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# Is Bitcoin Really Untethered?

JOHN M. GRIFFIN and AMIN SHAMS*

**ABSTRACT**

This paper investigates whether Tether, a digital currency pegged to the U.S. dollar, influenced Bitcoin and other cryptocurrency prices during the 2017 boom. Using algorithms to analyze blockchain data, we find that purchases with Tether are timed following market downturns and result in sizable increases in Bitcoin prices. The flow is attributable to one entity, clusters below round prices, induces asymmetric autocorrelations in Bitcoin, and suggests insufficient Tether reserves before month-ends. Rather than demand from cash investors, these patterns are most consistent with the supply-based hypothesis of unbacked digital money inflating cryptocurrency prices.

INNOVATION, EXCESSIVE SPECULATION, AND DUBIOUS behavior are often closely linked. Periods of extreme price increases followed by implosion, commonly known as "bubbles," are often associated with legitimate inventions, technologies, or opportunities. However, they can be carried to excess. In particular, financial bubbles often coincide with the belief that a rapid gain can be

*John M. Griffin is at the McCombs School of Business, University of Texas at Austin. Amin Shams is at the Fisher College of Business, Ohio State University. Helpful comments were received from Stefan Nagel (the editor); an associate editor; two anonymous referees; Cesare Fracassi; Sam Kruger; Shaun MaGruder; Gregor Matvos; Nikolai Roussanov; Clemens Sialm; and seminar and conference participants at the Chinese University of Hong Kong, Cryptocurrencies and Blockchain Conference at the University of Chicago, FBI CPA Conference, Financial Intelligence and Investigations Conference, Fintech Conference at the Hong Kong University, Hong Kong University of Science and Technology, Hong Kong Securities and Futures Commission, Korea Advanced Institute of Science and Technology, Korean Financial Supervisory Service, Japan Financial Services Agency, Santa Clara University, Texas Bitcoin Conference, Tsinghua University, U.S. Commodity Futures Trading Commission, University of Texas-Austin, University of Zurich, and Wharton Liquidity Conference at the University of Pennsylvania. Integra FEC purchased data and provided research assistant support for the project. Griffin is an owner of Integra FEC, which engages in financial consulting on a variety of issues related to financial fraud, including cryptocurrencies. See disclosure statement. We especially thank Tin Dinh for excellent conceptual assistance and Prateek Mahajan for research assistance.

Correspondence: Amin Shams, Department of Finance, Ohio State University, 2100 Neil Ave, Columbus, OH 43210; e-mail: shams.22@osu.edu.



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obtained from simply selling an asset to another speculator.[1] Perhaps because of the focus on speculative activity rather than verifiable fundamentals, bubbles have historically been associated with various forms of misinformation and fraud. For example, in the Mississippi Bubble of 1719 to 1720, promoters engaged in false marketing about the potential of income-generating assets, price support by the stock itself, and distribution of paper money that was not fully backed by gold as claimed (Dale (2004), Kindleberger and Aliber (2011)). As we briefly discuss in Section I, an abundance of evidence suggests that famous bubbles such as the 1840s Railroad bubble, the roaring 1920s stock market boom, the dot-com bubble, and the 2008 financial crisis all involved misinformation, false accounting, price manipulation, collusion, and fraud, often in sophisticated forms.

Cryptocurrencies grew from nearly nothing to over $300 billion in market capitalization in only a few years and fit the characterization of bubbles quite well–extreme speculation surrounding an innovative technology. To many, Bitcoin and other cryptocurrencies offer the promise of an anonymous, decentralized financial system free from banks and government intervention. The conception of Bitcoin corresponds to the 2008 to 2009 financial crisis, a time of growing disdain for government intervention and distrust of major banks. The promise of a decentralized ledger with independently verifiable transactions has enormous appeal,[2] especially in an age when centralized clearing is subject to concerns about both external hacking and internal manipulation.[3] Ironically, new large entities have gained centralized control over the vast majority of operations in the cryptocurrency world, such as centralized exchanges that handle the majority of transactions and stable coin issuers that can control the supply of money like a central bank. These centralized entities operate largely outside the purview of financial regulators and offer varying levels of limited transparency. Additionally, operating based on digital stable coins rather than fiat currency further relaxes the need for these entities to establish a legitimate fiat banking relationship.[4] Trading on unregulated exchanges, specifically on cross-digital-currency exchanges, could leave cryptocurrencies vulnerable to gaming and manipulation.

In this study, we examine the role of the largest stable coin, Tether, on Bitcoin and other cryptocurrency prices. Tether, which accounts for more Bitcoin transaction volume than the U.S. dollar (USD), is purportedly backed by USD

[1] For example, in the bubble model of Scheinkman and Xiong (2003), investors purchase assets not because of their belief in the underlying cash flows, but because they can sell the asset to another individual with a higher valuation.

[2] The appeal, underlying value, and mechanics of cryptocurrencies and decentralized ledgers have been described in recent descriptive and theoretical work (Yermack (2017), Sockin and Xiong (2018), Cong, He, and Li (2019), Cong, Li, and Wang (2019)).

[3] Recent examples of apparently manipulated markets include LIBOR (Mollenkamp and Whitehouse (2008)), FX manipulation (Vaughan and Finch (2013)), gold (Denina and Harvey (2004)), and the VIX index (Griffin and Shams (2018)). Kumar and Seppi (1992) and Spatt (2014) discuss conditions that may facilitate manipulation.

[4] By May 20, 2018, over 1,600 cryptocurrencies and digital tokens were trading on various digital exchanges.

reserves and allows for dollar-like transactions without a banking connection, which many cryptoexchanges have difficulty obtaining or keeping. Although some in the blogosphere and press have expressed skepticism regarding the USD reserves backing Tether,[5] the cryptocurrency exchanges largely reject such concerns and widely use Tether in transactions.

To shed light on the driving forces behind the 2017 boom of cryptocurrency markets, we examine two main alternative hypotheses for Tether: whether Tether is "pulled" (demand-driven), or "pushed" (supply-driven). Under the pulled hypothesis, Tether is driven by legitimate demand from investors who use Tether as a medium of exchange to enter their fiat capital into the cryptospace because it is digital currency with the stability of the dollar "peg." In this case, the price impact of Tether reflects natural market demand.

Alternatively, under the "pushed" hypothesis, Bitfinex prints Tether regardless of the demand from cash investors, and additional supply of Tether can create inflation in the price of Bitcoin that is not due to a genuine capital flow. In this setting, Tether creators have several potential motives. First, if the Tether creators, like most early cryptocurrency adopters and exchanges, have large holdings of Bitcoin, they generally profit from the inflation of the cryptocurrency prices. Second, coordinated supply of Tether creates an opportunity to manipulate cryptocurrencies—when prices are falling, the Tether creators can convert their large Tether supply into Bitcoin in a way that pushes Bitcoin up and then sell some Bitcoin back into dollars in a venue with less price impact to replenish Tether reserves. Finally, if cryptocurrency prices crash, the founders essentially have a put option to default on redeeming Tether, or to potentially experience a "hack" or insufficient reserves where by Tether-related dollars disappear. The "pushed" and "pulled" hypotheses have different testable implications for capital flows and cryptocurrency returns that we can take to the powerful blockchain data.

We begin our exercise by collecting and analyzing Tether and Bitcoin blockchain data using a series of algorithms that reduce the complexity of the blockchain. In particular, because of the semitransparent nature of the transaction history recorded on the blockchain, we are able to use variations of algorithms developed in computer science to cluster groups of related Bitcoin wallets. Large clusters are then labeled by identifying certain member wallets inside each group and tracking the flow of coins between major players in the market.

Figure 1 plots the aggregate flow of Tether among major market participants on the Tether blockchain from its conception in October 6, 2014 until March 31, 2018. The size of the nodes is proportional to the sum of coin inflow and outflow to each node, the thickness of the lines is proportional to the size of flows, and all flow movements are clockwise. Tether is authorized, moved to Bitfinex, and then slowly distributed to other Tether-based exchanges, mainly Poloniex and Bittrex. The graph shows that almost no Tether returns to the Tether issuer to

[5] For example, see posts by Bitfinex'ed account at https://medium.com/@bitfinexed and Popper (2017).

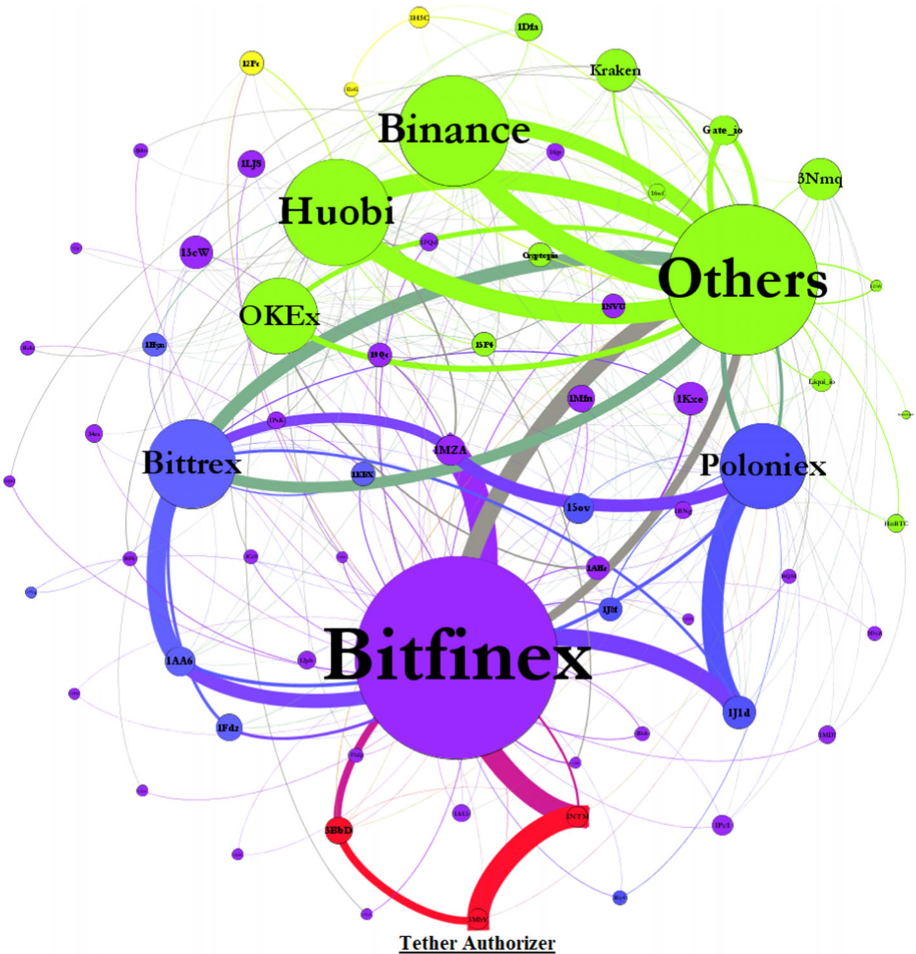



**Figure 1. Aggregate flow of Tether between major addresses**. This figure shows the aggregate flow of Tether between major exchanges and market participants from Tether genesis block to March 31, 2018. Tether transactions are captured on Omni Layer as transactions with the coin ID 31. The data include confirmed transactions with the following action types: Grant Property Tokens, Simple Send, and Send All. Exchange identities on the Tether blockchain are obtained from the Tether rich list. The thickness of the edges is proportional to the magnitude of the flow between two nodes, and the node size is proportional to aggregate inflow and outflow for each node. Intranode flows are excluded. The direction of the flow is shown by the curvature of the edges, with Tether moving clockwise from a sender to a recipient. (Color figure can be viewed at wileyonlinelibrary.com)

be redeemed, and the major exchange where Tether can be exchanged for USD, Kraken, accounts for only a small proportion of transactions. Tether also flows out to other exchanges and entities and becomes more common as a medium of exchange over time.

A similar analysis of the flow of coins on the much larger Bitcoin blockchain shows that the three main Tether exchanges for most of 2017 (Bitfinex, Poloniex, and Bittrex) also facilitate considerable cross-exchange Bitcoin flows among themselves.[6] Additionally, we find that the cross-exchange Bitcoin flows on Bitcoin blockchain closely match the Tether flows on the Tether blockchain. This result independently verifies our algorithm for categorizing exchange identities and also captures the direct exchange of Tether for Bitcoin. Additionally, we find that one large player is associated with more than half of the exchange of Tether for Bitcoin at Bitfinex, suggesting that the distribution of Tether into the market is from a large player and not from many different investors who bring cash to Bitfinex to purchase Tether.

We examine the flow of coins identified above to understand whether Tether is pushed or pulled, and the effect of Tether, if any, on Bitcoin prices. First, following periods of negative Bitcoin returns, Tether flows from Bitfinex to Poloniex and Bittrex, and in exchange, Bitcoin is sent back to Bitfinex. Second, when there are positive net hourly flows from Bitfinex to Poloniex and Bittrex, Bitcoin prices move up over the next three hours, resulting in predictably high Bitcoin returns. The price impact is present after periods of negative returns and periods following the printing of Tether, that is, when there is likely an oversupply of Tether in the system. This phenomenon strongly suggests that the price effect is driven by Tether issuances. Additionally, the price impact is strongly linked to trading of the one large player and not to other accounts on Poloniex, Bittrex, or other Tether exchanges.

To gauge the aggregate magnitude of the observed price impact, we focus on the top 1% of hours with the largest lagged combined Bitcoin and Tether net flows on the two blockchains. These 95 hours have large negative returns before the flows but are followed by large positive returns afterward. This 1% of our time series (over the period from the beginning of March 2017 to the end of March 2018) is associated with 58.8% of Bitcoin's compounded return and 64.5% of the returns on six other large cryptocurrencies (Dash, Ethereum Classic, Ethereum, Litecoin, Monero, and Zcash).[7] A bootstrap analysis with 10,000 simulations demonstrates that this behavior does not occur randomly, and a similar placebo analysis for flows to other Tether exchanges shows very little price impact.

Further analysis for the single largest player on Bitfinex shows that the 1%, 5%, and 10% of hours with the highest lagged flow of Tether by this one player are associated with 55%, 67.2%, and 79.2% of Bitcoin's price increase over our March 1, 2017 to March 31, 2018 sample period. This pattern is not present for the flows to any other Tether exchanges. Moreover, simulations show that these patterns are highly unlikely to be due to chance—this one large player or entity either exhibited clairvoyant market timing or exerted an

[6] For the period between March 1, 2017 and March 31, 2018, we grouped over 640,000 wallet addresses as Bitfinex, 720,000 addresses as Poloniex, and 1.22 million wallet addresses as Bittrex using our clustering algorithm.

[7] These findings are instructive but incomplete, and they may over- or understate the Tether effect. Fully quantifying the effect of Tether on Bitcoin depends on knowing precise price impacts and the various exchange, off-exchange, and cross-trading mechanisms on which these cryptocurrencies may trade.

extremely large price impact on Bitcoin that is not observed in the aggregate flows from other smaller traders. Such trading by this one player is also large enough to induce a statistically and economically strong reversal in Bitcoin prices following negative returns.

Investors hoping to stabilize and drive up the price of an asset might concentrate on certain price thresholds as an anchor or price floor, the idea being that if investors can demonstrate a price floor, then they can induce other traders to purchase.[8] Interestingly, Bitcoin purchases from Bitfinex strongly increase just below multiples of 500. This pattern is present only in periods following printing of Tether, is being driven by the single large account holder, and is not observed by other exchanges. To address causality, we use the discontinuity in Tether flow at the round threshold cutoffs as an instrument and find that Tether flows are causing the positive Bitcoin return.

The patterns observed above are consistent with either one large player purchasing Tether with cash at Bitfinex and then exchanging it for Bitcoin, or Tether being printed without cash backup and pushed out through Bitfinex in exchange for Bitcoin. If Tether is pushed out to other cryptoexchanges rather than demanded by cash investors, then it may not be always fully backed. To show the full reserve, Bitfinex might therefore have to liquidate their Bitcoin reserve to support their end-of-month (EOM) bank statements. Interestingly, we find a significant negative EOM abnormal return of 6% in the months with strong Tether issuance and no abnormal returns in months when Tether is not issued. Since these patterns are driven primarily by only a few EOMs with large Tether issuance, we test further and find that the EOM effect is stronger in a value-weighted index of the largest cryptocurrencies and is also present around a publicized mid-month balance statement. Moreover, Bitfinex's reserve wallets on the blockchain data exhibit large significant balance decreases in days prior to EOMs with large Tether printing. This pattern is not present in reserve wallets on any other exchanges.

Our results are generally consistent with Tether being printed unbacked and pushed out onto the market, which can have an inflationary effect on asset prices. While other tests do not speak to capital backing, the EOM patterns are inconsistent with the "pulled" hypothesis since they indicate a lack of dollar reserves. Nevertheless, we further examine a direct implication of the "pulled" hypothesis by testing whether the flows of Tether bear a relation to a proxy for its demand from investors, namely the premium for Tether relative to the USD. We find little evidence to support this demand-based hypothesis, but note that the demand-based proxies likely contain noise. In sum, while we expect that there are some sources of legitimate demand for Tether, they do not appear to dominate the Tether flow patterns observed in the data.

Overall, our paper demonstrates the usefulness of combining methodological approaches from computer science and finance, in particular, clustering

[8] Shiller (2000) and Bhattacharya, Holden, and Jacobsen (2012) describe trading signals that anchor around price thresholds. These thresholds can be used as coordination mechanisms as well. For instance, Christie and Schultz (1994) find collusion only around even numbers in spreads.

algorithms and capital flow analysis, to understand the role of central monetary entities in a cryptocurrency world. Previous studies show that none of the exposures to macroeconomic factors, stocks markets, currencies, or commodities can explain cryptocurrency prices (Liu and Tsyvinski (2018)). We find that Tether flows can largely explain Bitcoin prices. Our findings are generally consistent with evidence that sophisticated investors may profit from bubbles (Brunnermeier and Nagel (2004)), but more specifically provide empirical evidence on the intersection of potentially nefarious activity and bubbles. Although cryptocurrencies are relatively new, the trading mechanisms within and across exchanges are quite complex (Partnoy (2009)) and may obfuscate the influence of large players. This complexity also implies that there are limits to what we can learn from blockchain data, and additional research is certainly necessary to further understand the cryptocurrency market. Since our findings indicate that Bitcoin prices are subject to gaming by a small number of actors, they suggest that Bitcoin does not make a solid basis for more complex financial vehicles such as exchange-traded funds (ETFs) or derivatives. Market surveillance within a proper regulatory framework across many venues may be necessary for cryptocurrency markets to be a reliable medium for fair financial transactions.

The rest of the paper is organized as follows. Section I provides an overview of historical bubbles, cryptocurrencies, Tether, and the main pushed and pulled hypotheses to be tested. Section II describes our main data sources and explains the methodologies that we use to analyze the blockchain data and flows. Section III analyzes the potential influence of Tether on Bitcoin, and Section IV further tests whether the flows are consistent with pushed or pulled explanations. Section V concludes.

## I. Overview of Bubbles, Bitcoin, Tether, and Hypotheses

### *A. Speculative Bubbles and the Prevalence of Dubious Market Activity*

Periods of excessive price speculation often share the themes of optimism around a new technology, a focus on selling to others rather than economic cash flows, and questionable activities. The famous South Sea Bubble of 1719 to 1720 is often described as a sophisticated Ponzi scheme where old investors were paid high dividends not from operations but from new stock issuances with the hope of higher prices at future issuances (Hutcheson (1720), Temin and Voth (2013)). Scheinkman (2013) notes that many other companies around this time also seem to have been fraudulent. The Railroad Bubble of the 1840s led to a host of companies that merely sought to procure funds from investors and had no intention of actually building railroads (Robb (2002)). In the Roaring Twenties, investment pools would manipulate a stock price through "wash sales," collusion with stock-exchange specialists, and coordinated publicity from commentators to pump a stock at an inflated price to the public (Malkiel (1981)). The technology or "dot-com" bubble of 1997 to 2000 also contained strong elements of stock promotion through inflated forecasts from affiliated analysts

(Lin and McNichols (1998)), pushing or "laddering" prices through implicit agreements to purchase more IPO shares in the aftermarket (Griffin, Harris, and Topaloglu (2007)), and accounting fraud (e.g., Enron and Worldcom). Hedge funds and other institutional investors were the main net buyers of overpriced technology stocks during this period (Brunnermeier and Nagel (2004), Griffin et al. (2011)).

One line of thinking is that more fraud exists in economic booms because individuals monitor their investments relatively less closely (Povel, Singh, and Winton (2007)). Akerlof et al. (1993) argue that historical actors involved in "looting" an organization (such as banks in the U.S. savings and loan crisis) move capital into a space in a manner that systematically increases asset prices. In our analysis of Bitcoin and Tether, we are able to examine whether either of these two views fits the data.

### *B. Brief History of Bitcoin and Exchange "Hacks"*

On October 31, 2008, the whitepaper "Bitcoin: A Peer-to-Peer Electronic Cash System" was released by Satoshi Nakamoto (Nakamoto (2008)). The paper outlines a digital currency system where transactions are recorded on a chain of linked blocks, hence "blockchain," and verified electronically through a decentralized network of users. This decentralized feature avoids the traditional system of government-backed currencies controlled by centralized banks and clearing houses. On January 3, 2009, the first block was established on the Bitcoin blockchain by Nakamoto. On October 5, 2009, New Liberty Standard established the first exchange rates of Bitcoin (BTC) at 1309.03 for 1 USD, or \$0.00076 per BTC.[9] By April 23, 2011, Bitcoin exceeded parity with the USD, euro, and British pound, with the market cap passing 10 million USD, and by March 28, 2013, Bitcoin market cap passed 1 billion USD.

Mt. Gox, a leading exchange that by 2013 was handling approximately 70% of Bitcoin volume, declared bankruptcy due to a mysterious "hack" of the exchange which resulted in approximately \$450 million worth of Bitcoin missing from investors' accounts. Good reasons have been put forward as to why the "hack" may have been an inside job (Nilsson (2015)). Gandal et al. (2018) argues that fraudulent trading on the Mt. Gox exchange led to a significant spike in Bitcoin prices in late 2013.[10] Foley, Karlsen, and Putniņš (2019) detail hubs of illicit commerce in Bitcoin and estimate that 44% of transactions are associated with illegal activity.

[9] Most of these facts are available in multiple places, but an account of the first five years of Bitcoin can be found at http://historyofbitcoin.org and in Lee (2014).

[10] In the second-biggest hack in Bitcoin history, on August 2, 2016, the Bitfinex exchange announced that \$72 million had been stolen from investor accounts, leading Bitcoin to plummet 20% in value.

### *C. Brief History of Tether*

The objective of Tether is to facilitate transactions between cryptocurrency exchanges with a rate pegged to the USD. While this could also occur with fiat transactions, Tether is advantageous because many cryptoexchanges have difficulty securing banking relationships. Tether Limited, the issuer of Tether, historically claimed that "Tether Platform currencies are 100% backed by actual fiat currency assets in our reserve account."[11] However, Tether itself created ambiguity around this backing by later noting that they do not guarantee redemption rights.[12]

The Bitfinex exchange started in 2012, but experienced rapid growth and now claims to be "the world's largest and most advanced cryptocurrency trading platform." The Paradise Papers leaks in November 2017 named the Bitfinex exchange officials, Philip Potter and Giancarlo Devasini, responsible for setting up Tether Holdings Limited in the British Virgin Islands in 2014.[13]

Figure 2, Panel A, shows the cumulative authorization of Tether denominated in both USD and Bitcoin as well as Bitcoin prices. The first Tether was authorized on October 6, 2014, but the market cap was only $25 million as of March 6, 2017. Between March 7, 2017 and January 2018, however, more than $2.2 billion worth of Tether was issued.

Panel B of Figure 2 shows transactions of major cryptocurrencies in USD as compared to Tether, aggregated across all cryptocurrency exchanges available on *CoinAPI*. Although cryptocurrencies were historically denominated in dollars or yuan, a large share of Bitcoin and many other cryptocurrencies transactions are denominated in Tether as of 2017. Additionally, even after closely examining Bitfinex public statements, it is unclear as to whether Bitfinex transactions are denominated in dollar or Tether. Prices quoted on Bitfinex are significantly closer to prices on Tether exchanges than USD exchanges.[14] Hence, we term Bitfinex transactions as well as those explicitly denominated in Tether as Tether-related.

Many in the blogosphere as well as the mainstream press began to raise questions about Tether in the second half of 2017.[15] In April 2017, Tether lost its banking relationship with a Taiwanese bank linked to Wells Fargo. Since then, Tether has issued over $2 billion Tether without fully disclosing banking details. This could be due to not wanting to subject their bank to public scrutiny and risk losing their new banking relationship, as many large banks avoid the scrutiny associated with crypto-related deposits either because

[11] See https://tether.to/faqs/.

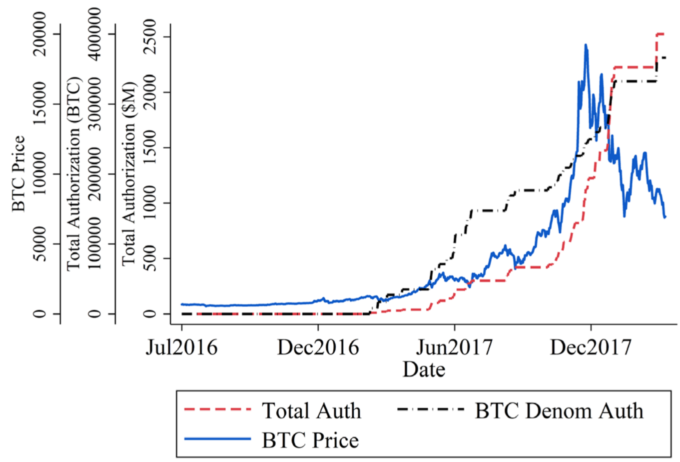
[12] "There is no contractual right or other right or legal claim against us to redeem or exchange your Tethers for money. We do not guarantee any right of redemption or exchange of Tethers by us for money" (Leising (2017)).

[13] See Popper (2017).

[14] The percentage deviation of hourly prices between Bitfinex and Poloniex and Bittrex are 19 and 42 basis points, while the deviation is 103, 56, and 111 basis points for Bitstamp, Gemini, and Kraken, respectively.

[15] See Leising (2017), Kaminska (2017), and Popper (2017).

Panel A. Tether and Bitcoin Price over Time




Panel B. Percentage of Trade Volume in USD and Tether

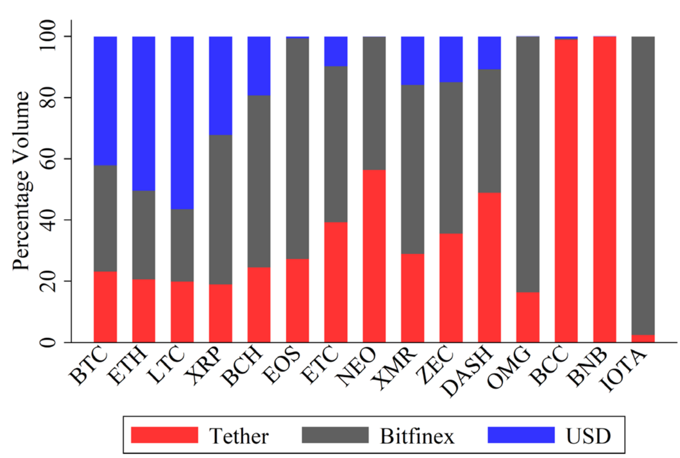



**Figure 2. Tether authorization and Bitcoin price over time, and trade volume in both dollars and Tether**. Panel A plots the cumulative authorization of Tether and the price of Bitcoin over time. The red dashed line shows cumulative authorization in millions of Tether tokens. The black dashed line shows Tether cumulative authorization denominated in contemporaneous Bitcoin price. The blue line shows the Bitcoin price. Authorizations are defined as transactions with transaction type "Grant Property Tokens" on Tether blockchain. Panel B shows the percentage of trade volume of USD and Tether for major cryptocurrencies between March 1, 2017 and March 31, 2018 aggregated over all exchanges. The major currencies include the 15 largest cryptocurrencies and tokens by aggregate trade volume across exchanges reported in *CoinAPI* data over the same period. The blue bars show the percentage of volume traded against USD, the red bars show the percentage against Tether, and the gray bars show the percentage against USD/Tether on the Bitfinex exchange. (Color figure can be viewed at wileyonlinelibrary.com)

of perceived reputation tainting or because of the need to comply with anti-money laundering (AML) or "know your customer" (KYC) banking regulations. Tether hired a consultant that released an internal memo showing reserves on September 15, 2017.

Immediately after the first draft of this paper, a law firm released a report on the sufficiency of Tether reserves in June 2018.[16] On February 25, 2019, Tether changed their definition of Tether backing to read "traditional currency and cash equivalents." In response to legal motions, on April 30, 2019, Bitfinex's former General Counsel admitted that Tether does not have cash reserves equal to 100% of the outstanding Tethers. In a May 15, 2019 court hearing, a Bitfinex attorney also admitted that Tether invested in instruments beyond cash, including Bitcoin, something clearly at odds with Tether's longstanding claims.

Bloggers have also conjectured about whether Tether authorizations are fueling Bitcoin.[17] One website, tetherreport.com, finds positive return effects after incidences of Tether authorizations.[18] Analysis by Wei (2018), however, finds no price effect at the time of Tether authorizations.

### *D. Main Hypotheses*

This section examines two main alternative "pulled" versus "pushed" hypotheses[19] about Tether. Under the first hypothesis, Tether is "pulled" or driven by legitimate demand from investors who use Tether as a medium of exchange to enter their fiat capital into the cryptospace. In this case, the price impact of Tether reflects natural market demand. Under the second hypothesis, Tether is "pushed" through a supply-driven scheme whereby an unbacked digital dollar is printed and used to purchase Bitcoin. In this case, additional supply of Tether can create inflation in the price of Bitcoin and other cryptocurrencies that is not due to a genuine capital flow.

Related to the "pulled" hypothesis, we first predict that Tether is driven by investor demand and is always fully backed by USD (as with a full-reserve bank).

[16] Tether Limited has also released EOM snapshot bank statements showing reserves at the EOM. Tether has not to our knowledge released a full audit, which is important since snapshot reports showing cash in a bank balance on a certain date could reflect borrowed funds or funds from related entities. Tether is closely related to Bitfinex, which has also not been audited, according to public sources.

[17] See Higgins (2018) and Leising (2017).

[18] The website shows that after 91 hourly events of Tether being granted and moved to Bitfinex, the Bitcoin return increases over the next two hours. They compound the return for those 182 hours (91 two-hour periods) and derive a compounded effect of 48.8%, then compare this effect to 6.5% average compounded returns for the same time period during normal times. The results are incorrectly interpreted as "Tether could account for nearly half of Bitcoin's price rise" or "a rough estimate of 40% price growth attributed to Tether." Indeed, Bitcoin prices increased by 1,422% (from \$893.19 to \$13,592.93) over their period of study. Interestingly, we find that the hours directly following Tether authorization are often not when the Bitcoin buying activity actually occurs.

[19] There is a literature in international finance examining whether capital flows are pushed or pulled across markets (Froot, O'connell, and Seasholes (2001), Griffin, Nardari, and Stulz (2007)).

A currency that can provide a stable store of value, support quick transactions, and potentially allow cryptocurrency exchanges to skirt banking regulations required for traditional deposits has an intuitive appeal. If an increase in demand is driven by new investors who hold dollars and wish to convert their dollars to Tether and then into cryptocurrencies, the increase in demand may result in a higher market rate for Tether. A lower price for Tether would thus be a consequence of weak demand for Tether, while a higher price (perhaps at or above one dollar) would be a consequence of strong Tether demand.

H1A: Tether's price relative to the USD may increase as a consequence of strong investor demand. Tether flows should be strongly related to this demand as proxied by changes in the Tether-USD exchange rate.

H1B: The printing of Tether may also be driven by its usefulness as a facilitator of cross-exchange arbitrage to eliminate pricing discrepancies across cryptocurrency exchanges. For example, Tether outflows from Bitfinex to another exchange should correspond to periods when Bitcoin sells at a premium on Bitfinex relative to that exchange.[20]

The main alternative hypothesis is that Tether is printed independent of demand and pushed onto the market. The issuers can print Tether and convert it into more widely accepted cryptocurrencies such as Bitcoin. In addition to issuance fees, transaction fees, and interest earned from trading in Tether, other possible benefits of "pushing" Tether could be as follows.

First, like an inflationary effect of printing money, issuing Tether increases the money supply in the cryptospace and can significantly push cryptocurrency prices up by generating artificial demand. Since most cryptocurrency exchanges and early movers are long in Bitcoin and other cryptocurrencies, they would generally benefit. For instance, if Bitcoin prices increase, the founders can cash out the acquired Bitcoins into dollars, likely at a slower pace and on an opaque channel that has less price impact than their initial buying behavior. If the Tether issuers wish to legitimize Tether and avoid scrutiny, they can slowly convert some of their cryptocurrencies to USD and retroactively provide either full or partial dollar reserves for Tether.

Second, since Tether issuances are large, if traded strategically, Tether could have further price impact and lead to further manipulation of Bitcoin prices. For instance, the issuers can stabilize and/or set regionalized price floors and push the price of Bitcoin and other cryptocurrencies upward.

Third, the Tether issuers create a valuable put option in the case of a future cryptomarket downturn or other losses. In particular, the founders of Tether have an option to not redeem Tether to dollars, and possibly experience an inside "hack" (McLannahan (2015)) when Tethers and/or their associated dollars suddenly disappear.

[20] This hypothesis is also consistent with the supply-driven view as unbacked money printing of Tether could cause Bitcoin to sell at a premium on Bitfinex relative to the other exchanges before Tether moves to those exchanges.

The key to the "pushed" hypothesis is that the Tether-USD price does not collapse. This can be accomplished by creating a limited set of venues to redeem Tether, sending signals to investors through periodic accounting reports, and creating Tether price support.

To examine the "push" hypothesis, we test the following predictions:

- H2A: If Tether issuers are trying to provide stability to the market during downturns, outflows of Tether and purchases of Bitcoin by Bitfinex may follow periods of negative Bitcoin returns.
- H2B: If Tether supply is large enough to have a material price impact on Bitcoin, Bitcoin prices should go up after Tether flows into the market, especially after periods with large authorization of Tether.
- H2C: Bitcoin returns may show a return reversal after negative returns, especially during times when Tether flows into the market.
- H2D: Since round-number thresholds can be price anchors to set a price floor and are often used as buying signals by investors, flow of Tether might increase if Bitcoin falls below these salient round-number thresholds. This effect should be more pronounced in periods with large Tether authorization.
- H2E: If Tether is not fully backed by dollars at the outset, but the issuers want to signal otherwise to investors by releasing EOM (or other interval) accounting statements, then Tether creators may liquidate Bitcoins into USD to demonstrate sufficient reserves. This could create negative returns in Bitcoin at the EOM, particularly in periods with large Tether issuances.

While the above hypotheses need not all follow from the pulled hypothesis, H2A through H2D shed light on whether the flow of Tether into the market is consistent with creating price support and inflating Bitcoin prices, and H2E sheds light on whether the potential price impact is due to unbacked printing of Tether, which can have an inflationary effect on Bitcoin. In the next section, we discuss the data and empirical methods used to test these hypotheses.

## II. Data, Algorithms, and Flows between Major Accounts

### *A. Data*

The price and the blockchain data obtained for this study amount to over 200 GB from more than 10 sources, with *CoinAPI*, *Coinmarketcap.com*, *Blockchain.info*, *Omniexplorer.info*, and *CoinDesk* as our main sources. The intraday pricing data on major cryptocurrencies come from *CoinAPI*. The starting date varies for different currencies. The sample covers 25 months from March 2016 to March 2018, but the main tests are implemented after March 2017, when Tether experienced a large issuance.[21]

[21] Daily prices are based on Coordinated Universal Time (UTC) time, and the close and open prices are calculated based on a 24-hour daily cycle that ends at midnight UTC. Daily prices of

Bitcoin blockchain data are obtained from *Blockchain.info* and cover the period from Bitcoin initiation in January 2009 to March 2018. The blockchain data contain the entire history of Bitcoin transactions between Bitcoin wallets and include variables such as wallet IDs of senders and recipients as a string of 34 characters and numbers, amount of coins transferred, timestamp, transaction ID, and previous transaction ID where the coin was received by the sender of each new transaction. Over the October 2014 to March 2018 period, Tether is issued via the Omni Layer Protocol based on the Bitcoin blockchain, and Tether blockchain data are from *Omniexplorer.info*.

To assign identities of grouped wallets to Tether-related exchanges on the Bitcoin blockchain, the addresses of a number of wallets belonging to Tether exchanges are collected from public forums and individual investors who transferred Bitcoin to these exchanges.[22] For the Tether blockchain, wallet identities of major exchanges are manually collected from the Tether rich list on tether.to at all snapshots available on Internet Archive.

Tether exchanges account for a large portion of cryptocurrencies' trading volume over our sample period. Table I, Panel A, shows the total trading volume on major exchanges of major cryptocurrencies from March 1, 2017 to March 31, 2018. Tether-based exchanges are marked with a "*." Some exchanges, including Gemini and Coinbase, specialize in a limited number of major coins such as Bitcoin and Ethereum. Others, especially the Tether-related exchanges, feature a large number of coins. Bitfinex has the largest volume, both for Bitcoin and across all major cryptocurrencies. Other Tether exchanges also play an important role among the top 10 exchanges in terms of aggregate volume. As shown in Panel B of Figure 2, a large share of major cryptocurrencies' transactions are denominated in Tether.

Panel B of Table I shows the cross-sectional correlation of cryptocurrencies' daily returns. Not surprisingly, the daily returns are positively correlated across all of the coins, but there is variation across different cryptocurrencies. For example, Bitcoin's correlation with Ethereum, Ripple, and Litecoin are 0.44, 0.20, and 0.45, respectively.

Panel C of Table I reports the autocorrelation of cryptocurrencies at various frequencies. The autocorrelations are generally negative. For example, a 1% change in lagged one-hour Bitcoin prices is followed by a 6 basis point reversal in the next hour. The reversal is 6 and 5 basis points at three- and five-hour intervals.

various coins are obtained from *Coinmarketcap.com*, which calculates the price of each coin by taking the volume-weighted average of prices reported at different exchanges. We also use the intraday *CoinDesk* price index, which aggregates prices across major markets. Hourly and five-minute returns are calculated from the last trade within each minute. Missing prices are carried forward for nontrading periods of up to five minutes. Prices are assumed to be missing if stale for more than five minutes.

[22] The Internet Appendix Section II includes the list of representative addresses that can be used to assign identities of major exchanges. The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

**Table I**

## Summary Statistics

This table summarizes the trading volume and pricing information of major cryptocurrencies on major exchanges. The major cryptocurrencies are the 15 coins and tokens with the highest aggregate volume in USD and Tether across exchanges reported in *CoinAPI* between March 1, 2017 and March 31, 2018, and the top exchanges are those with the highest aggregate volume for these major cryptocurrencies. Panel A shows the total volume for each cryptocurrency on each exchange in billions of dollars from March 1, 2017 to March 31, 2018 using data from *CoinAPI*. Tether-based exchanges are indicated with a star. Panel B shows the daily return correlation between major cryptocurrencies. The daily pricing data are from *CoinMarketCap*. Panel C reports the autocorrelations of the major cryptocurrencies at one-hour, three-hour, and five-hour intervals using price data from the most liquid exchange for each altcoin between March 1, 2017 and March 31, 2018. The three-hour and five-hour autocorrelations are calculated using hourly returns rolled over three-hour and five-hour windows. Standard errors are adjusted for heteroskedasticity and autocorrelation. The intraday pricing data are from *CoinAPI*.

Panel A: Total Volume ($B)

| | Binance* | Bitfinex* | Bitstamp | Bittrex* | Coinbase | Gemini | Huobi* | Kraken* | OKEx* | Poloniex* |
|---|---|---|---|---|---|---|---|---|---|---|
| BCC | 0.81 | 0.01 | – | 1.68 | – | – | – | – | – | – |
| BCH | 0.81 | 18.83 | 0.66 | – | 2.96 | – | 1.52 | 1.99 | 2.47 | 3.06 |
| BNB | 2.69 | – | – | – | – | – | – | – | – | – |
| BTC | 32.78 | 120.79 | 36.20 | 11.52 | 53.09 | 16.50 | 8.10 | 17.10 | 6.86 | 14.64 |
| DASH | – | 1.88 | – | 0.26 | – | – | 0.99 | 0.34 | 0.03 | 0.55 |
| EOS | – | 8.12 | – | – | – | – | 2.36 | 0.07 | 0.29 | – |
| ETC | – | 5.59 | – | 0.60 | – | – | 0.92 | 0.96 | 1.30 | 1.36 |
| ETH | 10.19 | 35.40 | 5.44 | 2.50 | 32.46 | 7.77 | 3.11 | 14.54 | 3.08 | 4.91 |
| IOTA | – | 2.51 | – | – | – | – | – | – | 0.06 | – |
| LTC | 2.69 | 13.13 | 2.44 | 1.02 | 24.51 | – | 1.10 | 1.80 | 2.78 | 2.48 |
| NEO | 3.88 | 4.54 | – | 1.46 | – | – | 0.24 | – | 0.18 | – |
| OMG | – | 3.77 | – | 0.49 | – | – | 0.21 | – | 0.01 | – |
| XMR | – | 2.84 | – | 0.30 | – | – | – | 0.77 | 0.00 | 0.60 |
| XRP | – | 17.11 | 7.41 | 1.86 | – | – | 1.46 | 3.28 | 0.26 | 2.87 |
| ZEC | – | 2.35 | – | 0.33 | – | – | 0.32 | 0.39 | 0.01 | 0.70 |

(*Continued*)

**Table I**—*Continued*

Panel B: Correlations

| | BCC | BCH | BNB | BTC | DASH | EOS | ETC | ETH | IOTA | LTC | NEO | OMG | XMR | XRP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BCH | 0.17 | | | | | | | | | | | | | |
| BNB | 0.31 | 0.21 | | | | | | | | | | | | |
| BTC | 0.47 | 0.24 | 0.46 | | | | | | | | | | | |
| DASH | 0.28 | 0.42 | 0.20 | 0.39 | | | | | | | | | | |
| EOS | 0.19 | 0.34 | 0.28 | 0.35 | 0.30 | | | | | | | | | |
| ETC | 0.25 | 0.42 | 0.28 | 0.42 | 0.36 | 0.38 | | | | | | | | |
| ETH | 0.30 | 0.40 | 0.37 | 0.44 | 0.44 | 0.45 | 0.61 | | | | | | | |
| IOTA | 0.29 | 0.25 | 0.35 | 0.48 | 0.42 | 0.32 | 0.54 | 0.53 | | | | | | |
| LTC | 0.24 | 0.31 | 0.34 | 0.45 | 0.36 | 0.35 | 0.50 | 0.42 | 0.43 | | | | | |
| NEO | 0.16 | 0.25 | 0.43 | 0.30 | 0.31 | 0.29 | 0.43 | 0.34 | 0.31 | 0.31 | | | | |
| OMG | 0.26 | 0.17 | 0.42 | 0.41 | 0.40 | 0.41 | 0.45 | 0.60 | 0.47 | 0.41 | 0.60 | | | |
| XMR | 0.26 | 0.35 | 0.26 | 0.49 | 0.55 | 0.34 | 0.43 | 0.52 | 0.54 | 0.42 | 0.24 | 0.40 | | |
| XRP | 0.15 | 0.24 | 0.17 | 0.20 | 0.10 | 0.29 | 0.17 | 0.19 | 0.30 | 0.26 | 0.12 | 0.32 | 0.23 | |
| ZEC | 0.22 | 0.41 | 0.34 | 0.38 | 0.58 | 0.42 | 0.49 | 0.52 | 0.54 | 0.36 | 0.34 | 0.45 | 0.54 | 0.27 |

*(Continued)*

**Table I**—*Continued*

Panel C: Autocorrelations

| | One-HourInterval | | Three-Hour Interval | | Five-Hour Interval | |
|---|---|---|---|---|---|---|
| Coin | Coefficient | $t$-Stat | Coefficient | $t$-Stat | Coefficient | $t$-Stat |
| BCC | −0.127 | −3.960 | −0.166 | −6.412 | −0.260 | −6.800 |
| BCH | −0.039 | −1.459 | −0.033 | −1.136 | −0.064 | −1.870 |
| BNB | −0.000 | −0.827 | 0.002 | 1.476 | 0.004 | 3.850 |
| BTC | −0.063 | −4.089 | −0.072 | −4.414 | −0.062 | −2.985 |
| DASH | −0.073 | −4.124 | −0.052 | −2.822 | −0.065 | −3.540 |
| EOS | −0.075 | −2.448 | −0.052 | −1.376 | −0.072 | −1.300 |
| ETC | −0.054 | −3.182 | −0.071 | −3.807 | −0.031 | −1.383 |
| ETH | −0.053 | −3.069 | −0.043 | −2.154 | −0.042 | −1.780 |
| IOTA | −0.202 | −6.775 | −0.241 | −6.820 | −0.224 | −6.022 |
| LTC | −0.009 | −0.341 | −0.047 | −1.356 | −0.018 | −0.476 |
| NEO | −0.081 | −3.657 | −0.064 | −2.341 | −0.069 | −2.263 |
| OMG | −0.068 | −3.745 | −0.039 | −1.677 | −0.039 | −1.319 |
| XMR | −0.075 | −3.243 | −0.067 | −3.391 | −0.066 | −2.877 |
| XRP | −0.104 | −3.348 | −0.042 | −1.374 | 0.049 | 1.035 |
| ZEC | −0.077 | −3.782 | −0.063 | −2.446 | −0.098 | −3.387 |

### B. Analyzing Bitcoin Blockchain

The Bitcoin blockchain up to March 31, 2018 is a 170 GB network database of more than 360 million wallet addresses and billions of transactions. It is common for each entity to have multiple wallet addresses, and transactions with multiple senders and recipients are frequent.[23] The complexity of the data is illustrated in Internet Appendix Figure IA.1, which depicts a 10-minute random sample of the blockchain in 2017. In the figure, each node represents a wallet address, and each edge shows the flow of coins.

To reduce the complexity of the network, we adopt methods from the computer science literature (Androulaki et al. (2013), Meiklejohn et al. (2013), Reid and Harrigan (2013), Ron and Shamir (2013)) to cluster-related Bitcoin wallets. The idea is that when multiple addresses are used as inputs to a single transaction, the entity controlling each of the inputs must have the private signing keys of all other inputs. It is therefore very likely that all such addresses are controlled by the same entity. For example, if wallets A and B appear as inputs in a single transaction, and wallets B and C appear as inputs in a different transaction, we group wallets A, B, and C together. We find connected components of this "same-input" relation throughout the entire Bitcoin blockchain and consider each component as a group of wallets controlled by the same entity. We then take three more steps. First, if a transaction has multiple recipients, the flow from the sender is allocated proportionally by the number of coins received by each recipient. Second, for each transaction, we exclude the portion of coins that have the same input and output wallets. Finally, we exclude the transaction fees as reflected in the difference between total Bitcoin sent and received in one transaction. The clustered group of wallets that contain exchange addresses are assigned to the identified exchanges. Between March 1, 2017 and March 31, 2018, a group of approximately 640,000 wallets are labeled as Bitfinex, 720,000 wallets as Poloniex, and 1.22 million wallets as Bittrex.

Figure 3 shows the flows on the Bitcoin blockchain. First, one can see that the Bitcoin blockchain has many more major players than the Tether blockchain, and we do not find identifying information for all nodes. Second, Bitfinex, Poloniex, and Bittrex are considerable players on the Bitcoin blockchain in terms of the aggregate flow of coins, and there is a reasonable flow volume between these exchanges. Third, there are substantial flows between Bitfinex and transitory addresses,[24] which we define as wallets with four or fewer transactions on the blockchain and zero net balance, and with the Bitfinex cold wallet.

[23] Internet Appendix Table IA.I shows an example of a Bitcoin transaction on the blockchain with 313 senders and 218 recipients. Addresses on the left column are senders of the Bitcoins and addresses on the right are the recipients.

[24] Transitory addresses may be tumblers or mixer wallets used to further mask Bitcoin transfer activities.

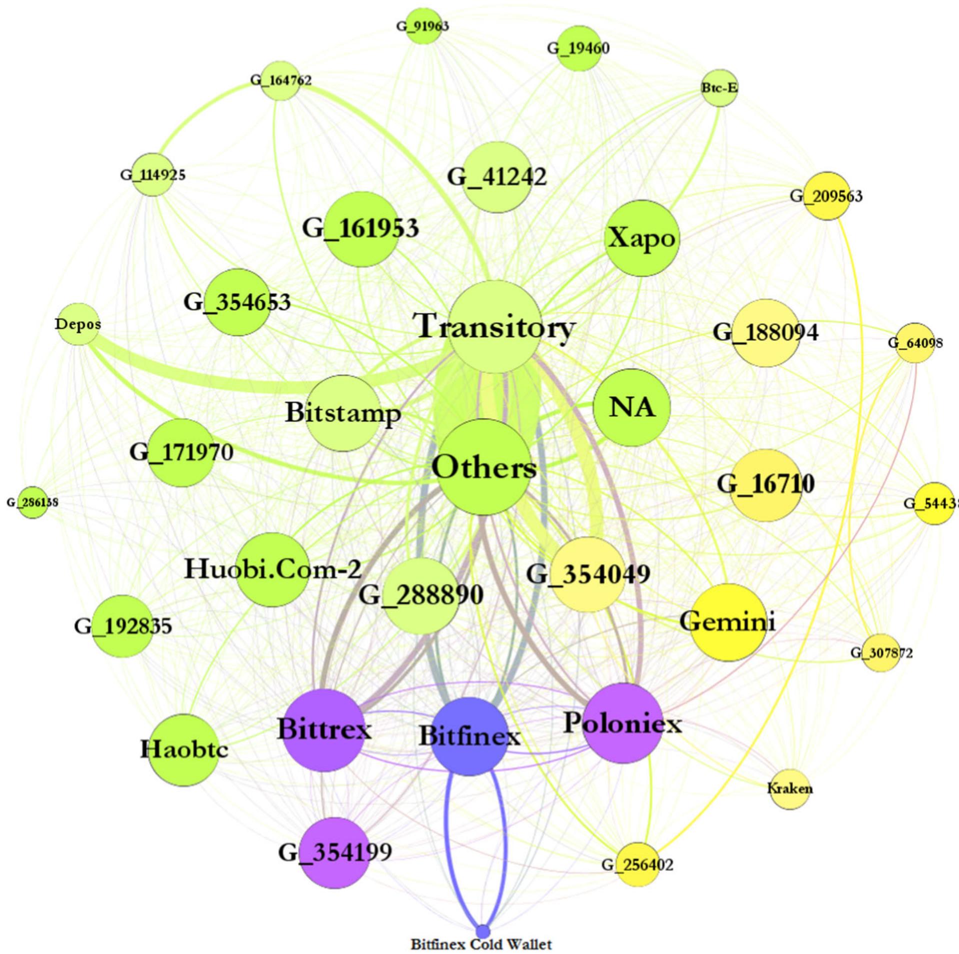



**Figure 3. Aggregate flow of Bitcoin between major addresses**. This figure shows the aggregate flow of Bitcoin between major exchanges and market participants from March 1, 2017 to March 31, 2018. Groups of addresses are clustered by finding the connected component of the same input relation on the Bitcoin blockchain, and each group is labeled with identities of members obtained from publicly available information and individual investors. The thickness of the edges is proportional to the magnitude of flow between two nodes, and the node size is proportional to aggregate inflow and outflow of each node. Intranode flows are excluded. The direction of the flow is shown by the curvature of the edges, with Bitcoin moving clockwise from a sender to a recipient. (Color figure can be viewed at wileyonlinelibrary.com)

### *C. Analyzing Tether Blockchain*

As previously described, Figure 1 provides insights into the structure of the Tether network. First, almost all Tether printed by Tether Limited (the red node in the bottom of the graph) is first moved to Bitfinex and then distributed through the network. The transfer of Tether from Tether authorizer (account labeled as 3MbY) to Tether treasuries (1NTM and 3BbD), all colored in red, is referred to as "authorization," and the transfer out of Tether treasuries, primarily to Bitfinex, is referred to as "issuance." Note that barely any flows move back to the initial Tether printing node, consistent with individuals stating that it is not feasible to move Tether back to Tether Limited to redeem for USD. Second, Poloniex and Bittrex, the largest Tether exchanges for most of 2017, are closely tied to Bitfinex through a large flow of Tether using an intermediary address. Third, Kraken, the small yellow node at the top of the graph, was the only official marketplace for trading the USD-Tether pair for the majority of 2017. Fourth, most of the Tether flows to and from Bitfinex are through Bittrex and Poloniex. Throughout the paper, we focus on the timing and amount of Tether flow from Bitfinex to these two major exchanges because as we will show, this is the primary channel through which Tether is converted to Bitcoin; however, we also examine flows to other exchanges. To calculate the flows between exchanges, we consider the intermediary wallets that receive Tether from Bitfinex and transfer them all to the same exchange as addresses belonging to that exchange.

Note that since the figure is proportional to the size of the flows, the graph puts substantial emphasis on the end of 2017 and early 2018, when Tether issuance increased rapidly. For this reason, in Internet Appendix Figure IA.2, we display four snapshots of the Tether flows over time. For the majority of 2017, Bitfinex, Poloniex, and Bittrex were by far the largest players in the market. Binance, Huobi, OKEx, and Kraken gained substantial market share in December 2017.

The flow of Tether from Bitfinex to the other exchanges increases on the day of Tether authorization, but it takes as many as three to four days to move the capital out of Bitfinex to the other exchanges.[25] It is the net flow of Tether out of Bitfinex to Poloniex and Bittrex and the net flow of Bitcoin back that we use in our tests.

### *D. Bitcoin and Tether Net Flows*

Flows between two parties on the blockchain are more formally defined as the signed net amount of capital transferred between those parties. Specifically, our tests require the flow of coins between major Tether exchanges, Bitfinex (BFX), Poloniex (PLX), and Bittrex (BTX), during our sample period. For Bitcoin, we simply aggregate the net amount of coins transferred between these exchanges

[25] We show this formally in a VAR model in Internet Appendix Figure IA.3. Examples are shown in Internet Appendix Figure IA.4.

in each period:

$$NetBTCFlow_t = \left(\sum_{t-1}^{t} BTC_{PLX\to BFX} - \sum_{t-1}^{t} BTC_{BFX\to PLX}\right) + \left(\sum_{t-1}^{t} BTC_{BTX\to BFX} - \sum_{t-1}^{t} BTC_{BFX\to BTX}\right), \tag{1}$$

where $BTC_{i\to j}$ is the amount of coins transferred from group of wallets $i$ to group of wallets $j$ between hours $t-1$ and $t$. For Tether, to measure the value relative to Bitcoin prices, we accumulate the Bitcoin-denominated value of Tether using Bitcoin prices at the time of the transaction. Similar to the flow of Bitcoin, we define the net flow of Tether as

$$NetTetherFlow_t = \left(\sum_{t-1}^{t} Tether_{BFX\to PLX} - \sum_{t-1}^{t} Tether_{PLX\to BFX}\right) + \left(\sum_{t-1}^{t} Tether_{BFX\to BTX} - \sum_{t-1}^{t} Tether_{BTX\to BFX}\right), \tag{2}$$

where $Tether_{i\to j}$ is the amount of coins transferred from exchange $i$ to exchange $j$ between hours $t-1$ and $t$.

We also verify that flows identified on the Tether blockchain moving from Bitfinex and to Poloniex and Bittrex correspond to opposite flows back on the Bitcoin blockchain that come out of Poloniex and Bittrex and into Bitfinex. Internet Appendix Figure IA.5 shows that the two series have a correlation of 0.72 for Poloniex and 0.71 for Bittrex at daily intervals, and that they also have similar magnitudes. The Bitcoin flow between other exchanges, even between other Tether-based exchanges and Bitfinex, have much lower correlations with the Tether flow to Poloniex and Bittrex and a much larger difference in magnitude. We also find a strong relation between inflow of Tether to Poloniex and Bittrex in the blockchain data and reported exchange trading volume on Poloniex and Bittrex that is not present in a placebo test for other Tether-related exchanges.[26]

The magnitude of the flow of coins on the two blockchains matches closely, and the correlation between the two flows is high, but the timing is not perfectly matched given different delays in moving coins to exchanges and clearing transactions on the blockchain. Given that the timing of blockchain transactions is a proxy for the actual capital flows, and to reduce noise in our measure of net flows of Tether out of Bitfinex and net flows of Bitcoin coming back, we average the two flows on the Bitcoin and Tether blockchains:

$$Tether/BitcoinFlow = (NetTetherFlow_t + NetBTCFlow_t)/2. \tag{3}$$

[26] Details on our verification method and the results are provided in the Internet Appendix Section I.

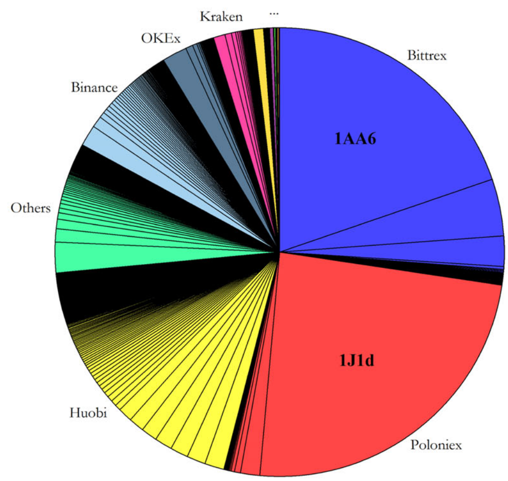
After printing, Tether is used to purchase Bitcoin primarily on Poloniex and Bittrex. We examine if the sensitivity of flow of Tether to Bitcoin returns is symmetric in response to positive and negative shocks. Tether is used to purchase Bitcoin when returns are negative, but we do not find considerable Tether flows following price increases (see Internet Appendix Figure IA.6 and Table IA.II).

### *E. Detailed Deposit Accounts*

We drill down on the nature of the Tether flows out of Bitfinex and the corresponding Bitcoin flows back by focusing on the exact deposit addresses used to move these coins. Typically, to electronically detect which user has deposited funds and to credit these funds to their account, each exchange user receives her own unique deposit wallet address. Interestingly, Panel A of Figure 4 shows that 81% of the Tether flows from Bitfinex to Poloniex and Bittrex are through one large deposit address for each exchange. This account is responsible for 47% of all Tether flows from Bitfinex to all Tether exchanges combined. The first four digits of these addresses are shown as 1J1d for Poloniex and 1AA6 for Bittrex in the figure. Additionally, 52% of the Bitcoin flows back to Bitfinex from all Tether exchanges goes to a single deposit address on Bitfinex, which we label with its first four digits on the Bitcoin blockchain, 1LSg. The relation is depicted in Internet Appendix Figure IA.7, which shows how Bitfinex sends Tether out on the Tether blockchain through 1J1d and 1AA6 and receives flows back from 1MZA. On the Bitcoin blockchain, a majority of the Bitcoin deposits from Poloniex and Bittrex to Bitfinex go through 1LSg, and the flows back to Poloniex and Bittrex go through 1DEc and 1PCw.

If the Tether flows to 1J1d and 1AA6 on the Tether blockchain correspond to Bitcoin flows to 1LSg on the Bitcoin blockchain, this would suggest that all of these wallets are likely controlled by the same entity, which sends the printed Tether into the market in exchange for Bitcoin. To examine this, we compare the Tether flows from Bitfinex to 1J1d and 1AA6 on Poloniex and Bittrex to the Bitcoin flow from Poloniex and Bittrex to the top-100 largest Bitcoin addresses on Bitfinex, including 1LSg. The correlation of Bitcoin flows from Bittrex to 1LSg with Tether flows from Bitfinex to 1AA6 on Bittrex is 0.69. The correlation is 0.64 for 1J1d on Poloniex. Flows to other large deposit accounts on Bitfinex do not come close in terms of the correlation or the magnitude of flows. Internet Appendix Section I (and Figures IA.8 and IA.9) provides more details on the procedure used to identify these wallet addresses that move Tether and Bitcoin between Bitfinex, Poloniex, and Bittrex and verify their relation. Analogous to our flow calculations in equations (1) to (3), we calculate the average net Tether/Bitcoin flows to these large, closely tied wallets and label them as "1LSg flows" throughout the paper. We also compare the effect of flows that are not part of this group of wallets.

Panel A. Tether Blockchain




Panel B. Bitcoin Blockchain

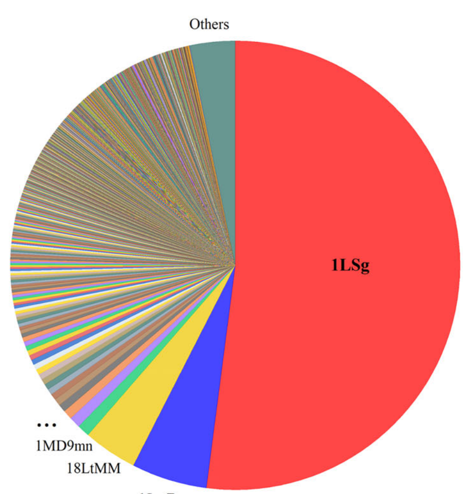



**Figure 4. Top accounts associated with the flow of Tether from and Bitcoin to Bitfinex**. Panel A shows the largest recipients of Tether from Bitfinex recorded on Tether blockchain between March 1, 2017 to March 31, 2018. Exchange wallet identities are obtained from the Tether rich list. Moreover, intermediary wallets that receive Tether from Bitfinex but send all Tether to wallets of a particular exchange are labeled as that exchange. Exchanges are distinguished by colors, and the partitions show unique wallets within each exchange. The two largest recipients of Tether from Bitfinex on Bittrex and Poloniex are labeled by the first four characters of their wallet ID as 1AA6 and 1J1d. Panel B shows the top recipients of Bitcoin on the Bitfinex exchange from other exchanges between March 1, 2017 to March 31, 2018. The largest recipient of Bitcoin on Bitfinex is labeled by the first four characters of its wallet ID as 1LSg. (Color figure can be viewed at wileyonlinelibrary.com)

## III. Are Bitcoin Prices Related to Tether?

In this section, we focus on the nature of the relationship between Bitcoin prices and Tether, and we discuss how this relationship is connected to our main hypotheses.

### A. Examining Flows and Bitcoin Prices

Since demand curves for financial securities are typically not flat, demand or supply shocks can have large effects on prices even in the absence of fundamental information (Harris and Gurel (1986), Shleifer (1986), Greenwood (2005)), and may persist for surprisingly long periods of time (Duffie (2010)). One should expect this effect to be stronger for cryptocurrencies because, first, there are no fundamental cash flows from which prices are derived, and second, the supply of coins is often fixed. In particular, if Tether issuances are sizable, Bitcoin prices should be affected by movements of Tether into the market. Moreover, as hypothesized in H2B, if Tether is being used to protect and inflate the market, the effect of Tether transactions on Bitcoin prices should be stronger following negative Bitcoin returns and on days after printing.

We estimate a regression of rolling three-hour average Bitcoin returns on lagged average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of Bitcoin back to Bitfinex. We use the average three-hour Bitcoin returns as our dependent variable, as the effect of flows might not be incorporated into exchange prices immediately. The traceable flows on the blockchains indicate when capital moves to the exchanges, not necessarily when the transactions occur within the exchange. We expect the flow of Tether to an exchange to precede the time when the Tether is used to purchase Bitcoin.[27] For controls, we include past returns to account for the effects of potential return reversals (Lehmann (1990)), daily volatility of hourly returns in the previous 24 hours to account for possible relations between returns and volatility, and lagged returns interacted with volatility to account for the potential of larger return reversals during periods of high volatility (Nagel (2012)).

Column (1) of Table II, Panel A, shows that on days right after Tether printing, for a 100 Bitcoin increase in lagged flow, the three-hour average future Bitcoin return goes up by 3.85 basis points, controlling for lagged returns, volatility, and the interaction of lagged returns and volatility. Column (2) shows that the effect exists only on days following Tether authorization, with no relationship between the flow of Tether and Bitcoin prices on days apart from printing Tether, consistent with the supply-driven price impact of hypothesis H2B. Moreover, columns (3) and (4) show that the effect exists only after a negative shock to Bitcoin prices. Finally, column (5) shows that the effect is even stronger with a 8.13 basis point increase in returns when conditioning on both Tether authorization and a lagged negative return.

[27] The standard errors are adjusted for heteroskedasticity and autocorrelation using the Newey-West procedure with up to three lags.

**Table II**

## The Effect of Flow of Bitcoin and Tether on Bitcoin Return

Panel A shows OLS estimates for which the dependent variable is the average three-hour Bitcoin returns,

$$\frac{1}{3}\sum_{i=0}^{2} R_{t+i} = \beta_0 + \beta_1 Flow_{t-1} + Controls + \epsilon_t,$$

where $R_t$ is the hourly return of an equal-weighted price index that aggregates Bitcoin prices on Tether exchanges Bitfinex, Poloniex, Bittrex, Binance, HitBTC, Huobi, and OKEx and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of Bitcoin from Poloniex and Bittrex to Bitfinex. The control variables include lagged returns, volatility calculated using hourly returns over the previous 24 hours, and the interaction of lagged returns and volatility. Column (1) shows the results for times when a Tether authorization occurred in the previous 72 hours and column (2) for other times. Columns (3) and (4) report results separately for observations with lagged negative and positive returns. Column (5) reports results conditioning on both 72 hours after Tether authorization and negative lagged returns. Panel B estimates the same regression but decomposes flows into 1LSg flows and flows to other Poloniex and Bittrex accounts (described in detail in Internet Appendix Section I). Panel B also controls for the net average flows of Tether and Bitcoin to other Tether recipient exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx). Standard errors are adjusted for heteroskedasticity and autocorrelation. $t$-Statistics are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{**}p < 0.001$.

Panel A: Regression of Returns on Lagged Flows

| | (1) Auth | (2) NoAuth | (3) L.Ret < 0 | (4) L.Ret > 0 | (5) L.Ret < 0_Auth |
|---|---|---|---|---|---|
| Lag PLX BTX Flow | 3.855* | −0.354 | 2.694* | −1.100 | 8.134** |
| | (2.30) | (−0.48) | (2.18) | (−1.20) | (2.93) |
| LagRet | −0.00600 | −0.00985 | 0.0634* | −0.0518 | 0.0897 |
| | (−0.18) | (−0.57) | (1.97) | (−1.72) | (1.46) |
| Volatility | 103.9 | 97.00 | −52.33 | −70.32 | −102.3 |
| | (1.17) | (1.38) | (−0.67) | (−0.89) | (−0.70) |
| Volatility*Lag Ret | −0.343 | −0.289 | −1.443*** | 0.609 | −1.660** |
| | (−0.94) | (−1.14) | (−3.40) | (1.58) | (−2.85) |
| Constant | −8.071 | −1.387 | 4.261 | 5.105 | 2.062 |
| | (−1.44) | (−0.46) | (1.26) | (1.50) | (0.24) |
| Observations | 2,645 | 6,856 | 4,488 | 5,009 | 1,258 |
| Adjusted $R^2$ | 0.012 | 0.005 | 0.020 | 0.001 | 0.045 |

Panel B: Regression of Returns on Lagged Decomposed Flows

| | (1) Auth | (2) NoAuth | (3) L.Ret < 0 | (4) L.Ret > 0 | (5) L.Ret < 0_Auth |
|---|---|---|---|---|---|
| Lag 1LSg Flow | 4.240* | −0.484 | 2.379* | −1.300 | 8.206*** |
| | (2.37) | (−0.57) | (1.97) | (−1.24) | (3.61) |
| Lag Other PLX BTX Flow | 5.531 | −0.513 | 4.602 | −0.372 | 12.22 |
| | (1.20) | (−0.26) | (1.23) | (−0.16) | (1.32) |
| Lag Other Flow | −6.483* | 1.599 | −0.514 | 0.322 | −8.328* |
| | (−2.36) | (1.43) | (−0.34) | (0.25) | (−2.38) |
| LagRet | −0.00562 | −0.0108 | 0.0650* | −0.0523 | 0.0958 |
| | (−0.17) | (−0.63) | (2.01) | (−1.73) | (1.57) |

*(Continued)*

**Table II**—*Continued*

Panel B: Regression of Returns on Lagged Decomposed Flows

| | (1) Auth | (2) NoAuth | (3) L.Ret < 0 | (4) L.Ret > 0 | (5) L.Ret < 0_Auth |
|---|---|---|---|---|---|
| Volatility | 121.7 | 94.23 | −51.05 | −71.01 | −84.21 |
| | (1.36) | (1.33) | (−0.65) | (−0.90) | (−0.57) |
| Volatility*Lag Ret | −0.346 | −0.281 | −1.457*** | 0.613 | −1.717** |
| | (−0.95) | (−1.10) | (−3.42) | (1.59) | (−2.95) |
| Constant | −8.621 | −1.334 | 4.203 | 5.108 | 1.784 |
| | (−1.53) | (−0.44) | (1.24) | (1.50) | (0.21) |
| Observations | 2,645 | 6,856 | 4,488 | 5,009 | 1,258 |
| Adjusted $R^2$ | 0.014 | 0.005 | 0.020 | 0.001 | 0.049 |

To more precisely examine the source of the flow effect, we analyze three different flow components: (i) the net Tether flows out from Bitfinex (and the Bitcoin back) to the closely tied 1LSg addresses discussed above, (ii) the net Tether flow out from Bitfinex (and the Bitcoin back) to the rest of Poloniex and Bittrex accounts not involving the 1LSg addresses, and (iii) the rest of the net Tether flows out from Bitfinex (and the Bitcoin back) to other Tether exchanges including Binance, HitBTC, Huobi, Kraken, and OKEx. Column (1) of Table II, Panel B, shows that on days right after Tether printing, for a 100 Bitcoin increase in 1LSg flow, the three-hour average future Bitcoin return goes up by 4.24 basis points, controlling for lagged returns, volatility, and their interaction. The results are significant at the 5% level. There is no significant positive relationship for the rest of the Poloniex and Bittrex flows (flow component 2). The same is true for flows into other Tether exchanges.

In Table III, we examine whether the effect related to Tether printing spills over into the six leading cryptocurrencies listed on Tether-related exchanges. The effects are generally larger across all coins when conditioning on both days after Tether authorization and following a negative return. For the equivalent of a 100 Bitcoin increase in flow, the average future return goes up by 7.89 to 10.19 basis points for different coins.[28]

### *B. Large Flows and Prices*

We now specifically focus on the 1% of hours (95 of 9,504 hours) with the largest Tether/Bitcoin flow. Figure 5, Panel A, plots an event study of Bitcoin and other cryptocurrency prices around these high-flow events. The high-flow hours occur between times −1 and 0 by construction. The results show that returns are large and negative between times −3 and −1. However, after the large flow, the pattern starts to change at time 0. The next hour's returns are large at 80 basis points per hour, and returns are positive at 1.23% over

[28] Internet Appendix Table IA.III reports similar results for the relationship between 1LSg flows and other major cryptocurrency prices.

**Table III**

**The Effect of Flow of Bitcoin and Tether on Other Cryptocurrency Returns**

This table shows OLS estimates for which the dependent variable is the average three-hour return for major cryptocurrencies other than Bitcoin,

$$\frac{1}{3}\sum_{i=0}^{2} R_{t+i} = \beta_0 + \beta_1 Flow_{t-1} + Controls + \epsilon_t,$$

where $R_t$ is the hourly return using price data from the most liquid exchange for each cryptocurrency between March 1, 2017 and March 31, 2018 and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of Bitcoin from Poloniex and Bittrex to Bitfinex. The control variables include lagged returns, volatility calculated using hourly returns over the previous 24 hours, and the interaction of lagged returns and volatility. Major cryptocurrencies are selected based on the criteria in Table I, conditional on being listed on at least one of the major Tether exchanges as of the beginning of March 2017. Panel A reports results for the 72 hours after Tether authorization and Panel B reports results for other days. Panel C reports results when the lagged return is negative and Panel D when the lagged return is positive. Panels E reports results conditioning on both 72 hours after Tether authorization and negative lagged returns. Standard errors are adjusted for heteroskedasticity and autocorrelation.

| Panel A: Days Following Authorization | | | |
|---|---|---|---|
| Coin | Coefficient | $t$-Stat | $N$ |
| DASH | 6.16 | 3.26 | 2,645 |
| ETC | 7.54 | 3.00 | 2,645 |
| ETH | 6.29 | 3.10 | 2,645 |
| LTC | 6.17 | 1.83 | 2,645 |
| XMR | 4.80 | 2.19 | 2,645 |
| ZEC | 5.65 | 2.46 | 2,645 |
| **Panel B: Other Days** | | | |
| Coin | Coefficient | $t$-Stat | $N$ |
| DASH | 0.59 | 0.61 | 6,833 |
| ETC | −0.57 | −0.52 | 6,833 |
| ETH | 0.54 | 0.58 | 6,833 |
| LTC | 1.32 | 1.27 | 6,833 |
| XMR | 0.13 | 0.12 | 6,833 |
| ZEC | 0.50 | 0.38 | 6,833 |
| **Panel C: Following Negative Returns** | | | |
| Coin | Coefficient | $t$-Stat | $N$ |
| DASH | 2.92 | 1.69 | 3,992 |
| ETC | 2.38 | 1.93 | 4,679 |
| ETH | 2.36 | 1.70 | 4,544 |
| LTC | 3.74 | 2.57 | 4,668 |
| XMR | 2.74 | 1.69 | 4,614 |
| ZEC | 3.12 | 2.00 | 4,785 |

(*Continued*)

**Table III**—*Continued*

| Panel D: Following Positive Returns | | | |
|---|---|---|---|
| Coin | Coefficient | $t$-Stat | $N$ |
| DASH | 3.47 | 2.26 | 3,985 |
| ETC | 1.92 | 0.99 | 4,732 |
| ETH | 1.65 | 1.27 | 4,878 |
| LTC | 1.99 | 0.94 | 4,581 |
| XMR | 0.59 | 0.48 | 4,752 |
| ZEC | 1.26 | 0.73 | 4,577 |

| Panel E: Negative Returns-Authorization | | | |
|---|---|---|---|
| Coin | Coefficient | $t$-Stat | $N$ |
| DASH | 10.19 | 3.26 | 1,063 |
| ETC | 8.84 | 3.00 | 1,271 |
| ETH | 8.86 | 3.10 | 1,246 |
| LTC | 8.54 | 1.83 | 1,293 |
| XMR | 7.44 | 2.19 | 1,244 |
| ZEC | 7.89 | 2.46 | 1,293 |

the next three hours after the flow. Panel B shows sharp positive returns in the three-hour window after the flow events for all six of the other major cryptocurrencies as well. We further examine the spillover in the cross-section of cryptocurrencies by constructing an exchange-level value-weighted return index of all coins other than Bitcoin using all other coin-BTC pairs for all exchanges in the sample. The altcoins listed on Bitfinex, Poloniex, and Bittrex have significantly larger Bitcoin-denominated returns than the coins listed on other exchanges in the hours right after the flows (see Internet Appendix Table IA.IV). Consistent with the effect being driven by Tether flows, the return is not different before the high-flow periods.

We also examine the results for the largest player, 1LSg. In Internet Appendix Figure IA.10, we focus on the largest 1% of the 1LSg flows and finds that returns are positive at 1.27% over the next three hours, while returns are −1.50% over the three hours before. We test whether this behavior is linked to a general increase in blockchain transactions by examining Bitcoin prices around the times with high flows from Bitfinex to non-1LSg Poloniex and Bittrex wallets or to other Tether exchanges. We find no statistical or economic effect around these times.

Note that the only conditioning variable for these hours is lagged flows, and we do not condition on past returns, but the large negative returns preceding the flows seem to be consistent with investors following a “buying-the-dips” strategy. To see if a normally occurring reversal pattern rather than the impact of flows is driving the returns, we find hours in the sample that are the closest match to our 95 high-flow hours in terms of lagged returns in the previous three hours, but we do not condition on the high flow of Tether. Internet Appendix Figure IA.11 shows that while the returns from times −3 to 0 are the same by construction, the returns in the three hours after are −0.06% and indistinguishable from zero, indicating that the higher returns after time 0 are not due to a general price reversal or a "buying-the-dips" pattern in the market.

### *C. Is the Price Effect Economically Important?*

What is the cumulative economic magnitude of the effects of Tether on Bitcoin and other cryptocurrencies? Such a question is difficult to address. We take a simple approach to partial economic assessment of the effect, but we also note its potential limitations. From March 1, 2017 to March 31, 2018, the actual Bitcoin price rose from around $1,191 to $6,929 for a return of 481.8%. In contrast, the price series without the 95 Tether-related hours ends at around $3,555, for an increase of 198.5%. Hence, the 1% of hours with the strongest lagged Tether flow are associated with 58.8% of the Bitcoin buy-and-hold return over the period.

We compare an actual Bitcoin price series to a series that is extremely similar, but that removes the 95 high-lagged-flow hours discussed above and replaces them with a random sample of 95 returns from other hours.[29] This process is repeated, with replacement, for 10,000 draws. Panel A of Figure 6 shows that the actual return including the Tether-related hours clearly falls to the far right of the bootstrapped distribution, indicating that it does not happen by chance.

Panel B of Figure 6 compares the actual buy-and-hold return and the return excluding hours after high flows for other major coins. The percentage of the buy-and-hold return that is attributable to the Tether-related hours ranges from 53% for Dash to 79% for Zcash.[30] Across the six other cryptocurrencies, returns are 64.5% smaller on average when removing the 95 Tether-related flow hours.

We now perform the same analysis by focusing only on hours following the top 1% of 1LSg flows. From March 1, 2017 to March 31, 2018, excluding the top 1% of times with high lagged flow of Tether and Bitcoin though 1LSg accounts, the Bitcoin price rises only 216%. Hence, only 1% of the hours (95 of 9504) with the strongest 1LSg flows are associated with 55.0% of the rise of Bitcoin in the next hour. As shown in Internet Appendix Table IA.V, when removing the top 5% and 10% of hours, returns are 67.2% and 79.2% lower, respectively. We also perform a bootstrap analysis for this account by replacing these 1% of hours with other randomly selected hours. Figure 7 shows that the simulated distribution of Bitcoin returns averages 221% and in none of the 10,000 simulations is the return close to the actual return. The return distributions when replacing the

[29] For example, for a three-period buy-and-hold return compounded as $(1+r1)\,(1+r2)\,(1+r3)$, if period 1 is a high-flow hour, we replace the next-period returns, $r2$, with $r2'$, where $r2'$ is a random draw from all other nonhigh-flow hours in our sample. The benchmark buy-and-hold return is calculated as $(1+r1)\,(1+r2')\,(1+r3)$. Note that this approach does not suffer from look-ahead bias, as it depends only on past flows in replacing returns.

[30] Ethereum, for example, experienced nearly a 2,400% return during this period, but if the Tether-related hours were excluded it would have experienced around a 900% return.

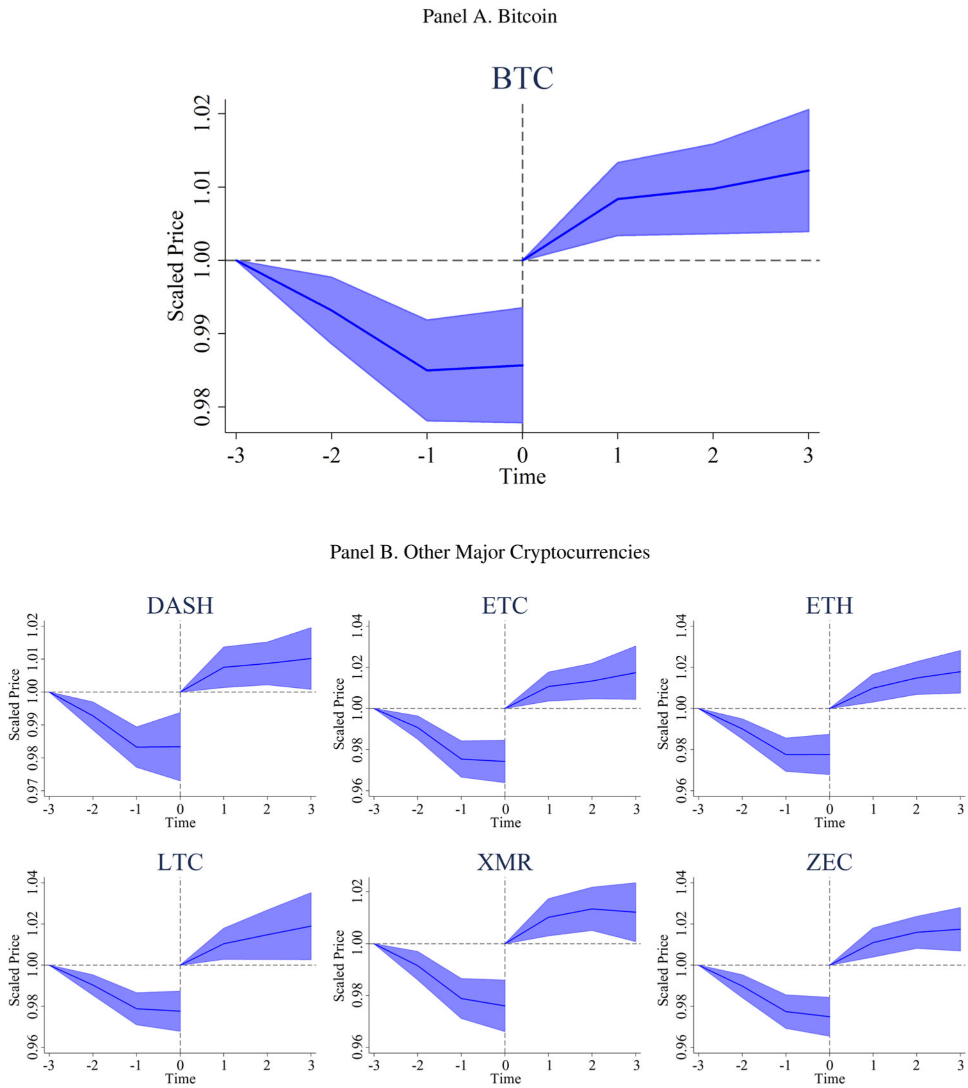



**Figure 5. Prices of Bitcoin and other cryptocurrencies around high-flow events**. Panel A shows Bitcoin prices three hours before and after the top 1% of high-flow hours to Poloniex and Bittrex. Prices are scaled to one at time −3 before the event and at time 0 at the end of the event window. Scaled prices are averaged across events. High-flow events are defined as the top 1% of hours with high net average flows of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin back from Poloniex and Bittrex to Bitfinex in the prior hour, which means that high flows occur between time −1 and time 0. Panel B depicts similar results for other major cryptocurrencies. (Color figure can be viewed at wileyonlinelibrary.com)

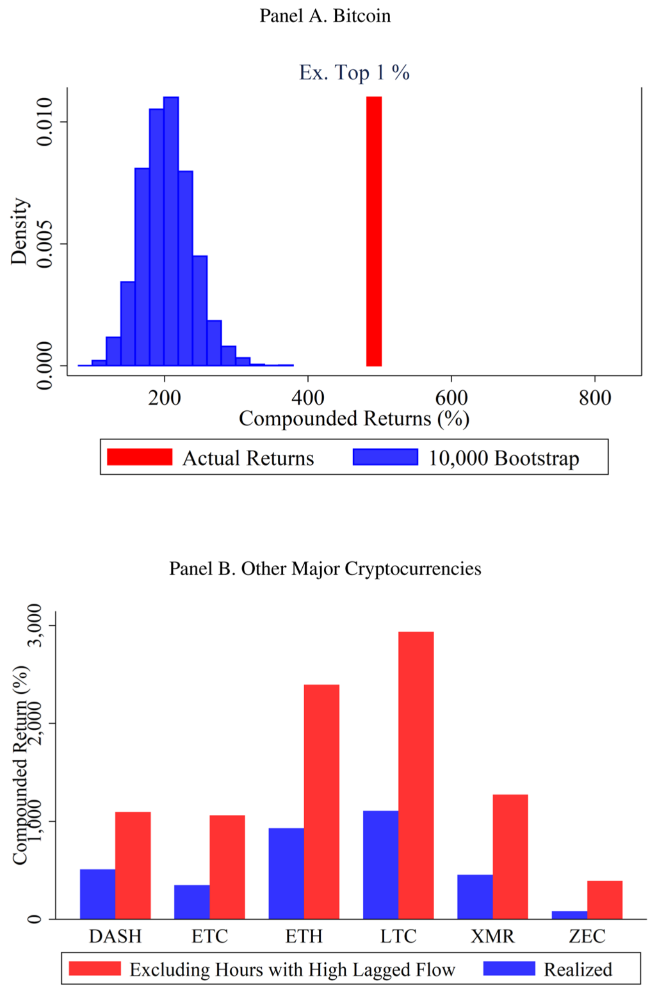



**Figure 6. Predictive effect of high-flow hours on cryptocurrencies returns**. The red bar in Panel A shows the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018. The blue bars show the distribution of returns if the top 1% hours with high lagged flow of Tether and Bitcoin are replaced with a random sample of returns in other hours, bootstrapped 10,000 times. High-flow hours are defined as in Figure 5. Panel B compares the actual buy-and-hold return (red bars) with the return excluding the top 1% high-flow hours (blue bars) for other major cryptocurrencies over the same time period. (Color figure can be viewed at wileyonlinelibrary.com)

hour following the top 5% and 10% of 1LSg flows are also considerably to the left of the actual returns and indicate that the observed patterns are not likely due to chance.

To determine whether the high-flow return relationship is a general result of extreme market events reflected in the blockchain data, in Internet Appendix Figure IA.12 we also perform simulations where we remove the top 1%, 5%,

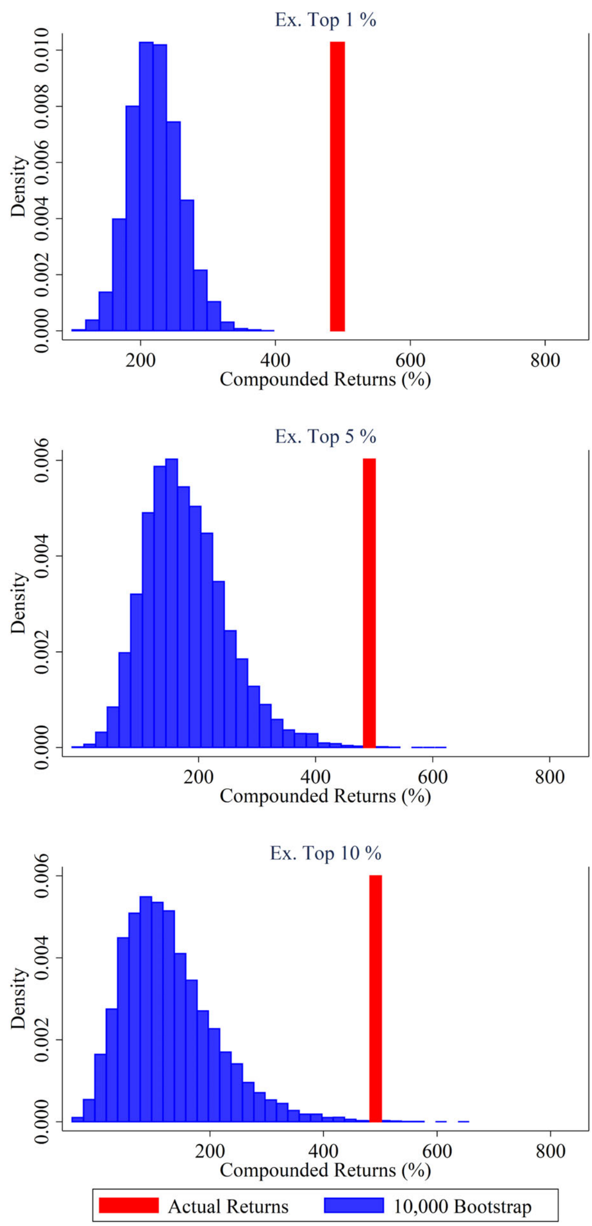



**Figure 7. Predictive effect of 1LSg high-flow hours on Bitcoin returns**. The red bars show the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018. The blue bars show the distribution of returns if the top hours with high lagged 1LSg flow are replaced with a random sample of returns in other hours, bootstrapped 10,000 times. The high 1LSg flow hours are the top 1% of hours with high 1LSg flows as defined in the Internet Appendix Section I. The return distribution in the top panel replaces the top 1% of high lagged 1LSg flow hours with a random sample of returns in other hours, and the middle and bottom panels replace the top 5% and 10%, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

and 10% of net flows from Bitfinex to other Poloniex and Bittrex addresses. There seems to be weak evidence that the extreme non-1LSg flows have some effects on prices for the top 1% of hours, but not the top 5% and 10%. For the net Tether/Bitcoin flows associated with the other five main Tether-based exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx), removing the top 1%, 5%, or 10% of the flows has no effect on simulated Bitcoin prices.

Overall, the findings indicate that a large player moves Tether out of Bitfinex in exchange for Bitcoin in such a way that she/he would either have to exhibit extreme market timing or, much more likely and consistent with the price impact literature, have a large price impact on Bitcoin price.

We note that this finding is subject to some caveats. The effect only considers the hourly periods with extreme flows. Measuring such findings over other intervals would be less precise and more difficult, but the flow could push prices up at other times as well. However, the effect does not consider the effect of selling price pressure if the Tether issuers later sell the Bitcoin and move the proceedings into dollars, though it seems feasible that the issuers could sell Bitcoin through channels with considerably less price impact. If the purchased Bitcoin is not permanently liquidated for dollars, then the inflationary effect due to increasing the money supply can be persistent. Overall, although it is difficult to fully assess the exact price impact of Tether, these back-of-the-envelope calculations demonstrate that the effect is plausibly large.

### *D. Negative Serial Correlation in Bitcoin Prices*

The flows of Tether and Bitcoin follow a specific pattern: accounts on Bitfinex buy Bitcoins with Tether when Bitcoin prices drop. If the flow of Tether moves Bitcoin prices, this may lead to a price reversal following a negative shock as described in H2C.

To test this hypothesis, we examine whether future Bitcoin returns can be explained by lagged returns, and in particular, whether the reversal effect is related to Tether flows. We include controls for lagged volatility and the interaction of lagged volatility and lagged returns similar to Table II. Table IV shows that after controlling for volatility, we observe a return reversal, but only for negative returns and only in periods with high net flows. Panel B shows that the reversal pattern is driven by 1LSg flows and is not present in flows to non-1LSg accounts on Poloniex and Bittrex, nor in flows to other Tether-based exchanges.[31] Panel C shows that the effect is strongest in periods right after the hours with the top 1% and 5% of flows. In the extreme case, if accompanied by top 1% net flows, each 1% drop in Bitcoin prices is followed by a large 61 basis point reversal in the next hour, whereas the reversal is on average only 6 basis points (and statistically insignificant) in other times.[32] Controlling for

[31] Internet Appendix Table IA.VI shows that if the specification controls for the interaction between flows and volatility, the flow effect remains significant for the full sample but becomes statistically insignificant when the sample is split into positive and negative lagged returns.

[32] Internet Appendix Table IA.VII shows that the results are driven entirely by top hours of 1LSg flows and that top hours of other flows are not related to the reversal. For example, each 1%

**Table IV**

## Bitcoin Return Reversals and 1LSg Flow

This table shows OLS estimates for the autocorrelation of Bitcoin returns,

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 Flow_{t-1} + \beta_3 R_{t-1} * Flow_{t-1} + Controls + \epsilon_t,$$

where $R_t$ is the hourly return of an equal-weighted price index that aggregates Bitcoin prices on Tether exchanges, $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of Bitcoin from Poloniex and Bittrex to Bitfinex, and the control variables include lagged returns, volatility calculated using hourly returns over the previous 24 hours, and the interaction of lagged returns and volatility. Panel A reports results for aggregate net flows to Poloniex and Bittrex. Panel B decomposes flows into 1LSg flows and the rest of Poloniex and Bittrex accounts and controls for flows into other Tether exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx). The flow variables are standardized by subtracting the mean and dividing by the standard deviation. Panel C estimates a similar regression for dummy variables that take the value of 1 for top 1%, 5%, and 10% of hours with high lagged flows and volatility. Standard errors are adjusted for heteroskedasticity and autocorrelation. $t$-Statistics are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$.

Panel A: Using Aggregate Flows to PLX and BTX

| | Full Sample | Neg Lagged Returns | Pos Lagged Returns |
|---|---|---|---|
| Lag Ret | −0.0198 | 0.0004 | −0.0420 |
| | (−0.62) | (0.01) | (−0.69) |
| Lag Flow | 0.0003 | −0.0002 | 0.0001 |
| | (1.68) | (−0.53) | (0.34) |
| Lag Flow × Lag Ret | −0.0326** | −0.0669** | −0.0073 |
| | (−2.73) | (−2.67) | (−0.36) |
| Lag Volatility | 0.0093 | 0.0060 | 0.0100 |
| | (1.38) | (0.49) | (0.88) |
| Lag Volatility × Lag Ret | −0.3961 | −0.5918 | −0.2719 |
| | (−0.98) | (−0.85) | (−0.37) |
| Constant | −0.0002 | −0.0000 | −0.0001 |
| | (−0.67) | (−0.07) | (−0.29) |
| Observations | 9,503 | 4,488 | 5,011 |
| Adjusted $R^2$ | 0.007 | 0.011 | 0.001 |

Panel B: Using Decomposed Flows

| | Full Sample | Neg Lagged Returns | Pos Lagged Returns |
|---|---|---|---|
| Lag Ret | −0.0125 | 0.0166 | −0.0320 |
| | (−0.38) | (0.27) | (−0.52) |
| Lag 1LSg Flow | 0.0003 | −0.0001 | −0.0000 |
| | (1.71) | (−0.19) | (−0.02) |
| Lag 1LSg Flow × Lag Ret | −0.0280* | −0.0545* | 0.0050 |
| | (−2.23) | (−2.17) | (0.22) |
| Lag Volatility | 0.0094 | 0.0060 | 0.0110 |
| | (1.40) | (0.49) | (0.97) |
| Lag Volatility × Lag Ret | −0.4986 | −0.7798 | −0.4123 |
| | (−1.20) | (−1.11) | (−0.55) |
| Lag PLX BTX Flow × Lag Ret | −0.0200 | −0.0272 | −0.0153 |
| | (−1.61) | (−1.41) | (−0.95) |

*(Continued)*

**Table IV**—*Continued*

| Panel B: Using Decomposed Flows | | | |
|---|---|---|---|
| | Full Sample | Neg Lagged Returns | Pos Lagged Returns |
| Lag Other Flow × Lag Ret | 0.0255 | 0.0404 | 0.0094 |
| | (1.81) | (1.63) | (0.56) |
| Constant | −0.0002 | 0.0000 | −0.0002 |
| | (−0.71) | (0.01) | (−0.42) |
| Observations | 9,503 | 4,488 | 5,011 |
| Adjusted $R^2$ | 0.008 | 0.012 | 0.001 |

| Panel C: Using the Top Percentile Flow and Volatility (Lagged Neg Returns) | | | |
|---|---|---|---|
| | Top 1% | Top 5% | Top 10% |
| Lag Ret | −0.0583 | −0.0169 | −0.0299 |
| | (−1.90) | (−0.49) | (−0.78) |
| Lag High Flows | 0.0041 | 0.0003 | −0.0011 |
| | (0.72) | (0.19) | (−0.85) |
| Lag High Flows=1 × Lag Ret | −0.6091* | −0.2720* | −0.1756 |
| | (−2.56) | (−2.53) | (−1.93) |
| Lag High Vol | 0.0167* | −0.0018 | 0.0008 |
| | (2.53) | (−0.73) | (0.51) |
| Lag High Vol=1 × Lag Ret | 0.2014 | −0.1192 | −0.0183 |
| | (1.09) | (−1.42) | (−0.26) |
| Constant | −0.0000 | 0.0003 | 0.0002 |
| | (−0.04) | (1.07) | (0.70) |
| Observations | 4,488 | 4,488 | 4,488 |
| Adjusted $R^2$ | 0.023 | 0.013 | 0.007 |

the interaction between lagged returns and volatility shows that the results cannot be explained by the possibility of larger return reversals during periods of high volatility (Nagel (2012)).

In conclusion, the results in this section provide considerable evidence that Tether is used to purchase Bitcoin following Tether authorization and a drop in Bitcoin price, and that this phenomenon has a sizable relation with future prices of Bitcoin and other coins. This relation is driven by one account holder and induces an asymmetric negative autocorrelation in Bitcoin returns.

## IV. Is Tether Pushed or Pulled?

The results in the previous section are consistent with a sizable price impact of Tether. In this section, we examine pushed H2D and H2E as well as variants of the pulled hypothesis to shed light on the nature of this price impact.

drop in Bitcoin prices is followed by a 52 basis point reversal in the next hour if accompanied by the top 1% of 1LSg flows.

### A. Currency Flows around Round Price Thresholds

Following Tversky and Kahneman (1974), a large literature demonstrates the importance of price anchoring for a variety of assets. Shiller (2000) extensively discusses the importance of psychological anchors for stock market prices, and indicates that one such anchor is the nearest round-number level. Bhattacharya, Holden, and Jacobsen (2012) find support for liquidity demanders buying just below round-number thresholds in stocks, consistent with investors anchoring prices to the round-number threshold. Such an anchor could be of particular importance for cryptocurrency prices, for which the underlying value cannot be gauged through fundamentals.

Additionally, cryptocurrency traders likely engage in technical trading whereby past price movements generate buy and sell signals. If Tether is used to stabilize market prices during a downturn, one might expect a spike in the flow of Tether around round thresholds, as this might induce other traders, upon observing technical support at the threshold, to purchase as well. Such a pattern could also be consistent with recent theories that suggest that higher participation of users and investors makes Bitcoin more appealing to other users/investors due to network effects (Sockin and Xiong (2018), Cong, Li, and Wang (2019)).

To test this prediction, we divide hourly *CoinDesk* prices by 500 and then group the remainders into bins of $10 width to examine how the flow of Tether for Bitcoin changes near the round thresholds. Figure 8 plots the net average flow of Bitcoin and Tether between Bitfinex and other Tether exchanges as a function of distance to the round thresholds. Panel A shows that on days after Tether authorization, the flow increases significantly just below the round cutoff but drops right above the cutoff. In contrast, there is no such effect on days with no prior Tether authorization. Panel B plots the flows after authorization for net 1LSg flows and flows to other accounts. We find evidence of strong flows below the threshold for 1LSg accounts. There is some weaker evidence of larger flows below the threshold for the rest of Bittrex and Poloniex (not coming from 1LSg) and no evidence of net Bitcoin buying around round number thresholds for Binance, HitBTC, Huobi, Kraken, or OKEx.

Table V, Panel A, formally tests whether Tether/Bitcoin flow is different below and above the round-price thresholds. The dependent variable is the net Tether/Bitcoin flow, and the independent variable is a dummy that takes the value of 1 if the Bitcoin price is in the $50 bandwidth below the round multiples of $500 and 0 if in the $50 bandwidth above. The results show that purchasing below the threshold is economically and statistically significant only after authorization.

In Panel B of Table V, we further examine the disaggregated flows following authorization and finds that the higher flow below round-number thresholds is driven by the 1LSg accounts, with a $t$-statistic of 3.71. Other accounts at Bittrex and Poloniex as well as other Tether exchanges do not have statistically or economically significant flows below the threshold. In addition, Panel C shows that no such pattern obtains in nonauthorization periods. Overall, the evidence

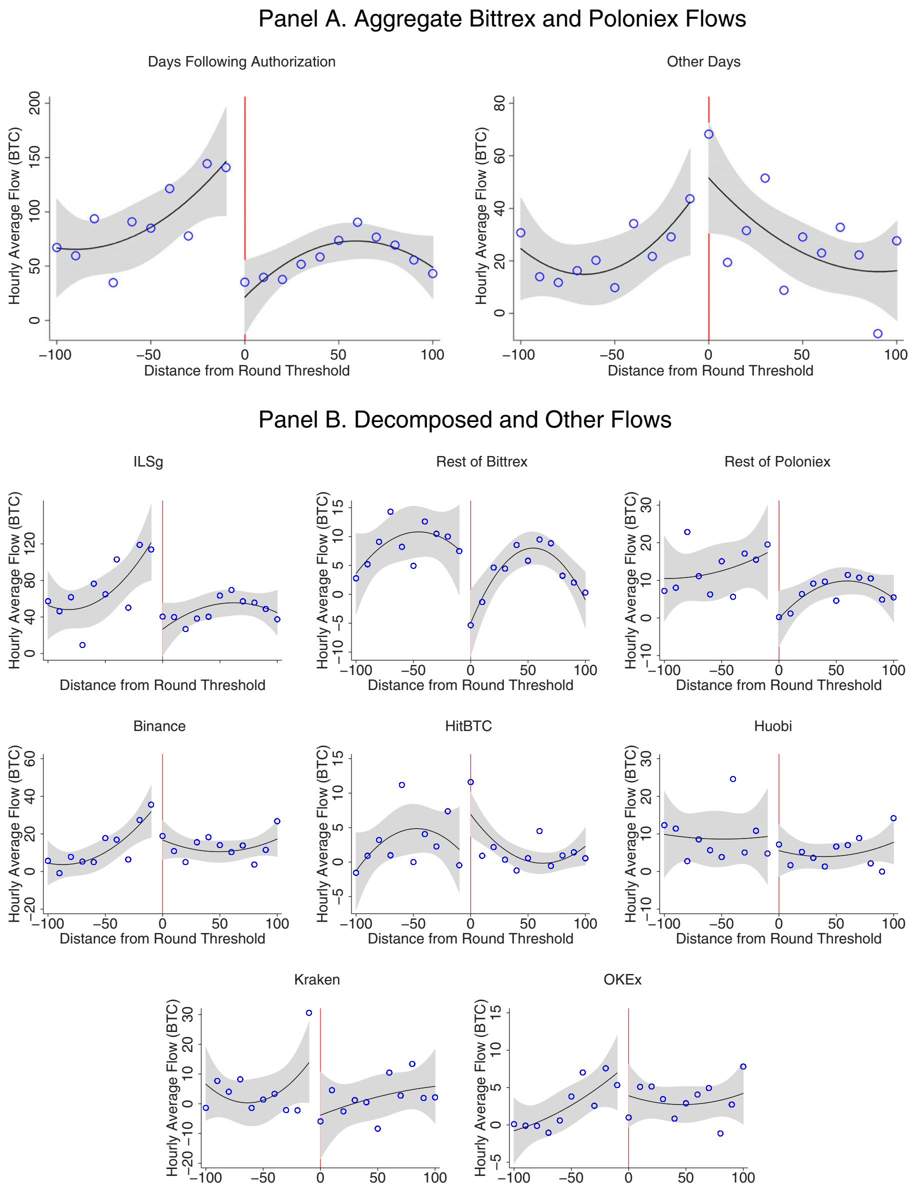



**Figure 8. Flows around round number thresholds**. This figure shows the average net hourly flows of Tether from Bitfinex to two major Tether exchanges, Poloniex and Bittrex, and of Bitcoin from these exchanges to Bitfinex, around round-number thresholds of Bitcoin prices. The Bitcoin prices are based on hourly prices reported by *CoinDesk*. The horizontal axis shows the distance of the price from round thresholds in multiples of \$500 at the end of the previous hour, and the vertical axis shows the flow within the hour. The hollow blue circles show the average flow for \$10-wide price bins, and the black lines show the fitted values of the flow as a second-order polynomial of the price distance to the round thresholds. The gray areas represent the 95% confidence interval for the fitted values. Panel A, left, plots the results for times when a Tether authorization occurred in the previous 72 hours, and Panel A, right, plots the results for other times. Panel B shows the results after Tether authorization for the flows decomposed into 1LSg flows and other Poloniex and Bittrex accounts, as well as flows to other Tether-based exchanges. The sample covers the period from March 1, 2017 to March 31, 2018. (Color figure can be viewed at wileyonlinelibrary.com)

**Table V**

**Flow of Coins around Round Thresholds of Bitcoin Price**

Panel A reports OLS estimates for which the dependent variable is hourly average net flow of Tether from Bitfinex to Poloniex and Bittrex and of Bitcoin from Poloniex and Bittrex to Bitfinex. $BelowRoundCutoff_t$ is a dummy variable that takes the value of 1 if the Bitcoin price, at the end of the hour, falls into the $50 price bucket below a $500 price multiple and 0 if it is in the $50 bucket above such a multiple,

$$Flow_t = \beta_0 + \beta_1 BelowRoundCutoff_{t-1} + \epsilon_t.$$

Panel B estimates the same regression for the net average flows into 1LSg accounts, the rest of Poloniex and Bittrex accounts, and the other Tether exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx). Standard errors are adjusted for heteroskedasticity and autocorrelation. $t$-Statistics are reported in parentheses. $^*p < 0.05$.

Panel A: Flows around Round Thresholds

| | Full | Auth | NoAuth |
|---|---|---|---|
| Below Round Cutoff | 14.75* | 60.83*** | 0.221 |
| | (2.02) | (3.52) | (0.03) |
| Constant | 36.26*** | 45.55*** | 31.93*** |
| | (8.52) | (5.19) | (6.78) |
| Observations | 1,603 | 464 | 1,139 |
| Adjusted $R^2$ | 0.002 | 0.028 | −0.001 |

Panel B: Flows to Different Exchanges—Days Following Authorization

| | 1LSg | Oth BTX | Oth PLX | Binance | HitBTC | Huobi | Kraken | OKEx |
|---|---|---|---|---|---|---|---|---|
| Below Round Cutoff | 52.60*** | 2.059 | 6.172 | 7.497 | 3.810 | 6.289 | 5.252 | 0.971 |
| | (3.71) | (0.60) | (1.62) | (1.27) | (1.92) | (1.90) | (0.83) | (0.46) |
| Constant | 34.75*** | 4.885*** | 5.915** | 13.66*** | 0.564 | 3.766** | −1.071 | 3.841*** |
| | (4.63) | (3.93) | (3.08) | (4.42) | (0.64) | (3.01) | (−0.38) | (3.52) |
| Observations | 464 | 464 | 464 | 305 | 464 | 464 | 464 | 260 |
| Adjusted $R^2$ | 0.030 | −0.001 | 0.004 | 0.002 | 0.007 | 0.008 | −0.000 | −0.003 |

Panel C: Flows to Different Exchanges—Other Days

| | 1LSg | Oth BTX | Oth PLX | Binance | HitBTC | Huobi | Kraken | OKEx |
|---|---|---|---|---|---|---|---|---|
| Below Round Cutoff | 5.815 | −2.825 | −2.768 | −1.085 | −0.835 | −0.476 | 0.207 | 2.043 |
| | (0.89) | (−1.33) | (−1.47) | (−0.47) | (−1.23) | (−0.12) | (0.17) | (0.71) |
| Constant | 19.93*** | 4.982*** | 7.015*** | 3.442* | 0.761* | 4.123 | −0.00519 | −0.542 |
| | (4.99) | (3.43) | (5.43) | (2.01) | (2.29) | (1.32) | (−0.01) | (−0.22) |
| Observations | 1,139 | 1,139 | 1,139 | 731 | 1,139 | 1,139 | 1,139 | 483 |
| Adjusted $R^2$ | −0.000 | 0.001 | 0.001 | −0.001 | 0.001 | −0.001 | −0.001 | −0.001 |

indicates that the flow below thresholds is driven by the 1LSg account, and only after authorization, that is, this flow pattern is not typically observed in the market.

We next examine what effect, if any, the inflow of Tether below the threshold might have on Bitcoin returns. In Panel A of Table VI, we report estimates of a regression of average three-hour future returns on the lagged round-number

**Table VI**

**Effect of Flow on Returns around Round Thresholds of Bitcoin Price**

Panel A estimates a regression of average three-hour Bitcoin returns on the $BelowRoundCutoff$ dummy. Panel B reports results for the second-stage estimates of a two-stage least squares regression of Bitcoin returns on flows,

$$\frac{1}{3}\sum_{i=0}^{2} R_{t+i} = \beta_0 + \beta_1 \hat{Flow}_{t-1} + \epsilon_t,$$

where in the first stage, $\hat{Flow}_t$ is instrumented using a dummy variable that takes the value of 1 if the Bitcoin price, at the end of the previous hour, is within the \$50 bucket below the round threshold and the time is within the three-day window after Tether authorization and 0 if within the \$50 bucket above or in days outside the three-day window after Tether authorization. Panel C reports the same results as in Panel B but where the flows are decomposed into 1LSg and the rest of Poloniex and Bittrex, and it also controls for aggregate net flows to other Tether exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx). Standard errors are adjusted for heteroskedasticity and autocorrelation. $t$-Statistics are reported in parentheses. $^{*}p < 0.05$.

Panel A: Returns around Round Thresholds

| | Auth | NoAuth | Auth_L.Ret < 0 | Auth_L.Ret > 0 |
|---|---|---|---|---|
| Below Round Cutoff | 20.61* | −3.397 | 32.87* | 11.91 |
| | (2.42) | (−0.74) | (2.58) | (1.29) |
| Constant | 1.765 | 5.466 | 11.75 | −7.205 |
| | (0.33) | (1.87) | (1.39) | (−1.15) |
| Observations | 464 | 1,138 | 214 | 250 |
| Adjusted $R^2$ | 0.012 | 0.000 | 0.025 | 0.002 |

Panel B: Instrumenting the Flow using the Round Thresholds

| | All | Auth | Auth_L.Ret < 0 | Auth_L.Ret > 0 |
|---|---|---|---|---|
| Flow | 26.42* | 33.88* | 45.34* | 22.92 |
| | (2.06) | (2.05) | (2.37) | (0.97) |
| Constant | −5.724 | −13.67 | −10.75 | −16.81 |
| | (−1.05) | (−1.27) | (−0.72) | (−1.23) |
| Observations | 1,602 | 464 | 214 | 250 |
| Wald $F$-statistic | 19.44 | 12.03 | 8.217 | 5.264 |

Panel C: Instrumenting the 1LSg Flow using the Round Thresholds

| | All | Auth | Auth_L.Ret < 0 | Auth_L.Ret > 0 |
|---|---|---|---|---|
| 1LSg Flow | 38.52* | 65.44* | 89.35 | 47.27 |
| | (2.09) | (2.03) | (1.79) | (1.11) |
| Oth PLX/BTX Flow | −21.19 | −52.65 | −76.91 | −47.82 |
| | (−1.78) | (−1.45) | (−1.08) | (−1.26) |
| Oth Flow | −10.18 | −38.09* | −35.38 | −40.03 |
| | (−1.92) | (−2.10) | (−1.73) | (−1.21) |
| Constant | −3.364 | −10.28 | −8.653 | −11.08 |
| | (−0.75) | (−1.01) | (−0.53) | (−0.99) |
| Observations | 1,602 | 464 | 214 | 250 |
| Wald $F$-statistic | 19.49 | 7.639 | 3.291 | 4.277 |

threshold dummy. On days following Tether authorization, when prices are below the round threshold, the future hourly return is 20.61 basis points higher on average. However, this return effect is not present on days apart from printing Tether or periods after authorization with positive lagged returns.

Note that it is possible that the Bitfinex-related wallets trade around round-number thresholds simply because they are following behavioral biases. However, in this case their trading is not likely to be profitable as documented in the behavioral finance literature (Bhattacharya, Holden, and Jacobsen (2012)). Large purchasing by 1LSg accounts provides a coherent explanation as to how prices can be pushed above the thresholds. In addition, if other traders see such large purchasing, they might join the buying due to either technical trading indicators being triggered or through the perception of stronger network effects (Sockin and Xiong (2018), Cong, Li, and Wang (2019)).

We also use the discontinuity around round-number thresholds as an instrument to identify the effect of Tether on Bitcoin prices by estimating a fuzzy regression discontinuity design. As an instrument for Tether-related flows, we set a dummy variable equal to 1 if Bitcoin price is within the $50 bucket below the round threshold and the time is within the three-day window after Tether authorization. Our identification assumption is that the only channel through which the cutoff affects future Bitcoin returns is through Tether flows. The exclusion restriction is supported by the fact that neither 1LSg flows nor the future Bitcoin returns differ below and above the thresholds on days not around Tether authorization, and flows associated with no other accounts differ below and above the thresholds even for periods after authorization.

In Panel B of Table VI, we estimate a two-stage least squares regression of three-hour future Bitcoin returns on the lagged net Bitcoin/Tether flow, where the flow is instrumented using the cutoff dummy. The reported Wald $F$-statistics show that the first-stage regressions are strong, suggesting a strong instrument. The second-stage regression indicates that for 100 Bitcoin purchased by Bitfinex, the average hourly Bitcoin return in the next three hours goes up by 26.42 basis points. The effect is 33.88 basis points if the sample is limited to days after authorization, and 45.34 basis points for periods after authorization with lagged negative returns. The effect is insignificant for periods after authorization with positive lagged returns. In Panel C, we perform the same analysis except we instrument for 1LSg flows rather than aggregate Poloniex and Bittrex flows, and we also control for the flows associated with other accounts on Poloniex and Bittrex as well as on other exchanges. The results are economically larger with a 100 Bitcoin flow by 1LSg associated with an average hourly Bitcoin return in the next three hours of 65.44 basis points after authorization. This result highlights a very strong effect of 1LSg flows on Bitcoin prices, especially on days after Tether authorization.

## *B. Demand from Investors with Fiat Currency?*

### *B.1. End-of-Month Returns*

The previous sections establish that the flow of Tether explains a sizable increase and predictable trading patterns in Bitcoin prices. These patterns are potentially consistent with fiat purchases of Tether through Bitfinex, but the purchases and trading would need to be driven by one large player who moved over 2 billion USD into Tether through the Bitfinex exchange. Alternatively, if the printed Tether is not backed by dollars and does not reflect the inflow of real capital into the cryptospace, such an increase in Bitcoin prices can reflect inflation caused by printing unbacked money. In this section we examine the backing of Tether by borrowing from the intermediary asset pricing literature, specifically Du, Tepper, and Verdelhan (2018) and He and Krishnamurthy (2018), who argue that banks' compliance with period-end capital requirements may have a sizable effect on asset prices. To assure traders of the existence of dollar reserves, Tether has issued EOM bank statements from December 2016 to March 2017 that were audited by a Chinese accounting firm.[33] If Tether does not maintain full reserves daily but seeks to release audited EOM statements that demonstrate full reserves to investors, there could be negative selling pressure on Bitcoin to convert it to USD reserves before the EOM as hypothesized in H2E. Such an EOM selling effect should be related to the Tether issuance. Moreover, if cash needs to be raised by liquidating other major cryptocurrencies, as they also show a large price increase around Tether flows, they should show an EOM effect as well. We test for this effect by constructing value-weighted returns of the top-five cryptocurrency returns.

Figure 9 depicts Bitcoin daily returns at EOM by dividing the sample months into four quantiles based on their monthly Tether issuance.[34] The blue bars show the raw EOM returns, and the red bars benchmark the EOM returns by subtracting the average return over the four days before and the four days after. As can be seen, there is a clear relationship between monthly Tether issuance and EOM negative price pressure. In months with no Tether issuance, there is no EOM effect. However, in months with large Tether issuance, there is a 6% negative benchmarked return.

We caveat this relation, however, by noting that there are only 25 months in our sample, and the two months with the largest Tether issuance, December 2017 and January 2018, exhibit a strong EOM effect. Because of the relatively

[33] As announced on https://tether.to/tether-update/, these audits were made publicly available on Tether.to. Tether also stated its intention to be audited by a non-Chinese firm, but it eventually canceled the audit due to "the excruciatingly detailed procedures." In an interview about the lack of an audit on Tether, Bitfinex's chief technology officer noted that "[w]hat we want to do is not [audit] the bank balances as of now, but we want to demonstrate to the community that we had the money *at the end of every single month*, since a reasonable date like January 2017 and on."

[34] Cryptocurrencies officially trade on UTC timestamp and daily prices close at midnight UTC time, when business hours have already ended in most countries and the next day has already started in East Asia. The effect must therefore be observed in the second-to-last day of the month, which we consider the EOM price.

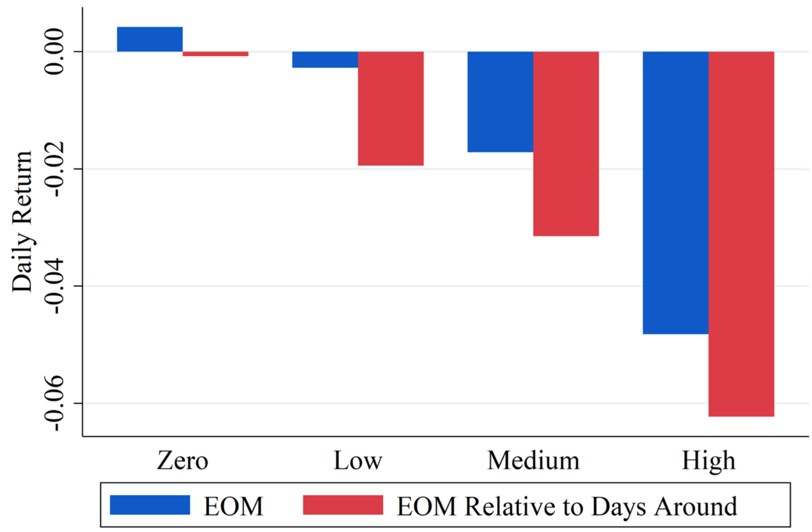



**Figure 9. End-of-month returns and quantiles of Tether issuance**. This figure shows end-of-month (EOM) daily Bitcoin returns for different quantiles of monthly Tether issuance. Four quantiles of Tether issuance are defined based on total Bitcoin-denominated Tether issuance each month. Issuance is calculated as the aggregate monthly Bitcoin-denominated flow of Tether from the Tether treasury to Bitfinex. All months with zero issuance are included in one group, and the other months are divided into three quantiles. The EOM return is defined as the daily return on the second-to-last day of the month closing at midnight UTC time. Daily prices are obtained from *CoinMarketCap*. The blue bars show the raw EOM return, and the red bars show the raw return minus the average return from the prior four days through the subsequent four days. The sample covers the period from March 2016 to March 2018. (Color figure can be viewed at wileyonlinelibrary.com)

small sample size, we check the sensitivity of the results by excluding the two months with the largest Tether issuances. In a simple regression of EOM Bitcoin returns on monthly Tether issuances, we obtain a $t$-statistic of $-2.85$ with all observations, but an insignificant $t$-statistic of $-1.26$ when excluding the two largest months.[35]

In Table VII, we examine this result further. In Panel A, column (1) shows that the EOM return is 2.3% less than returns in the four days before and after the EOM. Columns (2) and (3) indicate that there is no effect in months without Tether issuance, but the EOM return is 3.8% lower in months with Tether issuance ($t$-statistic of 3.65). Column (4) interacts the EOM dummy with the magnitude of the monthly Tether issuance and shows that for a one-standard-deviation higher Tether issuance, the EOM return is 2.2% more negative. Column (5) tests the plot in Figure 9 statistically and shows that relative to months with zero issuance, months with low, medium, and high issuance

[35] When using the value-weighted returns of top-five currencies, the same regression yields a $t$-statistic of $-4.85$ and $-2.97$ with and without the top two months, respectively (Internet Appendix Table IA.VIII).

**Table VII**

## EOM Bitcoin Returns and the Effect of Tether Issuance

This table reports OLS estimates for which the dependent variable is daily Bitcoin returns and the independent variables are the EOM dummy and monthly Tether issuance,

$$R_t = \beta_0 + \beta_1 EOM_t + \beta_2 Issuance_t + \beta_3 EOM_t * Issuance_t + \epsilon_t,$$

where $EOM_t$ takes the value of 1 on the second-to-last day of the month at midnight UTC time and $Issuance_t$ is the aggregate monthly Bitcoin-denominated flow of Tether from the Tether treasury to Bitfinex scaled by its standard deviation. Column (5) interacts the EOM dummy with quantiles of issuance as defined in Figure 9. The sample is from March 2016 to March 2018. Columns (6) to (8) report results after excluding the two months with extreme issuance, December 2017 and January 2018. Panel B estimates the results using the returns on a value-weighted portfolio of top-five cryptocurrencies. Each day in the sample, the top-five cryptocurrencies are selected based on average market cap in the previous week as reported on *CoinMarketCap*. Standard errors are robust to heteroskedasticity. $t$-Statistics are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

| Panel A: Bitcoin Returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | Excluding 12/2017 and 1/2018 | | |
| | (1) All | (2) NoIssuance | (3) Issuance | (4) All | (5) All | (6) Issuance | (7) All | (8) All |
| EOM | $-0.0230^{**}$ | $-0.000788$ | $-0.0377^{***}$ | $-0.00669$ | $-0.000788$ | $-0.0251^{***}$ | $-0.00869$ | $-0.000788$ |
| | $(-3.24)$ | $(-0.14)$ | $(-3.65)$ | $(-1.41)$ | $(-0.14)$ | $(-4.70)$ | $(-1.84)$ | $(-0.14)$ |
| Issuance | | | | 0.00123 | | | 0.00546 | |
| | | | | (0.39) | | | (1.63) | |
| EOM $= 1 \times$ Issuance | | | | $-0.0222^{**}$ | | | $-0.0107^{*}$ | |
| | | | | $(-2.85)$ | | | $(-2.04)$ | |
| Low $\times$ EOM | | | | | $-0.0187^{*}$ | | | $-0.0187^{*}$ |
| | | | | | $(-2.27)$ | | | $(-2.27)$ |
| Med $\times$ EOM | | | | | $-0.0307^{**}$ | | | $-0.0307^{**}$ |
| | | | | | $(-2.71)$ | | | $(-2.70)$ |
| High $\times$ EOM | | | | | $-0.0615^{*}$ | | | $-0.0232^{*}$ |
| | | | | | $(-2.40)$ | | | $(-1.98)$ |
| Low | | | | | $0.0117^{*}$ | | | $0.0117^{*}$ |
| | | | | | (2.08) | | | (2.08) |
| Med | | | | | 0.00933 | | | 0.00933 |
| | | | | | (1.33) | | | (1.32) |
| High | | | | | 0.00908 | | | 0.0126 |
| | | | | | (1.07) | | | (1.57) |

(*Continued*)

**Table VII**—*Continued*

Panel A: Bitcoin Returns

| | Full Sample | | | | | Excluding 12/2017 and 1/2018 | | |
|---|---|---|---|---|---|---|---|---|
| | (1) All | (2) NoIssuance | (3) Issuance | (4) All | (5) All | (6) Issuance | (7) All | (8) All |
| Constant | 0.0110*** | 0.00501 | 0.0150*** | 0.0101*** | 0.00501 | 0.0160*** | 0.00824** | 0.00501 |
| | (4.32) | (1.49) | (4.19) | (3.58) | (1.48) | (4.78) | (2.92) | (1.47) |
| Observations | 225 | 90 | 135 | 225 | 225 | 117 | 207 | 207 |
| Adjusted $R^2$ | 0.035 | −0.011 | 0.078 | 0.065 | 0.060 | 0.048 | 0.024 | 0.023 |

Panel B: Top Five Value-Weighted Returns

| | Full Sample | | | | | Excluding 12/2017 and 1/2018 | | |
|---|---|---|---|---|---|---|---|---|
| | (1) All | (2) NoIssuance | (3) Issuance | (4) All | (5) All | (6) Issuance | (7) All | (8) All |
| EOM | −0.0216** | 0.00107 | −0.0367*** | −0.00188 | 0.00107 | −0.0241*** | −0.00301 | 0.00107 |
| | (−3.19) | (0.25) | (−3.68) | (−0.46) | (0.25) | (−4.05) | (−0.79) | (0.25) |
| Issuance | | | | 0.00179 | | | 0.00460 | |
| | | | | (0.53) | | | (1.53) | |
| EOM = 1 × Issuance | | | | −0.0269*** | | | −0.0186*** | |
| | | | | (−4.45) | | | (−3.41) | |
| Low × EOM | | | | | −0.0175* | | | −0.0175* |
| | | | | | (−2.41) | | | (−2.40) |
| Med × EOM | | | | | −0.0196* | | | −0.0196* |
| | | | | | (−2.07) | | | (−2.07) |
| High × EOM | | | | | −0.0762*** | | | −0.0474*** |
| | | | | | (−3.99) | | | (−3.63) |
| Low | | | | | 0.0119* | | | 0.0119* |
| | | | | | (2.34) | | | (2.34) |
| Med | | | | | 0.00990 | | | 0.00990 |
| | | | | | (1.35) | | | (1.35) |
| High | | | | | 0.0106 | | | 0.0100 |
| | | | | | (1.31) | | | (1.39) |
| Constant | 0.0101*** | 0.00367 | 0.0145*** | 0.00884** | 0.00367 | 0.0143*** | 0.00719** | 0.00367 |
| | (4.08) | (1.18) | (4.06) | (3.16) | (1.18) | (4.35) | (2.69) | (1.17) |
| Observations | 225 | 90 | 135 | 225 | 225 | 117 | 207 | 207 |
| Adjusted $R^2$ | 0.033 | −0.011 | 0.076 | 0.083 | 0.084 | 0.045 | 0.030 | 0.030 |

have a negative EOM return of 1.9%, 3.1%, and 6.1%, respectively, all statistically significant. Finally, as a sensitivity check, in columns (6) to (8), we exclude the top two months of flow. As expected, the results are weaker but still statistically and economically significant.

Panel B examines the findings using the value-weighted return index. The findings are considerably more statistically significant. The index shows a return of −7.7% in the months with the highest issuance with a $t$-statistic of −4.00. If we remove December 2018 and January 2018, the magnitude is still 4.8% with a $t$-statistic of −3.64.

As a one-period example not at EOM, we also noticed that Tether released a limited audit of a snapshot of their cash balance as of September 15, 2017. Tether later fired the auditor. Prices dropped 25% from September 12, 2017 to September 15, 2017, the day of the audit (see Internet Appendix Figure IA.13).

Finally, we examine if there are any patterns in Bitfinex's Bitcoin wallets used to hold the exchange Bitcoin reserves.[36] If the founders attempt to sell Bitcoin and raise a cash reserve, the balance in the reserve wallets of Bitfinex might go down before the EOM. To examine this possibility, we compute the net flows of Bitcoins from Bitfinex's reserve wallets, including its main cold wallets. Internet Appendix Table IA.IX shows that in months with large Tether issuances, the Bitfinex balances experience a large net outflow in the last five days of the month, and the relationship is statistically significant with a $t$-statistic of 3.14. As a placebo test, we perform the same analysis on the reserve wallets of any of the top-20 largest exchanges for which we could obtain reserve wallet addresses, and we find no EOM net outflow from these wallet balances. This result suggests that a plausible channel for the decrease in Bitcoin prices is EOM liquidation of Bitfinex reserves. In summary, the strong negative effect on Bitcoin prices in months of Tether issuance is consistent with Tether not maintaining full dollar reserves at all times. Without a dollar backup, the Tether peg could be held when cryptocurrency prices increase and the liquidation of Tether is limited. But if market participants lose confidence in Tether and a run occurs, there can be a substantial risk of default without full cash reserves. Like most runs, this could also lead to substantial collateral damage to cryptocurrency investors.

### *B.2. Flows and the Tether-USD Rate*

Although the analysis above shows substantial support for a supply-based explanation, we further examine the demand-based explanations for Tether. If the demand for Tether comes mainly from investors who hold dollars and seek to invest in Bitcoin, the greater demand could translate into a higher market rate for the Tether-USD pair. Kraken was the most active market-based venue for exchanging Tether for dollars in 2017, although the market volume of the

[36] These wallets can include cold wallets or other wallets that hold a large balance of Bitcoin reserves for a specific exchange. The table header to Internet Appendix Table IA.IX describes how we identify these wallets on the blockchain.

pair was less than 1% of the Bitcoin-Tether volume. The rate on Kraken often stays close to one over our sample period from March 1, 2017 to March 31, 2018 but has a standard deviation of 2%. If part of the demand for Tether spills over to Kraken, one would expect changes in the Tether-USD rate to be related to the flow of Tether.

In Panel A of Table VIII, we regress Tether flow on different lags of Tether-USD returns as well as BTC-USD returns. We standardize the variables so that the magnitudes of the coefficients are comparable. The results show that Tether flow is highly sensitive to the BTC-USD pair (as shown previously) but bears little relation to the Tether-USD pair. Similarly, in Panel B, we examine Bitcoin flow and find that the corresponding flow of Bitcoin back is highly sensitive to BTC-USD rates but bears no relationship with the Tether-USD pair. We further examine this relationship by constructing different proxies for the Tether price using value-weighted and equal-weighted Tether-USD rates across all available exchanges as well as constructing a synthetic rate using Bitcoin prices on Bitfinex versus dollar exchanges. The results using these proxies instead of the Kraken Tether-USD rate are similar (Internet Appendix Tables IA.X, IA.XI, and IA.XII). We also examine results for the 1LSg account and other accounts on Tether exchanges and find similar results (Internet Appendix Table IA.XIII).

Another possibility is that the overall price difference between Tether and USD exchanges is driving the flow. To examine this possibility, we construct two lagged return measures: the three-hour lagged Bitcoin return averaged across all major exchanges, and the three-hour lagged difference in return between Tether exchanges and USD exchanges. The average return captures the effect of Bitcoin price changes and the difference captures the spread leading to the arbitrage opportunity between Tether and USD exchanges. We then estimate a regression of Tether and Bitcoin flows on the spread and average returns. Panel C of Table VIII shows that the flows are not sensitive to the spread. Moreover, Panel C of Internet Appendix Table IA.XIII shows that the flows to 1LSg and other Poloniex and Bittrex accounts have no relationships with the spread, whereas the flows to Binance and Huobi are positively related to the spread. These findings suggest that when the BTC-Tether pair trades at a higher discount relative to BTC-USD, capital flow to Binance and Huobi increases to buy Bitcoin at a lower price. This result indicates that Tether is used in arbitrage activities, but the 1LSg activities are not driven by these arbitrage proxies.

Overall, we do not find evidence to support the demand-based hypothesis (H1A), but we also note that noise and illiquidity in the Tether return series add noise to these tests. We believe that the various ways we construct for the actual and implied Tether return series substantially mitigate this concern.

### *C. Flows and Bitcoin Prices across Exchanges*

Tether may facilitate cross-exchange arbitrage among Tether exchanges. In particular, imagine that Bitcoin prices increase on Bitfinex, but Bitcoin prices

**Table VIII**

**The Relationship between Tether and Bitcoin Flows and Tether-USD versus BTC-USD Rates**

This table reports OLS estimates for which the dependent variables are the net flow of Tether from Bitfinex (Panel A) and the net flow of Bitcoin to Bitfinex (Panel B), and the independent variables are multiple lags of Tether-USD and BTC-USD returns,

$$Flow_t = \alpha + \sum_{i=1}^{5} \beta_i R_{t-i}^{Tether-USD} + \sum_{i=1}^{5} \gamma_i R_{t-i}^{BTC-USD} + \epsilon_t,$$

where $R_t^{BTC-USD}$ is the hourly return of Bitcoin prices in USD and $R_t^{Tether-USD}$ is the hourly return of the Tether-USD pair on the Kraken exchange. The sample period is from April 1, 2017 (when Kraken prices are first available) to March 1, 2018. Panel C estimates an OLS regression of Tether and Bitcoin flows on the lagged arbitrage spread and average returns between USD and Tether exchanges,

$$Flow_t = \beta_0 + \beta_1 \frac{1}{3} \sum_{i=1}^{3} ArbitrageSpread_{t-i} + \beta_2 \frac{1}{3} \sum_{i=1}^{3} AverageReturn_{t-i} + \epsilon_t,$$

where $AverageReturn_t = \frac{(R_t^{USD} + R_t^{Tether})}{2}$ and $ArbitrageSpread_t = R_t^{USD} - R_t^{Tether}$. All variables are standardized by subtracting the mean and dividing by the standard deviation. Standard errors are robust to heteroskedasticity. $t$-Statistics are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

| Panel A: Tether Flow | | | | | |
|---|---|---|---|---|---|
| L.Tether_USD_Ret | −0.0082 | −0.0016 | 0.0019 | 0.0018 | 0.0047 |
| | (−0.77) | (−0.13) | (0.16) | (0.14) | (0.36) |
| L2.Tether_USD_Ret | | 0.0080 | 0.0160 | 0.0180 | 0.0232 |
| | | (0.59) | (1.11) | (1.21) | (1.42) |
| L3.Tether_USD_Ret | | | 0.0138 | 0.0176 | 0.0257 |
| | | | (1.23) | (1.32) | (1.71) |
| L4.Tether_USD_Ret | | | | 0.0024 | 0.0172 |
| | | | | (0.20) | (1.05) |
| L5.Tether_USD_Ret | | | | | 0.0272 |
| | | | | | (1.50) |
| L.BTC_USD_Ret | $-0.0448^{**}$ | $-0.0472^{***}$ | $-0.0482^{***}$ | $-0.0489^{***}$ | $-0.0490^{***}$ |
| | (−3.14) | (−3.31) | (−3.40) | (−3.44) | (−3.45) |
| L2.BTC_USD_Ret | | $-0.0688^{***}$ | $-0.0698^{***}$ | $-0.0715^{***}$ | $-0.0719^{***}$ |
| | | (−4.80) | (−4.84) | (−4.96) | (−4.95) |
| L3.BTC_USD_Ret | | | $-0.0299^{*}$ | $-0.0316^{**}$ | $-0.0325^{**}$ |
| | | | (−2.56) | (−2.70) | (−2.73) |
| L4.BTC_USD_Ret | | | | $-0.0419^{**}$ | $-0.0426^{**}$ |
| | | | | (−3.05) | (−3.12) |
| L5.BTC_USD_Ret | | | | | −0.0263 |
| | | | | | (−1.85) |
| Constant | −0.0034 | −0.0032 | −0.0031 | −0.0030 | −0.0029 |
| | (−0.31) | (−0.29) | (−0.28) | (−0.27) | (−0.27) |
| Observations | 8,750 | 8,749 | 8,748 | 8,747 | 8,746 |
| Adjusted $R^2$ | 0.002 | 0.006 | 0.007 | 0.008 | 0.009 |

(*Continued*)

**Table VIII**—*Continued*

| Panel B: Bitcoin Flow | | | | | |
|---|---|---|---|---|---|
| L.Tether_USD_Ret | −0.0047 | 0.0029 | 0.0033 | 0.0061 | 0.0075 |
| | (−0.34) | (0.21) | (0.23) | (0.42) | (0.51) |
| L2.Tether_USD_Ret | | 0.0098 | 0.0085 | 0.0150 | 0.0167 |
| | | (0.74) | (0.58) | (1.02) | (1.10) |
| L3.Tether_USD_Ret | | | −0.0139 | −0.0012 | 0.0021 |
| | | | (−1.04) | (−0.08) | (0.14) |
| L4.Tether_USD_Ret | | | | 0.0212 | 0.0271 |
| | | | | (1.62) | (1.93) |
| L5.Tether_USD_Ret | | | | | 0.0084 |
| | | | | | (0.64) |
| L.BTC_USD_Ret | −0.1066*** | −0.1093*** | −0.1126*** | −0.1133*** | −0.1134*** |
| | (−6.72) | (−6.91) | (−7.18) | (−7.24) | (−7.27) |
| L2.BTC_USD_Ret | | −0.0775*** | −0.0808*** | −0.0825*** | −0.0829*** |
| | | (−4.97) | (−5.20) | (−5.30) | (−5.33) |
| L3.BTC_USD_Ret | | | −0.0734*** | −0.0750*** | −0.0761*** |
| | | | (−4.76) | (−4.85) | (−4.92) |
| L4.BTC_USD_Ret | | | | −0.0450** | −0.0460** |
| | | | | (−3.09) | (−3.17) |
| L5.BTC_USD_Ret | | | | | −0.0280 |
| | | | | | (−1.91) |
| Constant | 0.0154 | 0.0158 | 0.0160 | 0.0162 | 0.0163 |
| | (1.43) | (1.47) | (1.49) | (1.51) | (1.52) |
| Observations | 8,750 | 8,749 | 8,748 | 8,747 | 8,746 |
| Adjusted $R^2$ | 0.011 | 0.017 | 0.022 | 0.024 | 0.025 |

Panel C: Price Differences between USD and Tether Exchanges

| | (1) Tether | (2) BTC |
|---|---|---|
| Arbitrage Spread | 0.0032 | 0.0163 |
| | (0.22) | (1.08) |
| Average Return | −0.0823*** | −0.1372*** |
| | (−5.77) | (−8.37) |
| Constant | −0.0000 | 0.0001 |
| | (−0.00) | (0.01) |
| Observations | 9,501 | 9,501 |
| Adjusted $R^2$ | 0.007 | 0.020 |

on Poloniex adjust with a delay. Traders can respond to the spread by sending Tether to Poloniex and buying undervalued Bitcoins. This cross-exchange arbitrage also necessitates a flow of Tether back to Bitfinex when Bitfinex prices are lower than Poloniex prices. However, as Figure 1 shows, this reverse flow pattern is not commonly observed. On the other hand, the flow of printed Tether through Bitfinex might also cause prices to inflate first on Bitfinex before the Tether moves to other exchanges.

Internet Appendix Table IA.XIV shows that for a one-standard-deviation increase in the return spread measure, the net Tether and Bitcoin flow goes up from 0.0336 to 0.419 standard deviations, with $t$-statistics of 2.39 to 3.13. Consistent with the supply-based hypothesis of flows following returns, a one-standard-deviation decrease in the average Bitcoin return increases the flow by 0.043 to 0.12 standard deviations, with $t$-statistics of 3.15 to 6.68 even after controlling for the return spread.[37] The results show that Bitcoin is typically at a small premium on Bitfinex before the Tether flows to Bittrex and Poloniex. This finding could be due to the use of Tether to facilitate arbitrage or to the supply of Tether inflating prices at Bitfinex first. In either case, the results show that the pattern of flows following negative Bitcoin returns is the more economically sizable driver of the flow.

## V. Conclusion

Periods of rapid price appreciation are historically associated with innovation and growth but also with nefarious activities that lead to misallocation of capital. The semitransparent nature of the blockchain provides a unique opportunity to examine the mechanics behind the growth of an asset class during a period of massive speculation and understand the role of central monetary entities in a cryptocurrency world. In this paper, we examine whether the growth of the largest pegged cryptocurrency, Tether, is primarily driven by investor demand or is supplied to investors as part of a scheme to inflate cryptocurrency prices.

By mapping the blockchains of Bitcoin and Tether, we are able to establish that one large player on Bitfinex uses Tether to purchase large amounts of Bitcoin when prices are falling and following the printing of Tether. Such price supporting activities are successful as Bitcoin prices rise following the periods of intervention. Indeed, even 1% of the times with extreme exchange of Tether for Bitcoin have substantial aggregate price effects. The buying of Bitcoin with Tether also occurs more aggressively right below salient round-number price thresholds where the price support might be most effective. Negative EOM price pressure on Bitcoin in months with large Tether issuance points to a month-end need for dollar reserves for Tether, consistent with partial reserve backing. Our results are most consistent with the supply-driven hypothesis.

Overall, our findings provide support for the view that price manipulation can have substantial distortive effects in cryptocurrencies. Prices in this market reflect much more than standard supply/demand and fundamental news. These distortive effects, when unwound, could have a considerable negative impact on cryptocurrency prices. More broadly, these findings also suggest that innovative technologies designed to bypass traditional banking systems have not eliminated the need for external surveillance, monitoring, and a regulatory framework as many in the cryptocurrency space had believed. Our findings support the historical view that dubious activities are associated with bubbles and can contribute to further price distortions.

[37] We find similar results when decomposing the flows into those to 1LSg, other Poloniex and Bittrex, and other Tether-based exchange (Internet Appendix Table IA.XIV).

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

**Appendix S1**: Internet Appendix.
**Replication code**.
**Disclosure statement**