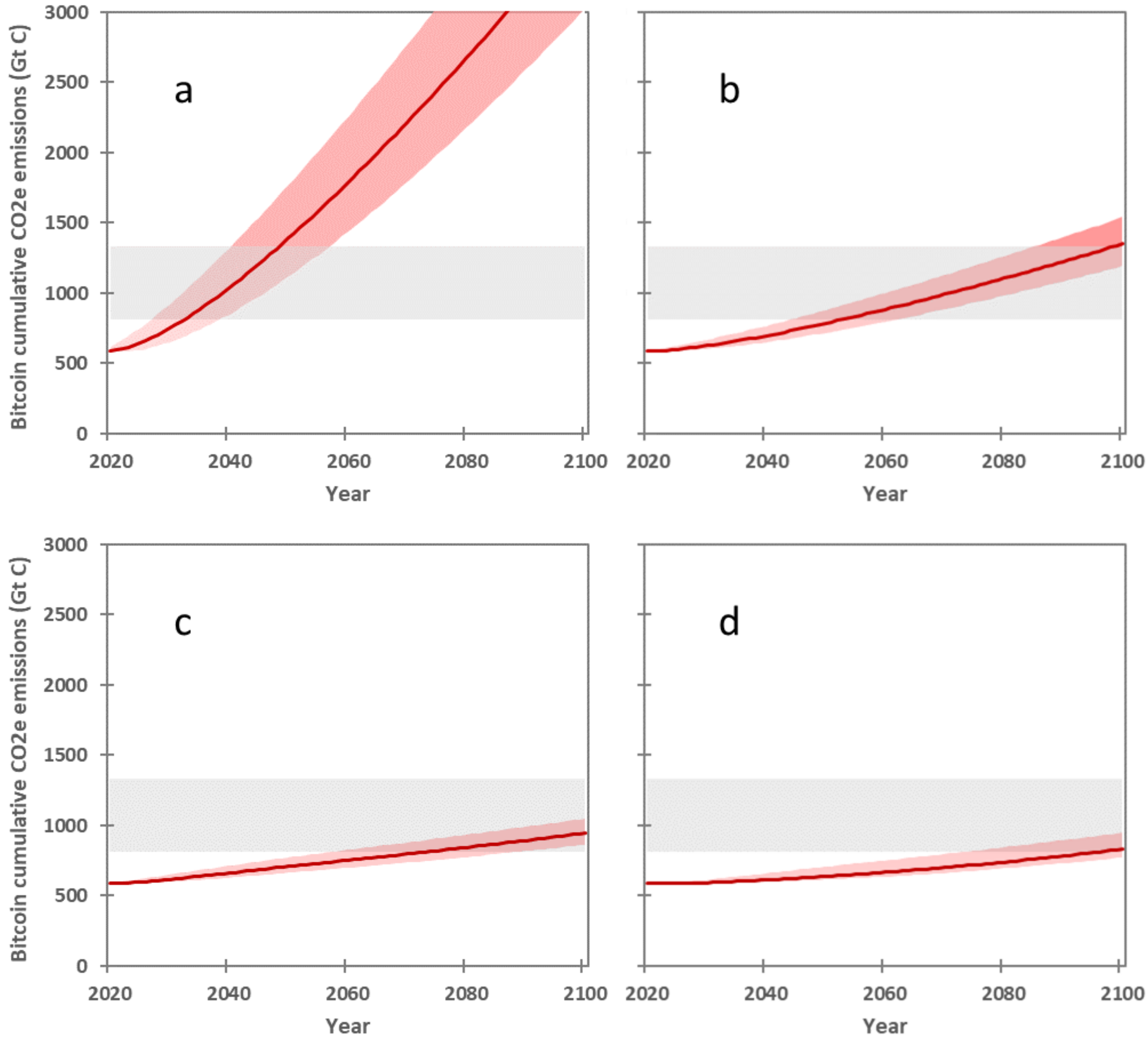
To illustrate this point, we repeated the authors' approach using more realistic values for the first year of technology usage obtained from the literature,[55-83] as summarized in Supplementary Table 2. Adoption rates in the initial years were estimated using linear interpolation. We also removed three duplicative entries from the authors' 40 product comparison pool (computers, refrigerators, and washing machines) and NOx controls (the rapid adoption of which was driven by regulatory mandates, not market demand), as noted in the table.

Our adjusted median, lower25, and upper75 curves are shown in Supplementary Fig. 8, which were based on the best-fitting regression models for each data series. It can be seen that more realistic estimates for the first year of technology use, and a more coherent comparison pool drawn from the same data sources, would result in a fast scenario (i.e., upper75) with less aggressive logarithmic growth and median and slow (i.e., lower25) scenario curves that are demonstrably less steep in the near term than those constructed by the authors.

To assess how the authors' errors in their own scenario derivations affected their results, we reran our replicated emissions projection once again using the adjusted Bitcoin adoption scenarios in Supplementary Fig. 8. The results are plotted in Supplementary Fig. 9d. By correcting the authors' own scenario analysis as the last step in the cascade of corrections we discuss, we show that their model would have now projected $CO_2$ emissions trajectories that would not have crossed the $2^{o}$C threshold until between 2075 to 2110.




**Supplementary Figure 8. The authors' Bitcoin adoption scenarios based on more realistic first year of usage estimates within the technology comparison pool.**




**Supplementary Figure 9: Comparison of Bitcoin $CO_2$ emissions projected by the Mora et al. model: (a) our replicated analysis showing close agreement with the authors' results; and the model's projections after first (b) removing unprofitable rigs in the base year, then (c) accounting for evolution of the electric power grid in mining locations, and finally (d) correcting errors in their stated adoption scenario approach.**

**Supplementary Table 2. Authors' selected versus more reasonable first year of usage values for comparative technologies**

| Technology | Authors' assigned first year of usage (YSI = 1) | Actual first year of usage (YSI = 1) | Initial years of availability omitted by the authors |
|---|---|---|---|
| Automatic transmission | 1951 | 1939 | 12 |
| Automobile | 1915 | 1901 | 14 |
| Cable TV | 1968 | 1948 | 20 |
| Cellular phone | 1994 | 1984 | 10 |
| Central heating | 1920 | 1892 | 28 |
| Colour TV | 1966 | 1954 | 12 |
| Computer | 1992 | Duplicate | - |
| Dishwasher | 1922 | 1922 | - |
| Disk brakes | 1966 | 1963 | 3 |
| Dryer | 1950 | 1938 | 12 |
| Ebook reader | 2009 | 1998 | 11 |
| Electric Range | 1933 | 1908 | 25 |
| Electric power | 1908 | 1882 | 26 |
| Electronic ignition | 1977 | 1963 | 14 |
| Flush toilet | 1860 | 1860 | - |
| Freezer | 1950 | 1947 | 3 |
| Home air conditioning | 1957 | 1931 | 26 |
| Household refrigerator | 1931 | Duplicate | - |
| Internet | 1993 | 1991 | 2 |
| Landline | 1903 | 1885 | 18 |
| Microcomputer | 1984 | 1984 | - |
| Microwave | 1975 | 1955 | 20 |
| Nox pollution controls | 1990 | 1990 | - |
| Podcasting | 2006 | 2003 | 3 |
| Power steering | 1951 | 1951 | - |
| RTGS adoption | 1970 | 1970 | - |
| Radial tires | 1972 | 1967 | 5 |
| Radio | 1925 | 1921 | 4 |
| Refrigerator | 1925 | 1918 | 7 |
| Running water | 1890 | 1833 | 57 |
| Shipping container port inf. | 1964 | 1955 | 9 |
| Smartphone usage | 2011 | 2000 | 11 |
| Social media usage | 2005 | 1997 | 8 |
| Stove | 1900 | 1900 | - |
| Tablet | 2010 | 1992 | 18 |
| Vacuum | 1922 | 1908 | 14 |
| Washer | 1920 | 1907 | 13 |
| Washing machine | 1930 | Duplicate | - |
| Water Heater | 1933 | 1904 | 29 |
| Debit card | 1995 | 1984 | 11 |

## References


[1] Our World in Data. Technology adoption by households in the United States. (2019). https://ourworldindata.org/grapher/technology-adoption-by-households-in-the-united-states?time=1903..2016

[2] Consumer Credit and Payment Statistics (Federal Reserve Bank of Philadelphia); https://www.philadelphiafed.org/consumer-finance-institute/statistics

[3] Encyclopaedia Brittanica, The Credit Card. https://www.britannica.com/topic/credit-card

[4] U.S. Federal Reserve. Credit Cards: Use and Consumer Attitudes, 1970–2000. (2000). https://www.federalreserve.gov/Pubs/Bulletin/2000/0900lead.pdf

[5] Vranken, H. Sustainability of bitcoin and blockchains. Current Opinion in Environmental Sustainability 28, 1-9, doi:https://doi.org/10.1016/j.cosust.2017.04.011 (2017).

[6] Krause, M. J. & Tolaymat, T. Quantification of energy and carbon costs for mining cryptocurrencies. Nature Sustainability 1, 711-718, doi:10.1038/s41893-018-0152-7 (2018).

[7] Bevand, M. Op Ed: Bitcoin Miners Consume A Reasonable Amount of Energy — And It's All Worth It, <https://bitcoinmagazine.com/articles/op-ed-bitcoin-miners-consumereasonable- amount-energy-and-its-all-worth-it/> (2017).

[8] Bitcoinity. Data.bitcoinity.org. (2019).

[9] Bitcoinity. Number of transactions - Bitcoinity.org. (2019). http://data.bitcoinity.org/bitcoin/tx_count/5y?t=l

[10] Koomey, Jonathan G, Chris Calwell, John A Laitner, Jane Thornton, Richard E Brown, Joseph H Eto, Carrie A Webber, and Cathy Cullicott. "Sorry, wrong number: The use and misuse of numerical facts in analysis and media reporting of energy issues." Ed. Socolow, Robert H, Dennis Anderson, and John Harte. Annual Review of Energy and the Environment 2002 27 (2002) 119-158. LBNL-50499.

[11] Koomey, Jonathan, Huimin Chong, Woonsien Loh, Bruce Nordman, and Michele Blazek. 2004. "Network electricity use associated with wireless personal digital assistants." The ASCE Journal of Infrastructure Systems (also LBNL-54105). vol. 10, no. 3. September. pp. 131-137. [http://ascelibrary.org/doi/abs/10.1061/(ASCE)1076-0342(2004)10%3A3(130)]

[12] Koomey, J. Turning Numbers into Knowledge: Mastering the Art of Problem Solving. (Analytics Press, 2017).

[13] Camilo Mora, Randi L. Rollins, Katie Taladay, Michael B. Kantar, Mason K. Chock, Mio Shimada & Erik C. Franklin. Bitcoin emissions alone could push global warming above 2°C. Nature Climate Changevolume 8, pages931–933 (2018)

[14] Smartbit. Bitcoin chart - Transaction fees per block. (2019). https://www.smartbit.com.au/

[15] Digiconomist. Bitcoin Electricity Consumption: An Economic Approach. Digiconomist (2017).

[16] Roberts, P. This Is What Happens When Bitcoin Miners Take Over Your Town. Politico Magazine (2018).

[17] Massena Electric. MED - For Our Business Customers. (2019). http://www.massenaelectric.com/businesscustomer/businesscustomer.htm.

[18] International Energy Agency. Power - Tracking Clean Energy Progress. (IEA, 2019). https://www.iea.org/tcep/power/

[19] International Energy Agency. Energy Technology Perspectives 2017. (IEA, 2017).

[20] International Energy Agency. World Energy Outlook 2017. (IEA, 2017).

[21] Shehabi, A. et al. United States Data Center Energy Usage Report. (2016).

[22] Robert Domm. Michigan Yesterday & Today. Voyageur Press. (2009)

[23] Ania Monaco. Edison's Pearl Street Station Recognized With Milestone: IEEE honors the world's first central power station. 27 July 2011. (2011). http://theinstitute.ieee.org/tech-history/technology-history/edisons-pearl-street-station-recognized-with-milestone810

[24] Amazon. Technical Details: KNCminer Jupiter. (2013). https://www.amazon.com/Jupiter-KNCminer/dp/B00GXA08E4/ref=cm_cr_arp_d_product_top?ie=UTF8.

[25] Amazon. Technical Details: Butterfly Labs Jalapeno BitForce 5 GH/s SC. (2013). https://www.amazon.com/Butterfly-Labs-Jalapeno-BitForce-Bitcoin/dp/B00GTB2ZR0/ref=cm_cr_arp_d_product_top?ie=UTF8.

[26] Amazon. Technical Details: Antminer S1 Dual Blade 180 Gh/s. (2013). https://www.amazon.com/d/Networking-Products/Antminer-S1-Blade-Bitcoin-Miner/B00HL4MEG6/ref=sr_1_5?s=electronics&ie=UTF8&qid=1540840622&sr=1-5&keywords=AntMiner+S1.

[27] Bitcoin Wiki. Comparatie hardware minat. (2019). https://ro.bitcoin.it/wiki/Comparatie_hardware_minat.

[28] Fargo, S. Review and Interview: Spondoolies-Tech SP30 Yukon 4.5 th/s Bitcoin ASIC Miner. (2014). https://www.ccn.com/review-interview-spondoolies-tech-sp30-yukon-4-5-ths-bitcoin-asic-miner.

[29] Fargo, S. Review: Rockminer R3-Box 470 gh/s+ Bitcoin ASIC Miner. (2014). https://www.ccn.com/review-rockminer-rk3-470-ghs-bitcoin-miner.

30 Amazon. Technical Details: Bitmain AntMiner S2 1000 Gh/s. (2014). https://www.amazon.com/Bitmain-AntMiner-1000-SHA-256-Miner/dp/B00KH9339O.

31 Amazon. Technical Details: RockMiner R-BOX 32 -37 GH/s. (2014). https://www.amazon.com/RockMiner-R-BOX-SHA-256-Miner-ASICMiner/dp/B00KLQHSM6/ref=sr_1_1?ie=UTF8&qid=1540842856&sr=8-1&keywords=rockminer+r-box&dpID=51zHZy9%252BbSL&preST=_SX300_QL70_&dpSrc=srch.

32 Amazon. Technical Details: Rockminer Rocket RK-Box 420 - 480 Gh/s. (2014). https://www.amazon.com/Rockminer-Rocket-RK-Box-420-Bitcoin/dp/B00LM00D4U/ref=cm_cr_arp_d_product_top?ie=UTF8.

33 Amazon. Technical Details: Spondoolies-Tech SP10 Dawson - 1.4 TH/s ASIC Bitcoin Miner. (2014). https://www.amazon.com/Spondoolies-Tech-SP10-Dawson-Bitcoin-Miner/dp/B00MTXNSZA/ref=cm_cr_arp_d_product_top?ie=UTF8.

34 Amazon. Technical Details: RockMiner NEW R-BOX 100 -110 GH/s. (2014). https://www.amazon.com/RockMiner-R-BOX-SHA-256-ASICMiner-100-135/dp/B00NFBBN16/ref=cm_cr_arp_d_product_top?ie=UTF8.

35 Amazon. Technical Details: Blackarrow Prospero X-1: 100 Gh/s. (2014). https://www.amazon.com/Blackarrow-Prospero-X-1-Bitcoin-Miner/dp/B00NUF2XWK/ref=cm_cr_arp_d_product_top?ie=UTF8.

36 Amazon. Technical Details: AntMiner S4. (2014). https://www.amazon.com/AntMiner-2000Gh-0-69W-Bitcoin-Miner/dp/B00NWHT18A.

37 Amazon. Technical Details: AntMiner S3 441Gh/s. (2014). https://www.amazon.com/AntMiner-S3-441Gh-0-77W-SHA-256/dp/B00NZDBWKG.

38 Amazon. Technical Details: Blackarrow Prospero X-3. (2014). https://www.amazon.com/Blackarrow-Prospero-X-3-0-50W-Bitcoin/dp/B00R50RDR6/ref=cm_cr_arp_d_product_top?ie=UTF8.

39 Amazon. Technical Details: Klondike K16. (2014). https://www.amazon.ca/Klondike-Miner-Avalon-5-7Gh-Mining/dp/B00O2HYQV6.

40 Amazon. Technical Details: RockMiner Ti-Box 800 GHs. (2014). https://www.amazon.com/RockMiner-Ti-Box-800-Bitcoin-ASIC/dp/B00QJ8CFJ6.

41 Amazon. Technical Details: AntMiner S5 ~1155Gh/s. (2014). https://www.amazon.com/AntMiner-S5-1155Gh-0-51W-Bitcoin/dp/B00RCTIY4G/ref=sr_1_5?s=electronics&ie=UTF8&qid=1540840694&sr=1-5&keywords=AntMiner+S5.

42 Amazon. Technical Details: Spondoolies-Tech SP20. (2014). https://www.amazon.com/Spondoolies-Tech-Jackson-1-3-1-7TH-Bitcoin-Miner/dp/B00RC288E4/ref=sr_1_1?s=electronics&ie=UTF8&qid=1540841967&sr=1-1&keywords=Spondoolies-Tech+SP20&dpID=41QqaKBeHsL&preST=_SX300_QL70_&dpSrc=srch.

[43] Spondooliestech. Spondooliestech SP35 User Guide. (2015). https://cdn.shopify.com/s/files/1/0389/3233/files/SP35_User_Guide.pdf.

[44] Amazon. Technical Details: Twin fury miner 5+GH/s usb. (2015). https://www.amazon.co.uk/d/USB-Flash-Drives/Twin-fury-miner-Bitcoin-basic/B00HR5Z1EQ.

[45] Amazon. Technical Details: AntMiner S5+ ~7.722TH/S. (2015). https://www.amazon.com/AntMiner-7-722TH-0-445W-Bitcoin-Miner/dp/B013WWTAV2/ref=cm_cr_arp_d_product_top?ie=UTF8.

[46] Amazon. Technical Details: Antminer S7. (2015). https://www.amazon.com/Antminer-4-73TH-Fans-Bitcoin-Miner-x/dp/B014OGCP6W.

[47] Amazon. Technical Details: Spondoolies-Tech SP31. (2016). https://www.amazon.com/dp/B01DQ1NU24.

[48] Bitman. Bitmain Antminer R4 profitability. (2017). https://www.asicminervalue.com/miners/bitmain/antminer-r4.

[49] Amazon. Technical Details: Ebit E9 Plus 9THs. (2017). https://www.amazon.com/Ebit-E9-Plus-9THs-bitcoin/dp/B075H99QQW.

[50] Amazon. Technical Details: 6.3 TH/s Bitcoin miner. (2017). https://www.amazon.com/6-3-TH-Bitcoin-miner-Ebit/dp/B075MWKX3S.

[51] Ebang. Ebang Ebit E9i profitability | ASIC Miner Value. (2018). https://www.asicminervalue.com/miners/ebang/ebit-e9i.

[52] Amazon. Technical Details: Antminer S9 ~14.0TH/s. (2018). https://www.amazon.com/Antminer-S9-14-0TH-Bitcoin-Supply/dp/B0792S9PZ8/ref=sr_1_3?s=electronics&ie=UTF8&qid=1540868994&sr=1-3&keywords=AntMiner+S9.

[53] Amazon. Technical Details: AntMiner T9+ 10.5TH/s. (2018). https://www.amazon.com/AntMiner-T9-10-5TH-0-136W-Bitcoin/dp/B079G8LH46/ref=sr_1_fkmr1_2?s=electronics&ie=UTF8&qid=1540869190&sr=1-2-fkmr1&keywords=antminer+t9+plus.

[54] Amazon. Technical Details: Ebang EBIT E10. (2018). https://www.amazon.com/E10-Ebang-EBIT-18TH/dp/B07BLGLPJ2.

[55] AT&T Corporation. Wikipedia (2019). https://en.wikipedia.org/wiki/AT%26T_Corporation

[56] Bryant, M. 20 years ago today, the World Wide Web was born. TNW Insider (2011).

[57] California Cable & Telecommunications Association. History of Cable. (2019). https://www.calcable.org/learn/history-of-cable/

[58] Disc brake. Wikipedia (2019). https://en.wikipedia.org/wiki/Disc_brake#Mass_production

[59] Electric stove. Wikipedia (2018). https://en.wikipedia.org/wiki/Electric_stove

[60] Electrolux. Electrolux Intl Company History. (2019). http://www.frigidaire-intl.com/company-history

[61] Frizzell, N. 'I felt like Morse tapping his first code' – the man who invented the podcast. The Guardian (2016).

[62] Ganapati, P. Oct 25, 1955: Time to Nuke Dinner. Wired (2010). https://www.wired.com/2010/10/1025home-microwave-ovens/

[63] Hydramatic. Wikipedia (2019). https://en.wikipedia.org/wiki/Hydramatic
[64] Hilpern, K. The Secret History Of: The dishwasher. The Independent (2010).
[65] History of mobile phones. Wikipedia (2019). https://en.wikipedia.org/wiki/History_of_mobile_phones
[66] History of personal computers. Wikipedia (2019). https://en.wikipedia.org/wiki/History_of_personal_computers#The_beginnings_of_the_personal_computer_industry
[67] Ignition system. Wikipedia (2019). https://en.wikipedia.org/wiki/Ignition_system#Electronic_ignition
[68] Keith. The History of Social Media: Social Networking Evolution! (History Cooperative, 2015). https://historycooperative.org/the-history-of-social-media/
[69] Morris, M. The History of the Clothes Dryer. Hunker (2019). https://www.hunker.com/13410374/the-history-of-the-clothes-dryer
[70] Nguyen, T. C. The History of Smartphones. ThoughtCo (2018). https://www.thoughtco.com/history-of-smartphones-4096585
[71] Personal Finance. History of Debit Cards: How Debit Cards Changed the Way We Bank. Bright Hub (2019).
[72] Power steering. Wikipedia (2018). https://en.wikipedia.org/wiki/Power_steering
[73] Real-time gross settlement. Wikipedia (2019). https://en.wikipedia.org/wiki/Real-time_gross_settlement#History
[74] Roberts, P. This Is What Happens When Bitcoin Miners Take Over Your Town. Politico Magazine (2018).
[75] Rocket eBook. Wikipedia (2018). https://en.wikipedia.org/wiki/Rocket_eBook
[76] Recently Discovered Vintage Water Heaters Reveal Time-Honored Quality and Durability. (2007). https://www.rheem.com/about/news-releases/recently-discovered-vintage-water-heaters-reveal-time-honored-quality-and-durability/
[77] Smith, W. D. Radial Tires Stir Battle in U.S. Rubber Industry. The New York Times (1972).
[78] Samsung. Center for Computing History - Samsung Pen Master Tablet. (2012). http://www.computinghistory.org.uk/det/18733/Samsung-Pen-Master-Tablet/
[79] Seale, W. The president’s house: a history. (Johns Hopkins University Press, 2008).
[80] Scott, C. The History of the Radio Industry in the United States to 1940. (Economic History Association, 2008).
[81] Thor washing machine. Wikipedia (2019). https://en.wikipedia.org/wiki/Thor_washing_machine
[82] Varrasi, J. Global Cooling: The History of Air Conditioning. (2019). https://www.asme.org/engineering-topics/articles/technology-and-society/global-cooling-the-history-of-air-conditioning
[83] William H. Hoover - Ohio History Central. (2019). http://www.ohiohistorycentral.org/w/William_H._Hoover