# Is Bitcoin Really Un-Tethered?

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**Abstract**

This paper investigates whether Tether, a digital currency pegged to U.S. dollars, influences Bitcoin and other cryptocurrency prices during the recent boom. Using algorithms to analyze the blockchain data, we find that purchases with Tether are timed following market downturns and result in sizable increases in Bitcoin prices. Less than 1% of hours with such heavy Tether transactions are associated with 50% of the meteoric rise in Bitcoin and 64% of other top cryptocurrencies. The flow clusters below round prices, induces asymmetric autocorrelations in Bitcoin, and suggests incomplete Tether backing before month-ends. These patterns cannot be explained by investor demand proxies but are most consistent with the supply-based hypothesis where Tether is used to provide price support and manipulate cryptocurrency prices.

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**I**nnovation, excessive speculation, and dubious behavior are often closely linked. Periods of extremely rapid 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. Financial bubbles often coincide with the belief that a rapid gain can be obtained from simply selling the asset to another investor with a stronger belief in the underlying business fundamentals.[1] Perhaps because of the focus on speculative activity rather than verifiable fundamentals, bubbles have historically been associated with various forms of fraud. For example, the Mississippi Bubble of 1719-1720, like the 1719-1720 South Sea Bubble, experienced inflated valuations around subsequent issuances and margin lending on the securities themselves [Dale (2004)]. The company also engaged in false marketing about the potential in its income generating assets, price support by the stock itself, and paper money that was not fully backed by gold as claimed [Aliber and Kindleberger (2015)]. As we will briefly discuss in the next section, famous bubbles such as the 1840s Railroad bubble, roaring 1920s stock, the dot-com, and 2008 financial crisis contained substantial evidence of misinformation, false accounting, price manipulation, collusion, and fraud, often in sophisticated forms.

Cryptocurrencies, which have grown from nearly nothing to over $300 billion in market capitalization in a few years, fit the historical narrative of previous bubbles quite well–there is an innovative technology with extreme speculation surrounding it. To many, Bitcoin and other cryptocurrencies offer the promise of a better financial system with anonymous transactions that are free from banks and government intervention. The conception of Bitcoin corresponds to the middle of the 2008-2009 financial crisis, a time of growing disdain for government intervention and distrust for major banks. The promise of a decentralized ledger with independently verifiable transactions has enormous appeal, especially in an age when centralized clearing is subject to concerns of both external hacking and internal manipulation.[2] Nevertheless, the vast majority of cryptocurrency

[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 investor with a higher valuation.

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

transactions occur on centralized exchanges. These exchanges largely operate outside the purview of financial regulators and offer varying levels of limited transparency. Additionally, Bitcoin and other cryptocurrencies often trade against digital currencies, even further relaxing the necessity for an exchange to establish a legitimate fiat banking relationship.[3] Trading on unregulated exchanges, and specifically on cross-digital-currency exchanges, could leave cryptocurrencies vulnerable to gaming and manipulation.

Our study examines the interaction between the largest cryptocurrency, Bitcoin, other major cryptocurrencies, and Tether, a cryptocurrency that accounts for more transaction volume than U.S. dollars. Tether is a cryptocurrency purportedly backed by U.S. dollar reserves and allows for dollar-like transactions without a banking connection, which many crypto-exchanges have difficulty obtaining or keeping. Although some in the blogosphere and press have expressed skepticism regarding the U.S. dollar reserves backing Tether,[4] the cryptocurrency exchanges have largely rejected such concerns and widely use Tether in transactions.

In this paper, to shed light on the driving forces behind the recent boom of cryptocurrency markets, we focus on variants of two main alternative hypotheses for Tether: whether Tether is 'pulled' (demand-driven), or 'pushed' (supply-driven). First, if Tether is 'pulled' or demanded by investors who own fiat currency, the issuance of Tether facilitates the demand of these investors who value the flexibility of a digital currency and yet the stability of the dollar 'peg'. The demand for Tether could also arise because of its practicality for engaging in cross-exchange pricing arbitrage.[5]

Alternatively, if Tether is 'pushed' on market participants, Bitfinex supplies Tether regardless of the demand from investors with fiat currency to purchase Bitcoin and other cryptocurrencies. The acquired Bitcoins can then gradually be converted into dollars. In this setting, the Tether creators have several potential motives. First, if the Tether founders, like most early cryptocurrency adopters and exchanges, are long on Bitcoin, they have a large incentive to create an artificial de-

[3]As of May 20, 2018, there are over 1,600 cryptocurrencies and digital tokens trading on various digital exchanges that are largely operating outside the traditional regulatory framework for securities and currencies.

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

[5]As suggested by Tether Limited on https://Tether.to regarding the use case for Tether: "Enhance your cross-exchange and currency arbitrage strategy".

mand for Bitcoin and other cryptocurrencies by 'printing' Tether. Similar to the inflationary effect of printing additional money, this can push cryptocurrency prices up. Second, the coordinated supply of Tether creates an opportunity to manipulate cryptocurrencies. When prices are falling, the Tether creators can convert their Tether into Bitcoin in a way that pushes Bitcoin up and then sell some Bitcoin back into dollars to replenish Tether reserves as Bitcoin price rises. Finally, if cryptocurrency prices crash, Tether creators essentially have a put option to default on redeeming Tether, or to potentially experience a 'hack' where Tether or related dollars disappear. Both the 'pushed' and 'pulled' alternatives have different testable implications for flows and cryptocurrency returns that we can take to the powerful blockchain data.

We begin our exercise by collecting and analyzing both the Tether and Bitcoin Blockchain data through a series of algorithms we implement to reduce the complexity of analyzing the blockchain. In particular, because of the semi-transparent nature of the transaction history recorded on the blockchain, we are able to use variants of methods developed in computer science [Meiklejohn et al. (2013) and Ron and Shamir (2013)] to cluster groups of related Bitcoin wallets. Large nodes are then labeled through identifying certain member wallets inside each group and tracking the flow of coins between major players in the market. For example, through this methodology for the Bitcoin blockchain, we grouped over 680 thousand wallet addresses as Bitfinex, 950 thousand addresses as Poloniex, and 1.4 million wallet addresses as Bittrex.

Figure 1 describes how Tether moves among major market participants on the Tether blockchain. 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 created, moved to Bitfinex, and then slowly moved out to other crypto-exchanges, mainly Poloniex and Bittrex. Interestingly, almost no Tether returns to the Tether issuer to 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 widespread over time as a medium of exchange.

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. Additionally, we find that the cross-exchange currency flows are closely matched on the Tether and Bitcoin blockchains. This independently verifies our algorithm for categorizing the exchange identities, and in addition shows that wallets associated with Bitfinex send Tether to Poloniex and Bittrex in exchange for Bitcoin.

We then examine the flow of coins identified above to understand whether Tether is pushed or pulled, and examine the effect of Tether, if any, on Bitcoin prices. First, following periods of negative Bitcoin return, Tether flows to other exchanges are used to purchase Bitcoin. Second, these flows seem to have a strong effect on future Bitcoin prices. They are present only 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. A placebo test finds no evidence of Bitcoin price movements following large flows of Bitcoin from Poloniex and Bittrex to major exchanges other than Bitfinex. This phenomenon strongly suggests that the price effect is driven by Tether issuances.

To illustrate the potential magnitude and predictive effect of Tether issuances on Bitcoin prices, we focus on the hours with the largest lagged combined Bitcoin and Tether flows on the two blockchains. These 87 hours have large negative returns before the flows but are followed by large return reversals. These 87 events account for less than 1% of our time series (over the period from the beginning of March 2017 to the end of March 2018), yet are associated with 50% of Bitcoin's compounded return, and 64% of the returns on six other large cryptocurrencies (Dash, Ethereum Classic, Ethereum, Litecoin, Monero, and Zcash).[6] A bootstrap analysis with 10,000 simulations demonstrates that this behavior never occurs randomly.

Consistent with Tether being used to buy Bitcoin when prices drop, we find a statistically and economically strong reversal in Bitcoin prices, but only following negative returns. The Bitcoin reversal did not exist before Tether was prevalent in the market and disappears during the period when Tether stops being printed.

[6]These findings are instructive, but incomplete and 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.

The results are consistent with the Tether issuers pushing out Tether to stabilize the price of Bitcoin, but we investigate these issues further. Investors hoping to stabilize and drive up the price might concentrate on certain price thresholds as an anchor or price floor. This follows the idea that if investors can demonstrate a price floor, then they can induce other traders to purchase.[7] Interestingly, Bitcoin purchases by Bitfinex strongly increase just below multiples of 500. This pattern is only present in periods following printing of Tether and not observed by other exchanges. To address causality, we use the discontinuity in Tether flow at the round threshold cutoffs as an instrument to measure the effect of Tether on Bitcoin prices. The instrumental regression results are even stronger, indicating that Tether flows are causing the positive return.

If Tether is pushed out to other crypto exchanges rather than demanded by investors with dollars in hand, Tether may not be fully backed by dollars when issued. However, if the issuers wished to post monthly bank statements to shore up dollar reserves and appear fully backed, this would necessitate the liquidation of the purchased Bitcoins at the end-of-the-month (EOM).[8] Interestingly, we find a significant negative EOM abnormal return of 6% in the months with strong Tether issuance. The EOM Bitcoin returns are highly correlated with the magnitude of Tether issuance, and no abnormal returns are observed in months when Tether is not issued.

Our results are consistent with Tether being pushed out onto the market and not primarily driven by investors' demand, but we nevertheless further examine two direct implications of the 'pulled' hypotheses. In particular, we examine if the flows of Tether bear much relation to a proxy for its demand from investors, the premium for Tether relative to the U.S. Dollar exchange rate. We find little evidence to support this hypothesis. Another related alternative is that the cross-exchange arbitrage to eliminate pricing discrepancies across exchanges is the primary driver of the Tether flow, but this hypothesis is not supported by the data. Although we find little support for demand-based proxies, we hypothesize that there are some sources for legitimate demand for

[7] 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) found collusion only around even numbers in spreads.

[8] Du, Tepper, and Verdelhan (2017) and He and Krishnamurthy (2018) argue that banks' compliance with period-end capital requirements may create a sizable effect on asset prices.

Tether, however, those are not the ones that dominate the flow patterns observed in the data.

Overall, we find that Tether has a significant impact on the cryptocurrency market. Tether seems to be used both to stabilize and manipulate Bitcoin prices. Although cryptocurrencies are relatively new, the trading mechanisms between and across exchanges are quite complex. This complexity [Partnoy (2009)] can obfuscate the true nature of trading and the influence of cross-trading across cryptocurrencies. Our findings suggest that market surveillance within a proper regulatory framework may be needed for cryptocurrency markets to be legitimate stores of value and a reliable medium for fair financial transactions. Additional research is necessary to further understand these markets.

The rest of the paper unfolds 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 and summarizes the main data sources, and Section III describes how we analyze the blockchain data. Section IV analyzes the potential influence of Tether on Bitcoin, and Section V further tests whether the flows are consistent with pushed or pulled explanations. Section VI concludes.

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

### *I.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, focusing on selling to others rather than economic fundamentals, and questionable activities. The famous South Sea Bubble 1719-1720 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) and Temin and Voth (2013)]. Scheinkman (2013) notes that there were also many other similar companies around this time that seem to have been fraudulent. The Railroad Bubble of the 1840s led to a host of companies who merely sought to procure funds from investors and had no intention of actually building railroads [Robb (1992)]. In the roaring 1920s, investment pools would manipulate a stock price through

’wash-sales’, collusion with the stock-exchange specialists, and coordinated hype from the commentators to pump a stock at an inflated price to the public [Malkiel (1981)]. The technology or ’dotcom’ bubble of 1997 to 2000 also contained strong elements of stock promotion through inflated analysts’ 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, the most notable being Enron and Worldcom.

One line of thinking is that more fraud exists in economic booms because individuals monitor their investments relatively less closely [Povel, Sing, and Winton (2007)]. Akerlof and Romer (1993) also argue that the deception often has an active role in causing the capital misallocation. They describe four financial crises in the 1980s (Chilean crisis, Savings and loan crisis, Dallas real estate, and the junk bond market crisis), where the behavior of actors involved in ’looting’ an organization played an unintended role of systematically moving capital into a space where asset prices are distorted. In our analysis of Bitcoin and Tether, we are able to examine if either of these views fits the data.

### *I.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. 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 Federal banks and clearing houses. On January 3rd, 2009, the first block was established on the Bitcoin blockchain by Nakamoto. On October 5, 2009, the New Liberty Standard established the first exchange rates of Bitcoin (BTC) at 1309.03 BTC for $1 USD, or $0.00076 per BTC.[9] One of the largest Bitcoin exchanges of the time, the Mt. Gox exchange, was established on July 17, 2010. By April 23, 2011, Bitcoin exceeded parity with the US Dollar, Euro, and British Pound with the market cap passing $10 million USD,

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

and by March 28, 2013, the total Bitcoin market cap passed $1 billion USD.[10]

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.[11] Good reasons have been put forward as to why the 'hack' may have been an inside job.[12] Gandal et al. (2018) argues that fraudulent trading on Mt. Gox exchange led to a significant spike in Bitcoin prices in late 2013. 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.[13]

### *I.C Brief Tether History*

The objective of Tether is to facilitate transactions between cryptocurrency exchanges with a rate pegged to the U.S. dollar. It allows performing high speed capital transfers without resorting to slow bank wires. While this could also occur with fiat transactions, Tether is advantageous since many crypto exchanges have a hard time securing banking relationships. Tether Limited, the issuer of Tether, claims that "Tether Platform currencies are 100% backed by actual fiat currency assets in our reserve account."[14] However, Tether itself has created ambiguity around this backing by noting that they are not guaranteeing redemption rights.[15]

The Bitfinex exchange started in 2012, but experienced rapid growth and now claims that they "are the world's largest and most advanced cryptocurrency trading platform." 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.[16]

Figure 2, Panel A, shows the cumulative issuance of Tether denominated in both U.S. dollars and Bitcoin as well as Bitcoin prices. The first Tether was issued on October 6th 2014, but the

[10] http://historyofbitcoin.org/
[11] See Vigna (2014).
[12] For example, see Nilsson (2015).
[13] See Kumar (2016).
[14] https://tether.to/faqs/
[15] "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 (December 7, 2017)]
[16] https://offshoreleaks.icij.org/nodes/82024464

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. As of May 25th, 2018, Tether is ranked the 14th highest market cap cryptocurrency in the world, with a market cap around $2.5 billion USD.

Panel B of Figure 2 shows transactions of major cryptocurrencies in U.S. dollars 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 now denominated in Tether. 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.[17]Hence, we term Bitfinex transactions as well as those explicitly denominated in Tether as Tether-related.

Those in the blogosphere and the mainstream press began to raise questions regarding Tether in the second half of 2017.[18] On 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. However, this could be due to not wanting to subject their bank to public scrutiny and lose their new banking relationship, since many large banks avoid the scrutiny of crypto-related deposits either because of perceived reputation tainting, or due to the burden of needing to comply with anti-money laundering (AML) or 'know your customer' (KMC) banking regulations. Additionally, Tether has not disclosed whether it has consistently been employing an external auditor. Bloggers have also conjectured about whether Tether issuances are fueling Bitcoin.[19] One website, tetherreport.com, finds positive return effects after incidences of Tether issuances,[20] and analysis by Wei (2018) finds no price effect at the time of Tether issuances.

[17]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. The deviations are statistically different with $t$-statistics ranging from 18 to 49, supporting the claim that transactions on Bitfinex could be denominated in Tether.

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

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

[20]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 that 182 hours (91 two-hour periods) and derive a

### I.D Main Hypotheses

This section examines two main alternative 'pulled' versus 'pushed' hypotheses[21] about Tether functions: 1) Tether is driven by legitimate demand for a pegged digital currency, or 2) Tether is 'pushed' through a supply-driven scheme to make up a currency, convert it into Bitcoin, and then manipulate the price of Bitcoin and other cryptocurrencies.

Our first hypothesis is that Tether is driven by the investor demand and is always fully backed by U.S. dollars (as with a full-reserve bank). There is an intuitive appeal for investors demanding a currency that can provide a stable store of value, support quick transactions, and potentially allow cryptocurrency exchanges to skirt banking regulations required for deposits. If driven by the investor demand as a medium of exchange, Tether issuance and flow should be sensitive to the demand from the market participants who have dollars or other fiat currencies in hand. The 'pulled' or demand-driven hypotheses comes in two major variants.

H1A: Tether should be printed when Tether's premium relative to U.S. dollar increases and not printed at times when it decreases. Tether flows should be strongly related to the changes in Tether-USD exchange rate.

H1B: The printing of Tether might 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 primarily correspond to periods when Bitcoin sells at a premium on Bitfinex relative to that exchange.

The alternative key hypothesis is that Tether is being printed independently of demand and pushed onto the market. The issuers can print Tether and can convert it into more widely-accepted cryptocurrencies such as Bitcoin. In addition to issuance and transaction fees earned from trading in Tether, other possible valuable benefits of such a plan could be as follows.

compounded effect of 48.8%, and they compare it to 6.5% for 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 issuances are often not when the Bitcoin buying activity actually occurs.

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

First, like an inflationary effect of printing money, issuing Tether could significantly push cryptocurrency prices up by generating an artificial demand for them. Since most cryptocurrency exchanges and early movers are long in Bitcoin and other cryptocurrencies, they would benefit from such a large price appreciation.

Second, since Tether issuances are large, if traded strategically, Tether could be used to manipulate the price of Bitcoin. This enables Tether issuers to stabilize and/or set regionalized price floors and push the price of Bitcoin and other cryptocurrencies upward. If Bitcoin prices increase, then 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 convert some of their cryptocurrencies to U.S. dollars and retrospectively provide dollar reserves for Tether.

Third, the Tether issuers create a valuable put option in the case of a future crypto market downturn. The founders of Tether have a valuable option to not redeem Tether to dollars, and possibly experience an inside 'hack' (perhaps, similar to the one on Mt. Gox) when Tethers and/or their associated dollars suddenly disappear.[22] To examine the supply-driven manipulation hypothesis, we examine the following predictions:

H2A: If Tether issuers are trying to purchase Bitcoin at low prices and provide stability to the market during the downturn, outflows of Tether and purchases of Bitcoin by Bitfinex should follow periods of negative Bitcoin returns.

H2B: If the Tether supply is large, Bitcoin purchases with Tether from Bitfinex could push the Bitcoin and other cryptocurrency prices up. This effect should be more pronounced in periods with large Tether issuances.

H2C: Bitcoin returns should show a return reversal after negative returns, especially during times when Tether is actively printed.

H2D: Since round-number thresholds can be price anchors to set a price floor and are often used as buying signals by investors, bitcoin purchases using Tether might increase if Tether falls

[22] See McLannahan (2015).

below these salient thresholds. This effect should be more pronounced in periods with large Tether issuances.

H2E: If Tether is not fully-backed by dollars at the outset and instead is engaged in fractional-reserve-banking activity, but the issuers want to signal to investors otherwise by releasing EOM accounting statements, then Tether creators must liquidate the Bitcoins into U.S. dollar to demonstrate sufficient reserves. This could create negative returns in Bitcoin at the EOM. This effect should be more pronounced in periods with large Tether issuances.

In the next section, we discuss the data and details behind testing the developed hypotheses.

## II. Data

The price and the blockchain data obtained for this study amount to over 200 GB from more than ten sources, with *CoinAPI*, *Coinmarketcap.com*, *Blockchain.info*, *Omniexplorer.info*, and *CoinDesk* as our main sources. The intraday pricing data on major cryptocurrencies are from *CoinAPI*. Hourly and 5-minute returns are calculated from the last trade within each minute. Missing prices are carried forward for non-trading periods of up to five minutes. Prices are assumed missing if stale for more than five minutes. The starting date varies for different currencies. The sample covers 25 months from March 2016 to March 2018, but the main set of tests is implemented after March 2017 when Tether experienced a large issuance. Daily prices of 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. The daily prices are based on the UTC time, and the close and open prices are calculated based on a 24-hour daily cycle that ends at midnight UTC. We also use intraday *CoinDesk* price index, which is one of the most tracked price indices in the cryptocurrency market. *Coindesk* calculates a Bitcoin index using prices across major markets.[23]

Bitcoin blockchain data is obtained from *Blockchain.info* and covers the period from Bitcoin initiation in January 2009 to March 2018. The blockchain data contain all the history of Bitcoin transactions between Bitcoin wallets and include variables such as wallet IDs of senders and re-

[23]The criteria for calculating the index is reported at https://www.coindesk.com/price/bitcoin-price-index/.

cipients as a string of 34 characters and numbers, the amount of coins transferred, timestamp, transaction ID, and the previous transaction ID where the coin was received by the sender of each new transaction. A transaction can have multiple senders and recipients. In fact, it is common to see Bitcoin transactions with hundreds of senders and recipients, making tracking of the coins on the blockchain extremely complex.

Tether is issued via the Omni Layer Protocol based on the Bitcoin blockchain, and Tether blockchain data are from *Omniexplorer.info* from October 2014 to March 2018. Each transaction of Tether includes the wallet IDs of the sender and recipient (usually a string of 34 characters and numbers), amount of coins transferred, timestamp, transaction status, type of action, and transaction ID as a 64-character hash string. Wallet identities of major exchanges are manually collected from the Tether rich list on tether.to at multiple snapshots between January and March 2018. These exchanges account for a major part of Tether transactions.

Flows between two parties on the blockchain are defined as the signed net amount of capital transferred between those entities. 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 in each period:

$$\begin{aligned} NetBTCFlow_t = &(\sum_{t-1}^{t} BTC_{PLX \to BFX} - \sum_{t-1}^{t} BTC_{BFX \to PLX}) \\ &+(\sum_{t-1}^{t} BTC_{BTX \to BFX} - \sum_{t-1}^{t} BTC_{BFX \to BTX}) \end{aligned} \tag{1}$$

where $BTC_{i \to j}$ shows 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 transaction. Based on the wallets labeled in Figure 1, we define the net flow of Tether as below[24]:

$$
\begin{aligned}
NetTetherFlow_t = &\sum_{t-1}^{t} Tether_{BFX\to 1J1d} + \sum_{t-1}^{t} Tether_{BFX\to 1AA6} \\
&+ \sum_{t-1}^{t} Tether_{BFX\to 1Fdz} - \sum_{t-1}^{t} Tether_{1MZA\to BFX}
\end{aligned}
\tag{2}
$$

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

Tether exchanges account for a large portion of cryptocurrencies trade volume over our sample period. Table I, Panel A, shows the total traded volume on major exchanges for major cryptocurrencies, in billion U.S. dollars, from March 1, 2017 to March 31, 2018. Some exchanges including Gemini and Coinbase specialize in a limited number of major currencies such as Bitcoin and Ethereum. Others, especially the Tether-related exchanges, list 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.

Panel B of Table I shows the cross-sectional correlation of cryptocurrencies' daily returns. Not surprisingly, the daily returns are positively correlated across all the coins, but there seems to be a good variation across different cryptocurrencies. For example, Bitcoin's correlation with Ethereum, Ripple, and Litecoin are 0.44, 0.20, and 0.45 respectively. This highlights a reasonable degree of cross-sectional variation in coins' returns.

Panel C of Table I shows the autocorrelation of cryptocurrencies at various frequencies. The autocorrelations are generally negative. For example, a 1% change in the lagged 3-hour Bitcoin prices is followed by 6 basis points reversal in the next three hours. At 3-hour intervals, Dashcoin, Ethereum Classic, Ethereum, and Ripple seem to have the highest reversals at 7 basis points.

[24]As shown in Figure 1, 1J1d, 1AA6, 1Fdz, and 1MZA are the first four characters of wallet numbers acting as intermediaries for the flow of Tether between Bitfinex, Poloniex, and Bittrex.

## III. Tracking Currency Movements

### *III.A Analyzing Bitcoin Blockchain*

The Bitcoin blockchain is an approximately 170 GB network database that includes 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.[25] These features contribute to the Bitcoin blockchain's complexity. The complexity of the data can be observed in a 10-minute random sample of the blockchain in 2017, where each node represents a wallet address, and each edge shows the flow of coins. (Figure IA1)

To reduce the complexity of the network, we adopt methods from computer science literature [Meiklejohn et al. (2013) and 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 the other inputs. Therefore, it is 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 identify connected components between different groups of wallets across the entire blockchain. For example, consider another group with members X, Y, and Z. If wallets A and X appear as inputs in the same transaction at some point on the blockchain, all the wallets A, B, C, X, Y, and Z need to be grouped together. Hence, 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.

To assign identities of grouped wallets to Tether-related exchanges, 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. The clustered group of wallets that contains such addresses are assigned to the identified exchanges. Through this methodology, a group of approximately 950 thousand addresses are labeled as Poloniex and a group of approximately 1.4 million

[25] Table IAI 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.

wallets as Bittrex. Due to limited public information on Bitfinex wallets, the Bitfinex exchange is identified by tracking the flow of coins from Poloniex and Bittrex. A large amount of coins from Poloniex and Bittrex are transferred into a group of 680 thousand wallets, which then deposits a large balance of coins into a single wallet informally known as the Bitfinex cold wallet. We tentatively label this group of 680 thousand wallets and then verify in the next section as the Bitfinex exchange. Note that this group of wallets could be associated either with entities closely tied to Bitfinex or with normal traders that have accounts on Bitfinex. Therefore, any inflow or outflow of coins to Bitfinex is captured by our cluster of 680 thousand wallets.

Lastly, two more steps are taken to accurately track the flow of Bitcoins between different entities. First, we exclude change transactions that account for the difference between total Bitcoin sent and received in one transaction. This change amount arises from the blockchain transaction structure and is returned to the sender. Second, if a transaction has multiple recipients, the flow from the sender is allocated proportionally by the number of coins received by each recipient.

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 did 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,[26] which we define as wallets with four or less transactions on the blockchain and zero net balance, and with the Bitfinex cold wallet.

### *III.B Analyzing Tether Blockchain*

As previously described in Figure 1, the graph 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. Note that there are barely any flows moving back to the initial Tether printing node, consistent with sources stating

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

that it is not viable to move Tether back to Tether Limited to redeem for U.S. dollars. 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 USD-Tether pair for the majority of 2017. The magnitude of Tether flow to Kraken is significantly smaller than the other exchanges used to trade Tether for other cryptocurrencies, mainly Bitcoin. Fourth, most of the Tether flows to and from Bitfinex are through Bittrex and Poloniex. There are other flows to nodes that are unidentified. Our calculations show that approximately 2.99 billion Tether were sent by Bitfinex to Poloniex and Bittrex until February 2018. The two exchanges sent 1.89 billion back to Bitfinex, making them the net recipient of 1.11 billion Tether from Bitfinex. Throughout the paper, we focus on the timing and the amount of Tether flow from Bitfinex to these two major exchanges, because as we will show later, this is the primary channel through which Tether is converted to Bitcoin through wallets associated with Bitfinex.

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 as Tether issuance increased rapidly. For this reason, we also display four snapshots of the Tether flows through time (Figure IA2). 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.

### *III.C Verification of the Labeling Algorithm*

In this subsection we match the flow of Tether with the flow of Bitcoin as well as reported exchange volume to simultaneously test: 1) if the correct groups of wallets are identified on bitcoin blockchain, and 2) if Tether from Bitfinex is directly exchanged for Bitcoin. Matching the exact timing of transactions between the two blockchains is complicated because transactions done through exchanges or online platforms need not be settled immediately and might be verified on the blockchain at certain intervals. Moreover, there are different recording delays on Tether and Bitcoin blockchain. This makes examination of exact lead and lag relations between flows complicated. For these reasons, we compare a rolling 3-hour average of our hourly variables in most tests.

Figure 4, Panel A plots the moving average hourly flow of Bitcoin-denominated Tether from Bitfinex to Poloniex, and the flow of Bitcoin back from Poloniex to Bitfinex. The correlation of the two time-series is 47%, and the magnitude of the flow is almost the same. This demonstrates first that, the labeling of Bitcoin wallets through the algorithm described above correctly matches the exchanges of interest with wallets identities on tether blockchain obtained from the tether rich list. If we had incorrectly labeled Bitfinex on Bitcoin blockchain, then there would be no reason to expect a high correlation with the flow on Tether blockchain.[27] Second, the strong correlation between Tether flowing from Bitfinex to Poloniex and Bitcoin flowing back from Poloniex to Bitfinex demonstrates that Tether is directly exchanged for Bitcoin. A similar pattern is shown between Bitfinex and Bittrex, again demonstrating the strong link between Tether and Bitcoin flows through Bitfinex.

As a further check on the relation between Tether and exchange transactions, we examine the 3-hour moving average inflow of Tether to Poloniex and Bittrex and the official reported exchange volume. Panel B of Figure 4 shows that the inflow of Tether to Poloniex is highly correlated with the exchange volume for Bitcoin-Tether pair. The slope of 3.55 suggests that an inflow of Tether into the exchange is associated with 3.55 times increase in exchange volume. The slope is 1.57 for Bittrex.

### *III.D Timing and Characteristics of Currency Movements*

This section examines the timing and characteristics of the flow of coins between Bitfinex and other exchanges. First, we examine the timing of the flow relative to the time that Tether is printed. Throughout the text, 'printing,' 'issuance,' or 'authorization' of Tether refers to the release of coins from the Tether issuer as shown at the bottom of Figure 1. There are cases where Tether moves quickly in and out of Bitfinex right after printing, but it is also common to see a delay of a few

[27] Indeed, we compare the flows of Tether from Bitfinex to Poloniex and the flow of Bitcoin from Poloniex to three other major exchanges (Bitstamp, BTCC, and Gemini) and find correlations between 9% to 15%.

days between Tether printing and the flow of coins from Bitfinex. For example, 50 million Tether was printed on December 20, 2017 and was subsequently moved to Bitfinex the following day, increasing the Bitfinex net balance of Tether by almost 50 million.[28] However, it took almost four days for this amount to be fully moved out of Bitfinex.

To better understand the timing of the Tether flows, we examine inflows of Tether to Bitfinex as well as the outflows of Tether from Bitfinex to the two exchanges in response to printing of Tether by Tether Limited. Here we estimate a VAR model with five lags and examine the impulse response functions, which have been used extensively to examine the flows of capital between countries [Froot, O'Connell, and Seasholes (2001)]. The impulse response of Tether flows demonstrates the response of flows to a one standard deviation shock to printing of Tether. The regression used to estimate the VAR model is as follows:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + ... + A_5 y_{t-5} + \varepsilon_t \tag{3}$$

where $y_t$ is a 2-by-1 vector of Tether issuance and Tether flow, $A_i$ is a time-invariant 2-by-2 matrix of coefficients, $c$ is a 2-by-1 vector of constants, and $\varepsilon_t$ is a 2-by-1 vector of error terms.

Panel A of Figure 5 indicates that the inflow to Bitfinex significantly increases after Tether is printed at Tether Limited, but not all the Tether immediately flows into Bitfinex. On average, it can take between three and four days for most of the Tether to move to Bitfinex. Similarly, Panel B shows that the flow of Tether from Bitfinex to the other exchanges increases on the day of Tether authorization, though not as much as the inflow to Bitfinex in Panel A. Even after three days, there are still flows moving out from Bitfinex to the other exchanges. In Section IV, we use this delay in the flow of Tether to formally test how Bitcoin prices are influenced when there is an oversupply of Tether in the system.

[28] Examples are shown in the Internet appendix Figure IA3.

## IV. Are Bitcoin Prices Related to Tether?

Flow of Tether could be systematically related to Bitcoin prices. In this section, we focus on understanding the nature of the relationship between Bitcoin prices and Tether and also discuss how this relationship is connected to the main hypotheses.

### *IV.A Timing of Tether in Response to Bitcoin Prices*

After printing, Tether is used to purchase Bitcoin on crypto exchanges. We examine if the sensitivity of flow of Tether to Bitcoin returns is symmetric in response to positive and negative shocks. Figure 6 shows that Tether is used to purchase Bitcoin when returns are negative, but we do not find considerable Tether flows following price increases. Specifically, controlling for lagged volatility, Bitfinex wallets send out Tethers (Panel A) and purchases Bitcoin (Panel B) when the lagged return of Bitcoin is negative. But, there is no relationship when the previous Bitcoin return is positive. Consistent with Hypothesis H2A, the results are sizable and statistically significant. For a 1% drop in the average lagged return, when the lagged return is negative, 72 more Bitcoins are obtained per hour with a $t$-statistic of 7.7. However, the relationship is insignificant when the lagged return is positive (Table IAII). The fact that Tether is not being bought back to the same extent following positive returns is suggestive of Tether being used to protect Bitcoin prices during downturns rather than benign market making activities where Tether would be returned in periods of high Bitcoin returns.[29]

### *IV.B Do Flows of Tether Generally Affect Cryptocurrency Returns?*

The previous section established that wallets associated with Bitfinex transfer Tether to other exchanges following periods of negative Bitcoin returns. This has testable implications for Bitcoin returns. It has been shown that supply and demand for stocks does influence prices [for example,

[29]To further check the robustness of the finding, Figure IA4 shows the cumulative impulse response functions of a VAR estimate of the flow and Bitcoin return with five lags. The results show that the outflow of Tether from and inflow of Bitcoin to Bitfinex is sensitive to negative Bitcoin returns, but the inflow of Tether to and outflow of Bitcoin from Bitfinex is not sensitive to positive Bitcoin returns.

Cohen, Diether, and Malloy (2007)]. 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 a movement of Tether into the market. Moreover, as discussed in H2B, if Tether is being used to protect and push up the market, the effect of Tether transactions on Bitcoin prices should be stronger following negative Bitcoin returns. If a large flow of Tether is required to move prices, Figure 6 shows that such a large flow happens following negative returns. Additionally, if the flow of Tether is supply-driven, and there is an oversupply of Tether in the network in days following printing of Tether, the price effect of Tether on Bitcoin should be stronger on days after printing.

To test these hypotheses, Table II estimates a regression of rolling 3-hour average Bitcoin returns on lagged average net flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin back to Bitfinex. We use the average 3-hour Bitcoin returns as our dependent variable to capture the full effect of the cross-exchange flow of coins, as the effect might not be incorporated in exchange prices immediately. The standard errors are adjusted for heteroscedasticity and autocorrelation using Newey-West procedure with up to three lags. Moreover, as shown previously in Figure 4, the magnitude of the flow of coins on the two blockchains matches closely, and the correlation of the two flows is high, but the timing is not perfectly matched. Given that the timing of blockchain transactions is not an exact measure, but a proxy for the actual time of trade, we average the two flows on the two blockchains to reduce the noise in the timing. Column (1) shows that on days right after Tether printing, for a 100 Bitcoin increase in the flow, the 3-hour average future Bitcoin return goes up by 4.37 basis points, controlling for lagged return. Column (2) shows that the effect only exists in days following Tether issuance and there is no relationship between the flow of Tether and Bitcoin prices on days apart from printing Tether, consistent with the supply-driven 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 when conditioning on both Tether issuance and a lagged negative return. For a 100 Bitcoin increase in the flow, the average future Bitcoin return goes up by 8.59 basis points.

A placebo test examining the relationship between the flow of coins between other major USD exchanges and Bitcoin prices sheds more light on whether the strategic price movement is specific to Tether exchanges. Panel B of Table II estimates a regression similar to Column (5) where the independent variable is the cross-exchange flow of Bitcoin from Poloniex and Bittrex to major exchanges including Bitstamp, BTCC, Kraken, and Gemini identified on the blockchain. The results demonstrate that only the flow to Bitfinex is significantly related to future returns. Moreover, the effect of Bitfinex flow stays similar after controlling for the flow from all other exchanges.

Table III estimates similar regressions of return on lagged flow for other major cryptocurrencies. The currencies are chosen from the list of high volume currencies used in Table I, conditioning on trading on at least one of the Tether-related exchanges as of March 1, 2017. Panel A shows that there is a significant effect of flow on return in days following Tether issuance for all other major cryptocurrencies. Five out of six currencies show significant effect following a negative return, while only one is significant following a positive return. Finally, the effects are larger across all coins when conditioning on both days after Tether issuance and following a negative return. For equivalent of a 100 Bitcoin increase in the flow, the average future return goes up by 8.78 to 15.66bp for different coins.

Overall, these results show that there is a strong relation between Tether flows and major cryptocurrencies returns. However, they are prone to endogeneity issues that would cause underestimation or overestimation of the effect. We will discuss ways to address these concerns in the subsequent sections.

### *IV.C Large Flows and Prices*

We now specifically focus on the largest Tether purchases of Bitcoin. In line with the evidence of purchases following Tether issuances and negative returns, we condition on Tether issuance in the prior three days, negative returns in the prior hour, and flows above 200 coins on both the Tether and Bitcoin blockchains in the prior hour. The joint conditioning on both blockchains addresses the noise in the timing of recording on the blockchains and focuses on cases where Tether is being used to purchase Bitcoin. There are 87 hours out of a total of 9,504 hours that meet such criteria. This is less than 1% (0.92%) of the return series over the period. Interestingly, these 87 events have a large relation to returns; the next hour return is a large, 64 basis points per hour, and significantly different from normal times.

Figure 7 implements an event study of Bitcoin and other cryptocurrencies prices around these 87 high-flow events. Panel A shows scaled Bitcoin prices. Consistent with conditioning on negative lagged returns, returns are large and negative between time -1 and 0. Moreover, prices are falling even before time -1, which is not by construction. However, after the large flow, the pattern changes at time zero. The price, scaled to one at time zero, consistently increases for the three hours after the flow.

To examine this effect on other major cryptocurrencies, we examine return patterns around these 87 large Tether-related events for the major coins previously examined in Table III. Panel B reports sharp positive returns in the three-hour window following these events for other major cryptocurrencies.

### *IV.D 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. We compare an actual Bitcoin price series to a series that is extremely similar, except it removes the 87 hours where it seems most likely that Tether is used to move Bitcoin. We then compare the actual buy-and-hold Bitcoin returns to the series with the Tether-related hours removed.[30]

From March 1, 2017 to March 31, 2018, the actual Bitcoin price rises from around \$1190 to \$7000 for a 488% return. In contrast, the price series without the 87 Tether-related hours ends at around \$4100, a 245% rise. Hence, the hours with the strongest lagged Tether flow, which account

[30] 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, then $r2$ is assumed zero, and buy-and-hold return is calculated as $(1 + r1)(1)(1 + r3)$.

for less than 1% of the time-series, seem associated with 50% of the Bitcoin buy-and-hold return over the period.

Panel A of Figure 8 compares the compounded return of the 87 returns to a bootstrap distribution of compounded returns over the same period, if instead 87 random hours are excluded. The return excluding the Tether-related events clearly falls to the left of the distribution, and not even one in 10,000 observations yields a return as low. The results are also similar if we condition the random selection of the 87 observations on times following Tether issuance and negative returns. (Figure IA5)

Panel B of Figure 8 compares the actual buy-and-hold return and the synthetic return excluding Tether-related hours for other major coins. The percentage of the buy-and-hold return that are attributable to the Tether-related hours range from 42% for Dash to 82% for Zcash. Ethereum, for example, experienced near 2400% return during this period, while it would alternatively experience around 900% return if the Tether-related hours were excluded. Across the six other crypto currencies, returns are 64% smaller on average when removing the 87 Tether-related flow hours.

Note that this finding has some caveats. First, the effect only considers the hourly periods with extreme flow. Although measuring such findings over other intervals will be less precise and more difficult, the flow effect could push up prices at other times as well. However, the effect does not consider the selling price-pressure effect if the Tether issuers later sell the Bitcoin and move the proceedings into dollars. Such a behavior would push Bitcoin prices down. However, it seems feasible that the issuers could sell the Bitcoin in a manner with considerably less price impact than their strong buying force, such as selling slowly, off the exchange, or in a non-transparent trading venue. Overall, although it is difficult to fully assess the exact price impact of Tether on Bitcoin and other cryptocurrencies, these back-of-the-envelope calculations demonstrate that the effect is plausibly large.

### IV.E Negative Serial Correlation in Bitcoin Prices

The flows of Tether and Bitcoin follow a very specific pattern: Bitfinex buys Bitcoins with Tether when Bitcoin prices drop. If the flow of Tether moves Bitcoin prices, this may cause a price reversal following a negative shock as described in Hypothesis H2C. We do not expect any effect following positive shocks because Tether flow is only sensitive to return when return is negative. Moreover, we would expect to see a stronger pattern during the time that Tether is actively printed.

To test this, we examine the rolling 3-hour average lagged and future Bitcoin returns and test if the future returns are related to the lagged returns. Our previous tests rely on measures of cross-exchange flows, but this test only utilizes returns and does not require flows. Hence, we can expand the period and estimate the test separately for the period between March 2016 and the end of February 2017, when less than 25 million Tether was printed and the flow of Tether was minimal, and between March 2017 and March 2018, when more than a hundred times as much Tether was printed. Column (1) of Table IV, Panel A, shows that when printing of Tether was virtually zero, future return is not related to the lagged return. However, Column (2) demonstrates that when Tether was printed regularly, a 1% drop in Bitcoin prices is followed by 14.8 basis points reversal. This is an economically large reversal that is highly statistically significant. On the other hand, Columns (3) and (4) indicate that there is no price reversal after positive lagged returns, regardless of whether Tether is printed or not. These results are consistent with the price impact of Tether used to purchase Bitcoin when prices drop.

On January 30, 2018, it was publicly announced that the U.S. Commodity Futures Trading Commission sent subpoenas to Bitfinex and Tether to investigate claims questioning Tether's validity. Tether issuance was virtually halted in February and March 2018. We use this period of no-issuance to test if the negative serial correlation disappears when Tether is not printed.

Table IV, Panel B, shows that the effect is only 0.1 basis points for February and March 2018, and not statistically different from zero. This is much smaller than the return reversal of 22 basis points during December 2017 and January 2018. There is no significant reversal effect after positive price movements in either periods.

In conclusion, this section finds considerable evidence that Tether is used to buy Bitcoin following Tether printing and negative returns and that this phenomenon has a sizable effect on future Bitcoin prices. This effect also holds for other coins and induces an asymmetric negative autocorrelation in Bitcoin returns.

## V. Is Tether Pushed or Pulled?

Overall, the results in the previous section are most consistent with the supply-driven manipulation hypothesis through which Tether is being pushed on market participants. We will further examine possible predictions of the supply hypothesis (H2D and H2E) as well as variants of the demand-driven hypothesis that states that Tether is driven by legitimate demand from investors with fiat currencies (H1A) or for use in cross-exchange arbitrage (H1B).

### *V.A Currency Flows Around Round Price Thresholds*

Following Tversky and Kahneman (1974) there is a large literature demonstrating the importance of anchoring for a variety of prices including stocks. Shiller (2000, p. 137) extensively discusses the importance of psychological anchors for stock market prices, indicating one of the anchors as 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 value to the round-number threshold. Such an anchor could be specifically important for cryptocurrency prices where prices cannot be gauged with a fundamental value.

Additionally, cryptocurrency traders likely engage in technical trading in which past price movements generate buy and sell signals. If Tether is used to stabilize market prices during the downturn, one might expect a spike in the flow of Tether around round thresholds as this might engage other traders in purchasing as well upon observing a technical support at the threshold.

To test this, we first divide hourly prices from *Coindesk* by 500, and then put the remainder into bins of \$10 width to examine how the flow of Bitcoin for Tether changes near the round thresholds. Figure 9 shows 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 issuance, the flow significantly increases just below the round cutoff but drops right above the cutoff. Panel B of Figure 9 shows that there is not such an effect on days apart from Tether issuance. This relation is despite the fact that the transaction timestamps on Bitcoin and Tether blockchains are a noisy proxy for the actual time of the trades. Otherwise, even a sharper spike could be expected.

Table V, Panel A, formally tests whether the Tether flow is different below and above the round price thresholds. The dependent variable is the average net outflow of Tether from and inflow of Bitcoin to Bitfinex, and the independent variable is a dummy that takes the value of one if Bitcoin price is in the $50 bandwidth below the round multiples of $500 and zero if in the $50 bandwidth above. Column (1) shows that Bitfinex obtains significantly more Bitcoin per hour when prices are just below the thresholds. More notably, Column (2) shows that the results are more pronounced on days after Tether issuance; the flow of coins to Bitfinex increases to more than twice per hour. Column (3) shows that there is no difference in flow below and above the cutoff on days apart from Tether issuance. This result is consistent with the hypothesis that Tether is used strategically to stabilize Bitcoin prices below the round price thresholds.

Panel B of Table V estimates a regression of average 3-hour future returns on the lagged round threshold dummy. Column (1) shows that, on days following Tether issuance, when price is below the round threshold, the future hourly return is 21 basis points higher on average. Column (2) shows that there is no difference in return below and above the threshold on days apart from Tether issuance. Columns (3) and (4) indicate that the return is 33 basis points higher if the lagged return is negative and insignificant if positive.

Note that it is possible that the Bitfinex-related wallets are trading around round-number thresholds because they are following behavioral biases. However, their trading in this case would be unlikely to be profitable as documented in the behavioral finance literature. Indeed, Bhattacharya, Holden, and Jacobsen (2012) shows that trading just below round-number thresholds is extremely costly to market makers. The fact that the Bitfinex wallets exhibit such a large coordinated buying behavior provides a coherent explanation as to how prices can be successfully pushed above the thresholds. If other traders see such a large coordinated buying by Bitfinex-related wallets, it is probably optimal for them to join the buying and contribute to the large subsequent price increases.

### *V.B Do the Tether Flows around Round Thresholds Cause Price Increases?*

In this section we use the discontinuity around round-number thresholds as an instrument to identify the effect of Tether on Bitcoin prices. We estimate fuzzy regression discontinuity design around the round cutoff. A dummy variable is defined as one if Bitcoin price is within the $50 bucket below the round threshold and the time is within the three-day window after Tether issuance and 0 if within the $50 bucket above or in days apart from Tether issuance. We use this dummy as an instrument for the Tether-related flows, and our identification assumption is that the only channel the cutoff affects future Bitcoin returns is through Tether flows. Our identification assumption and the exclusion restriction criteria are supported by the fact that, as discussed above, on days apart from Tether issuance, neither the amount of Bitcoin obtained by Bitfinex nor the future Bitcoin return is different below and above the thresholds.

A concern is that the observed trading behavior may be due to some general trade clustering on Bitcoin prices and not specific to Bitfinex-related wallets. To examine this possibility, we perform a placebo test using the cross-exchange flow of coins between Poloniex and Bittrex to other major exchanges including Bitstamp, BTCC, Gemini, and Kraken on Bitcoin blockchain. There is no difference in flows below and above the threshold, neither in days after issuance nor in other days, for any of these exchanges (Table IAIII).

Panel C of Table V estimates two-stage least squares regression of 3-hour future bitcoin returns on the lagged net flow of coins between Tether exchanges, where the flow is instrumented using the cutoff dummy. The reported Wald $F$-statistics show that the first stage regressions are strong, suggesting a valid instrument. The $F$-statistics range from 7.9 to 22 for different specifications. The second stage regression indicates that for 100 Bitcoin purchased by Bitfinex, the average hourly Bitcoin return in the next 3 hours goes up by 26.5 basis points. The effect is 35 basis points if the sample is limited to days after issuance, 45 basis points if the lagged return is negative, and 49 basis points under both scenarios. This result highlights a very strong effect of Tether on Bitcoin prices, especially on days after Tether issuance and during the market drop.

### *V.C Demand from Investors with Fiat Currency?*

#### *V.C.1 End-of-the-Month Returns*

Due to the lack of full transparency regarding audit processes and banking relationships, the blogosphere has questioned whether Tether is always fully backed by dollars. We shed more light on this by borrowing from the intermediary asset pricing literature, specifically Du, Tepper, and Verdelhan (2017) and He and Krishnamurthy (2018), that argue that banks' compliance with period-end capital requirements may create 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 audited by a Chinese accounting firm.[31] Tether planned to be audited by Friedman LLP as well, but it eventually canceled the audit due to "the excruciatingly detailed procedures." If Tether does not maintain a full reserve daily but does seek to maintain the reserve at the EOM, there could be negative selling pressure on Bitcoin prices to convert Bitcoin to USD reserves before the EOM. We test this by looking at EOM daily Bitcoin returns.[32] Additionally, the EOM selling effect should be stronger for months with a higher Tether issuance.

The sample includes 25 months from March 2016 to March 2018. Figure 10 divides the monthly issuance of Tether into four quantiles. The blue bars show the raw EOM returns, and the red bars benchmarks the EOM returns by subtracting the average return in four days before and four days after. There is a clear monotonic relationship between monthly Tether issuance and the 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. Further in

[31] As announced on https://tether.to/tether-update/, audits were made publicly available by Tether.to.

[32] Cryptocurrencies officially trade on UTC timestamp and daily prices close at midnight UTC time, when business time has already ended in most countries and the next day has already started in East Asia. Therefore, the effect must be observed in the closing price of the second to last day of the month, and we consider that as the EOM price.

supplemental results, we also estimate a regression of EOM return on monthly Tether issuance and find that it explains 37% of the variations in EOM returns. (Table IAIV)

Table VI reports formal regression results for the same sample of the EOM returns and four days before and four days after. Column (1) shows that the EOM return is 2.3% less than in days around. Columns (2) and (3) indicate that even though there is no effect in months without Tether issuance, in months with Tether issuance the EOM return is 3.8% less than the days around. The $t$-statistic is 3.65 despite the relatively small sample. Interestingly, even though returns are noisy and difficult to explain, the simple EOM dummy variable explains near 8% of the variation in daily returns. Finally, Column (4) interacts the EOM dummy with the magnitude of the Tether issued in each month. Again, there is no effect in months without Tether issuance. However, for a one-standard deviation higher Tether issuance, the EOM return is 2.2% more negative. To formally test the monotonicity of the effect, Column (5) interacts the EOM dummy with 4 quantiles of Tether issuance. Relative to months with zero issuance, months with low, medium, and high issuance has a negative EOM return of 1.9%, 3.1%, and 6.1% respectively, all statistically significant.

In summary, the strong negative effect on Bitcoin prices in months of Tether issuance, suggest that Tether may induced price effects related to a need to raise month-end reserves. This finding is inconsistent with Tether being just a facilitator technology driven by investor demand because there is no reason to expect a relation between Tether printing and EOM returns in that case.

### *V.C.2 Sensitivity of the Flow to Tether-USD Rate*

Although the above analysis has shown substantial support for a supply-based explanation, we further examine the demand-based explanations for Tether. Imagine investors with billions of dollars who cannot easily move their money into the cryptocurrency world. A cryptocurrency that has a stable value tied to the U.S. dollar can be of benefit to such investors. We examine the demand pressure for this currency by focusing on the Tether-USD exchange rate. If the demand for Tether mainly comes from investors holding dollars and seeking 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 dollar in 2017, although the market volume of the pair was less than 1% of the Bitcoin-Tether volume. The rate on Kraken often stays close to one 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 explain the flow of Tether.

Panel A of Table VII estimates a regression of Tether flow on different lags of Tether-USD returns as well as the 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. In fact, the flow is not sensitive to the first and second lags of Tether-USD. It does become marginally significant at higher lags, but the magnitude is considerably smaller than the BTC-USD pair. Panel B shows that the corresponding flow of Bitcoin is highly sensitive to BTC-USD rates but bears no relationship with the Tether-USD pair.

Another argument might be that the price difference between Tether and USD exchanges is driving the flow. If Bitcoin prices increase on USD exchanges but not on Tether exchanges, an investor may exploit the opportunity by selling Bitcoin on USD exchanges, converting the USD to Tether, moving Tether to Tether exchanges, and purchasing Bitcoin. To test this possibility, two lagged return measures are constructed: first, a 3-hour lagged Bitcoin return averaged across all major exchanges, and second, a 3-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. We then estimate a regression of Tether and Bitcoin flows on the spread and the average returns. Panel C of Table VII shows that the flows are not sensitive to the spread, but highly sensitive to variations in the average Bitcoin returns. Again, these results support that the spread between Tether and USD exchanges is not the driver of the Tether and Bitcoin flow.

### *V.D Cross-Exchange Arbitrage among Tether Exchanges*

Tether may facilitate cross-exchange arbitrage among Tether exchanges. In particular, imagine that Bitcoin prices increase on Bitfinex, but Bitcoin prices on Poloniex have a delay to adjust. Bitfinex exchange or traders using the exchange 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. However, as discussed previously, this reverse flow pattern is not commonly observed. Nevertheless, we formally test whether cross-exchange spread is the main driver of the flow or it is the average Bitcoin returns across exchanges that drives the flow. To test this, two lagged return measures are constructed similar to the previous section: first, a 3-hour lagged return averaged between Bitfinex and Poloniex, and second, a 3-hour lagged difference in return between the two exchanges. The former captures the effect of average price changes and the latter captures the arbitrage opportunity. The same measures are constructed for the Bittrex exchange, and all the variables are standardized for comparison.

Table VIII shows that for a one-standard deviation increase in the return spread measure, Tether and Bitcoin flow goes up from 0.02 to 0.06 standard deviations, with $t$-statistics of 1.39 to 3.71. On the other hand, and consistent with the supply-based hypothesis, both Tether and the Bitcoin flows are considerably more sensitive to changes in average Bitcoin returns. A one-standard deviation drop in the average return increases the flows by 0.08 to 0.11 standard deviations, with $t$-statistics of 3.85 to 6.27. These results show that although the flow is used to exploit the cross-exchange arbitrage to some extent, the overall Bitcoin returns across all exchanges are the main driver of the flow.

## VI. Conclusion

Historical periods of rapid price appreciation are associated with innovation and growth, but also activities that leads to misallocation of capital. The semi-transparent 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. Our analysis centers on examining potential manipulation of Bitcoin and other major cryptocurrencies. We examine whether the growth of a pegged cryptocurrency, Tether, is primarily driven by investor demand, or is supplied to investors as a scheme to profit from pushing cryptocurrency prices up.

By mapping the blockchains of Bitcoin and Tether, we are able to establish that entities associated with the Bitfinex exchange use Tether to purchase Bitcoin when prices are falling. Such price supporting activities are successful, as Bitcoin prices rise following the periods of intervention. These effects are present only after negative returns and periods following the printing of Tether. Indeed, even less than 1% of extreme exchange of tether for Bitcoin has 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 only in months with large Tether issuance indicates a month-end need for dollar reserves related to Tether. Proxies for Tether demand receive little support in the data, but our results are consistent with the supply-driven manipulation hypothesis.

Overall, our findings provide substantial support for the view that price manipulation may be behind substantial distortive effects in cryptocurrencies. These findings suggest that external capital market surveillance and monitoring may be necessary to obtain a market that is truly free. More generally, our findings support the historical narrative that dubious activities are not just a by-product of price appreciation, but can substantially contribute to price distortions and capital misallocation.

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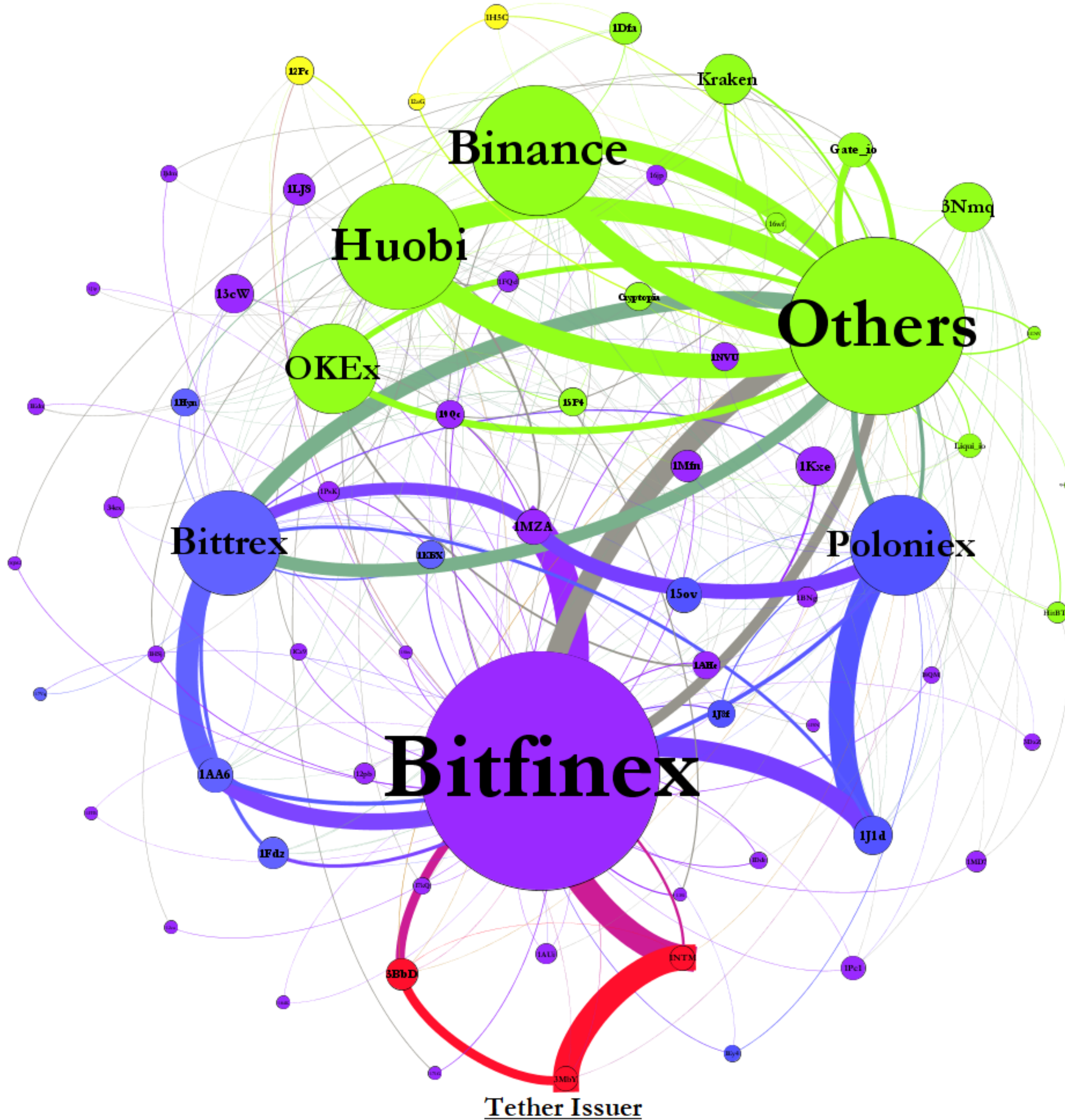
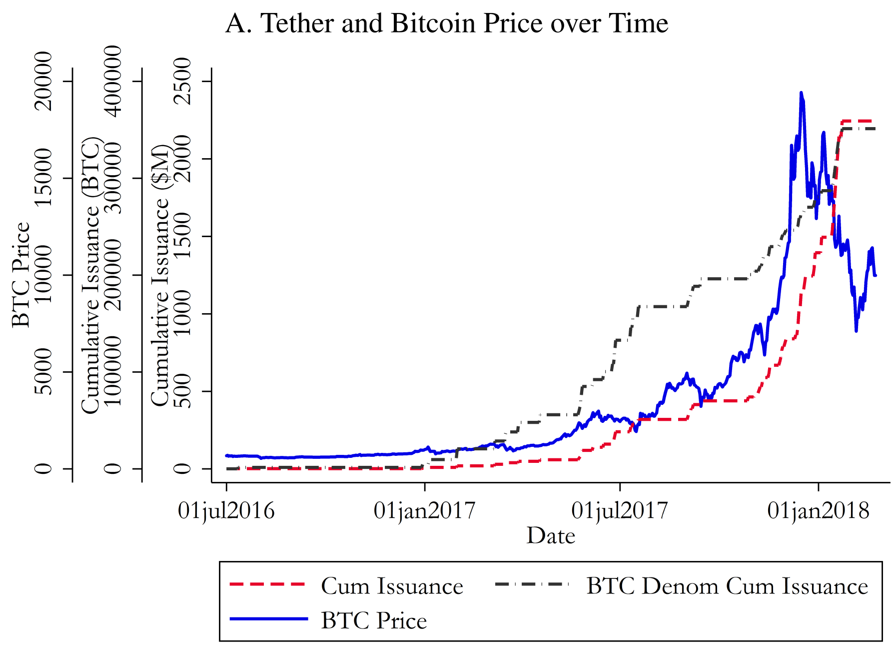



**Figure 1. Aggregate Flow of Tether between Major Addresses.** This figure shows the aggregate flow of Tether between major exchanges and market participants, from Tether genesis block to March 31, 2018. Tether transactions are captured on the Omni Layer as transactions with the coin ID 31. The data 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. Intra-node 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.



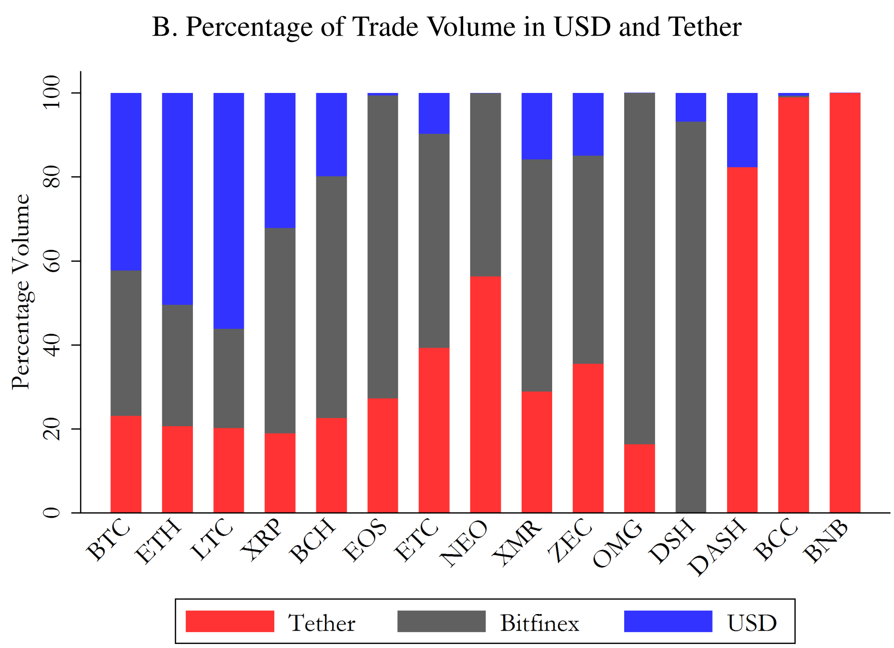




**Figure 2. Issuance of Tether and Bitcoin Price over Time and Trade Volume in Dollar and Tether.** Panel A shows the cumulative issuance of Tether and Bitcoin price over time. The red dashed line shows cumulative issuance in million Tether tokens. The black dashed line shows Tether cumulative issuance, denominated in contemporaneous Bitcoin value. The blue line shows Bitcoin price. Panel B plots 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 largest 15 cryptocurrencies and tokens by trade volume 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.

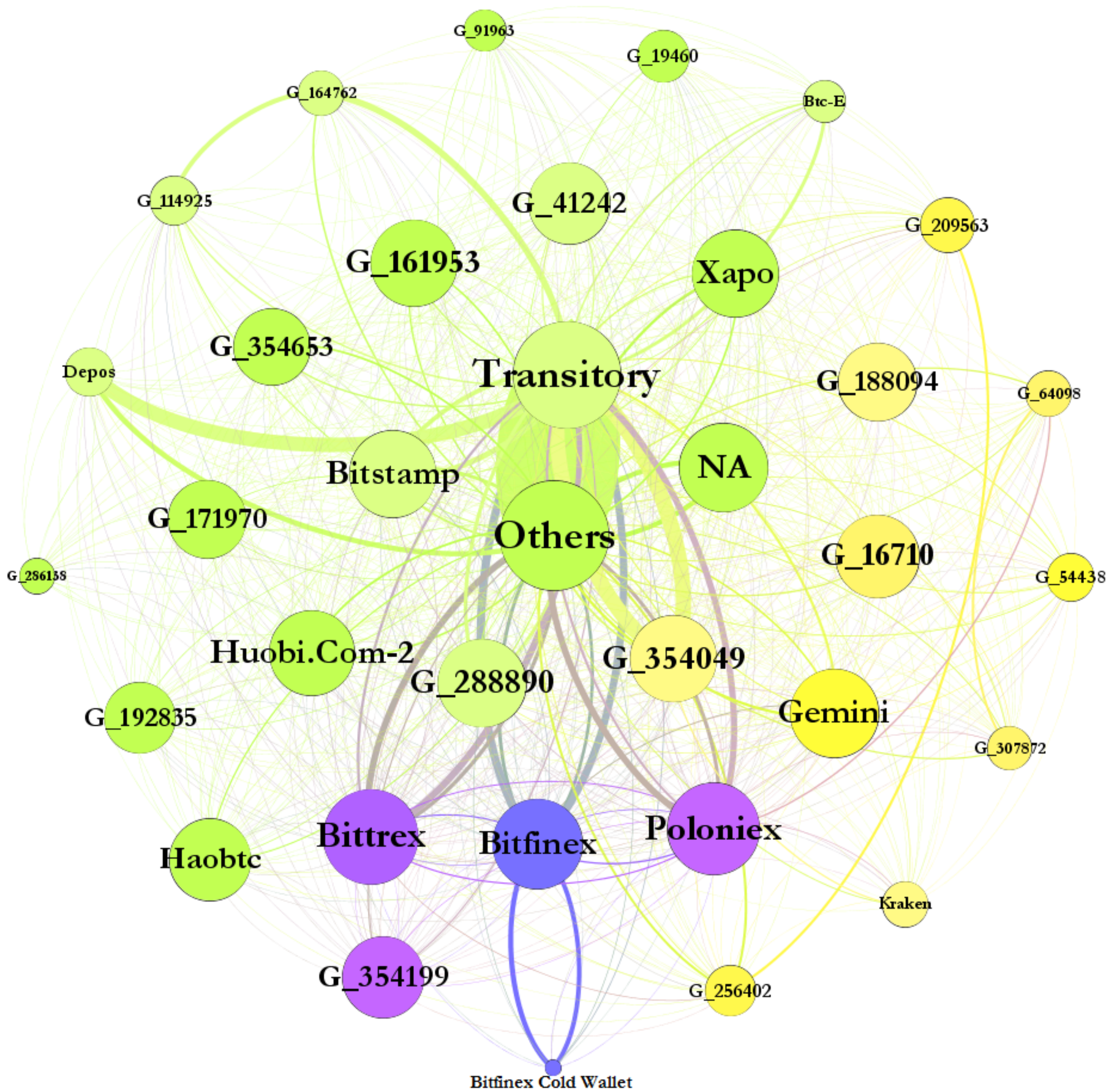



**Figure 3. Aggregate Flow of Bitcoin between Major Addresses.** This figure shows the aggregate flow of Bitcoin between major exchanges and market participants from March 1, 2017 to March 31, 2018. Groups of addresses are clustered by finding the connected component of the same input relation on the 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. Intra-node 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.

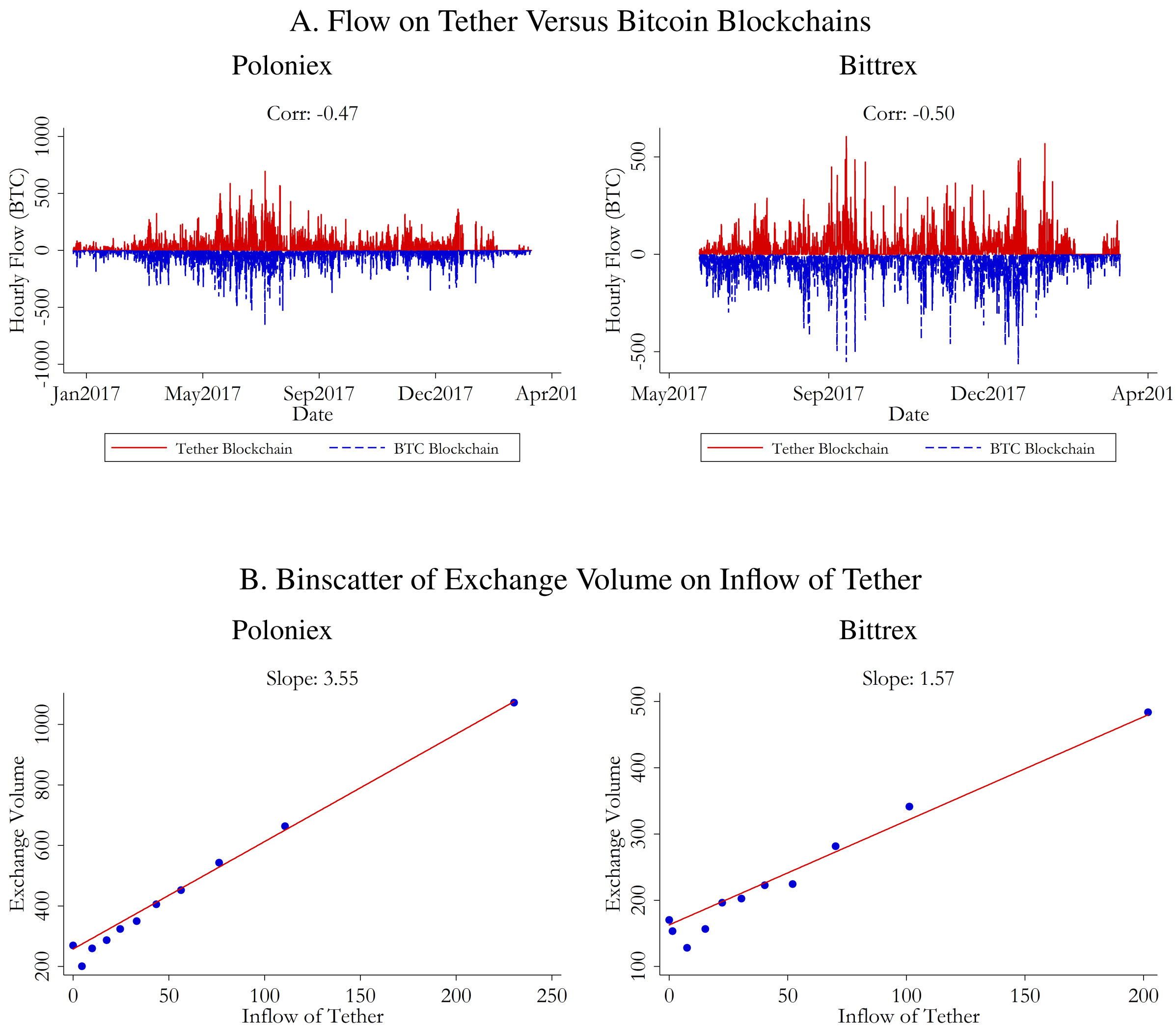
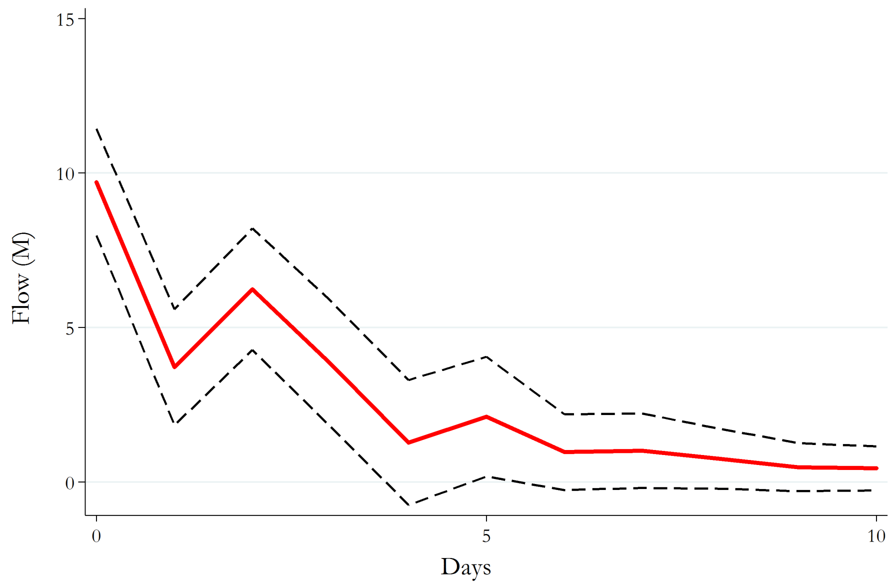



**Figure 4. 3-Hour Moving Average of Tether and Bitcoin Flow and Exchange Volume.** Panel A plots the hourly flow of Tether from Bitfinex to two major Tether exchanges, Poloniex and Bittrex, on the Tether blockchain with the flow of Bitcoin from these two exchanges to Bitfinex on the Bitcoin blockchain. Exchange identities on the Tether blockchain are obtained from the Tether rich list. Corresponding groups of Bitcoin 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 red line shows 3-hour moving average of Tether flow and the dashed blue line shows 3-hour moving average of Bitcoin flow. Panel B shows the scatter plot of 3-hour moving average trade volume on Poloniex and Bittrex for different bins of Tether inflow to these exchanges.

A. Inflow to Bitfinex




B. Outflow from Bitfinex

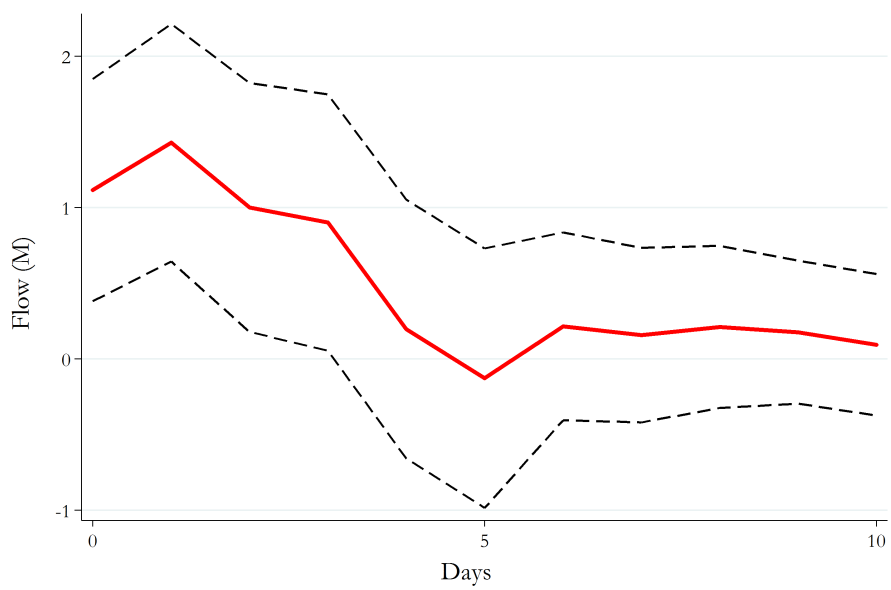



**Figure 5. Flow of Tether to Bitfinex, Poloniex, and Bittrex after Printing Tether.** This figure plots impulse response functions describing the change in Tether flow between major exchanges in response to a one standard deviation shock to Tether issuance. Panel A shows the inflow of Tether to Bitfinex for ten days after Tether printing. Panel B shows the outflow from Bitfinex to Poloniex and Bittrex. The sample period is from March 1, 2017 to March 31, 2018. The VAR is estimated using daily data with five lags, and shocks are orthogonalized through a Cholesky factorization. The dashed line shows the 95% confidence interval.

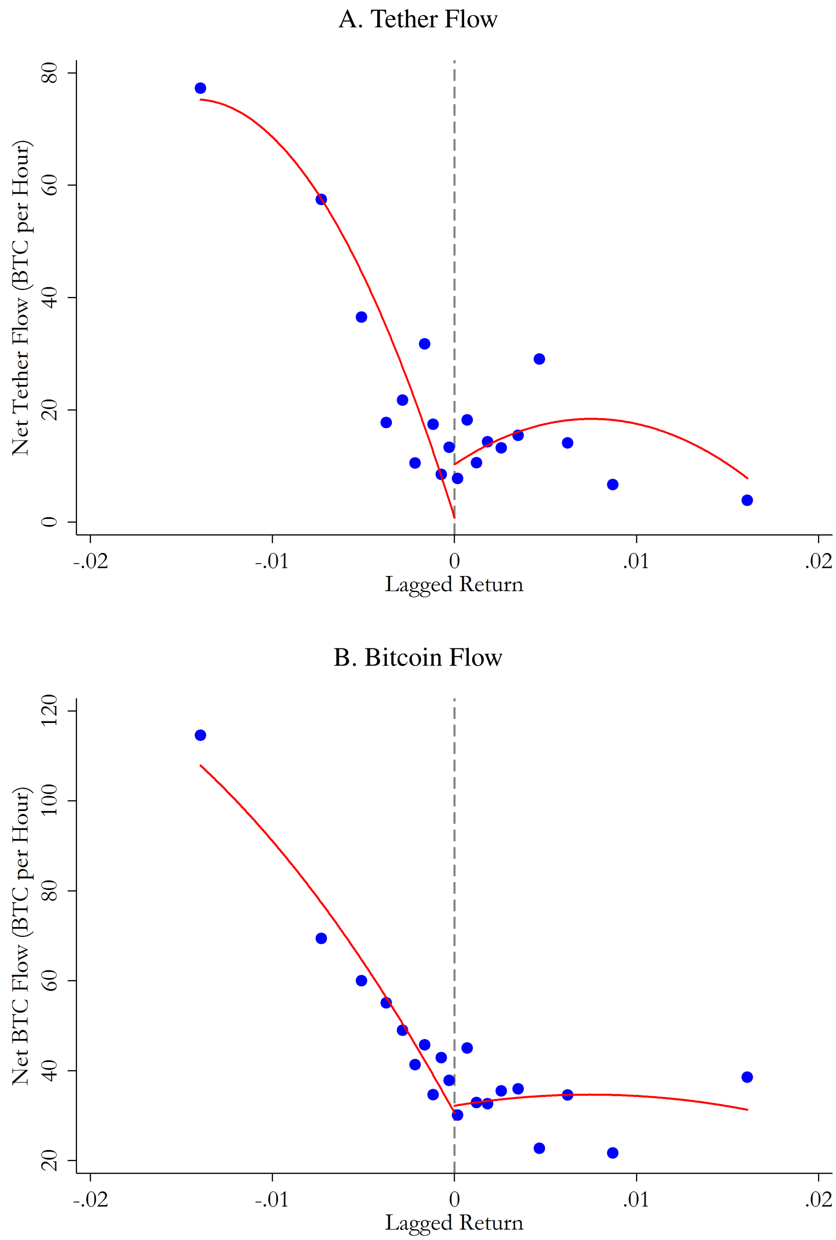



**Figure 6. Net flow of Bitcoin and Tether for Quantiles of Lagged Return.** This figure shows net hourly flow of Bitcoin and Tether between Bitfinex and two major Tether exchanges, Poloniex and Bittrex, as a function of lagged 3-hour average return. The sample period is from March 1, 2017 to March 31, 2018. The graphs show the average flow per quantiles of lagged return, controlling for 3-hour lagged volatility calculated using five-minute returns. Panel A shows the net outflow of Tether from Bitfinex to Poloniex and Bittrex and Panel B shows the net inflow of Bitcoin from Poloniex and Bittrex to Bitfinex. The red lines show the fitted values of the flow as a second order polynomial function of the lagged return, controlling for lagged volatility.

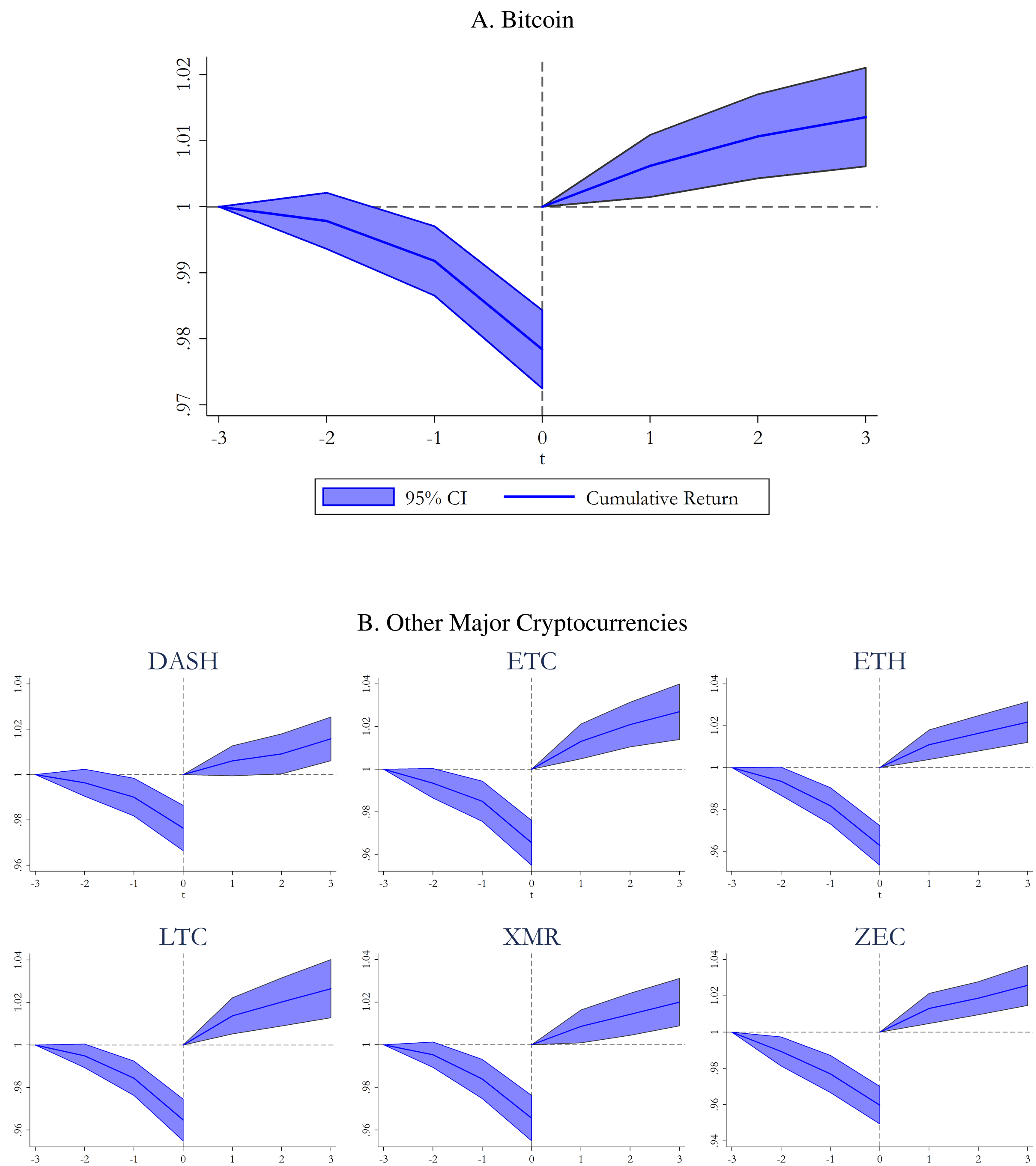



**Figure 7. Prices of Bitcoin and Other Cryptocurrencies around High-Flow Events.** Panel A shows Bitcoin prices in 3 hours before and after the 87 high-flow hours. Prices are scaled to one at time -3 before the event and at time zero after the event. Scaled prices are averaged across the events. These 87 events are defined as hours with at least 200 Bitcoin-denominated Tether flow from Bitfinex to Poloniex and Bittrex and at least 200 inflow of Bitcoins back to Bitfinex in the prior hour, conditional on Tether issuance in the prior three days and negative returns in the prior hour. Panel B shows similar results for other major cryptocurrencies.

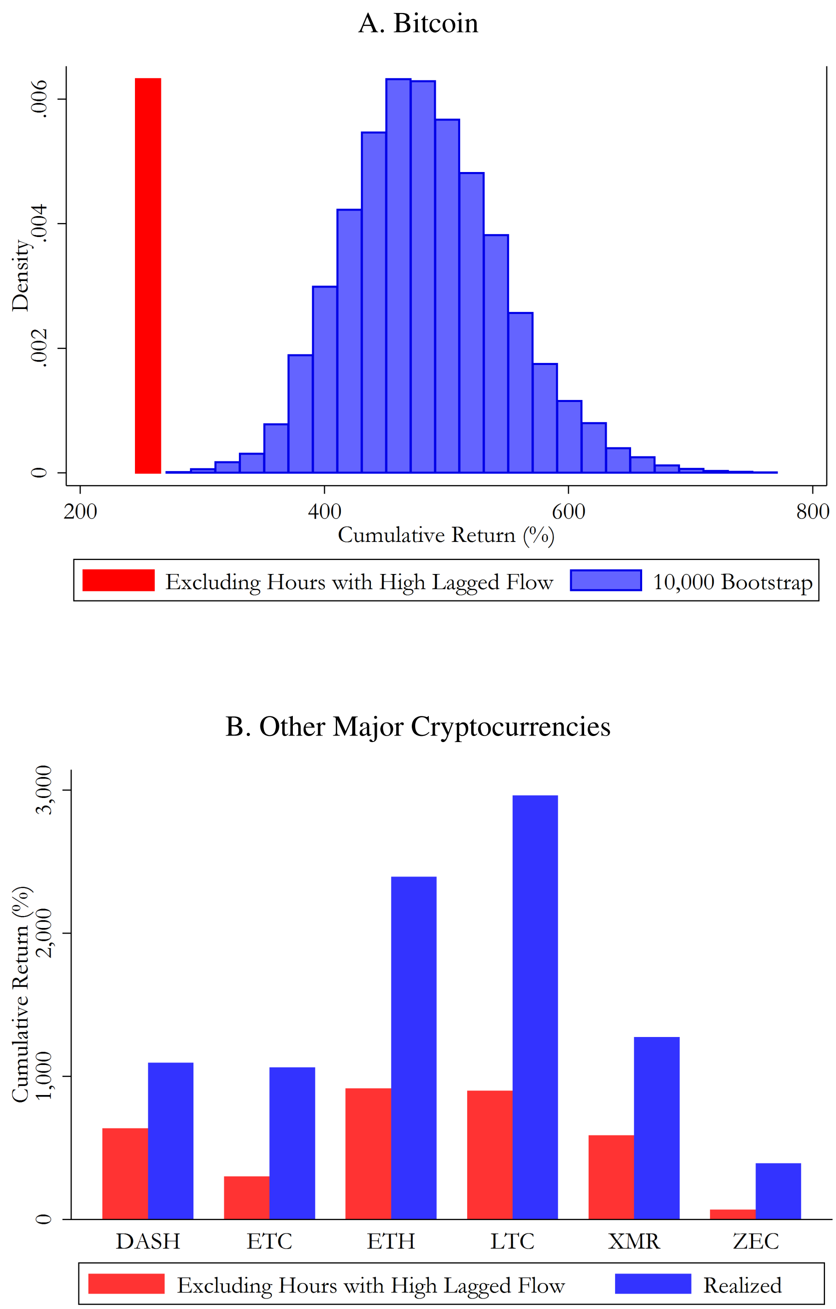



**Figure 8. Predictive Effect of High-Flow Hours on Aggregate Cryptocurrencies Returns.** Panel A shows the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018, excluding 87 hours with high lagged flow of Tether and Bitcoin (the red bar). The high-flow hours are defined as in Figure 7. The blue bars show the distribution of the returns if 87 random hourly returns are excluded from the sample. Panel B compares the actual buy-and-hold return (blue bars) with the return excluding the 87 high-flow hours (red bars) for other major cryptocurrencies over the same time period.

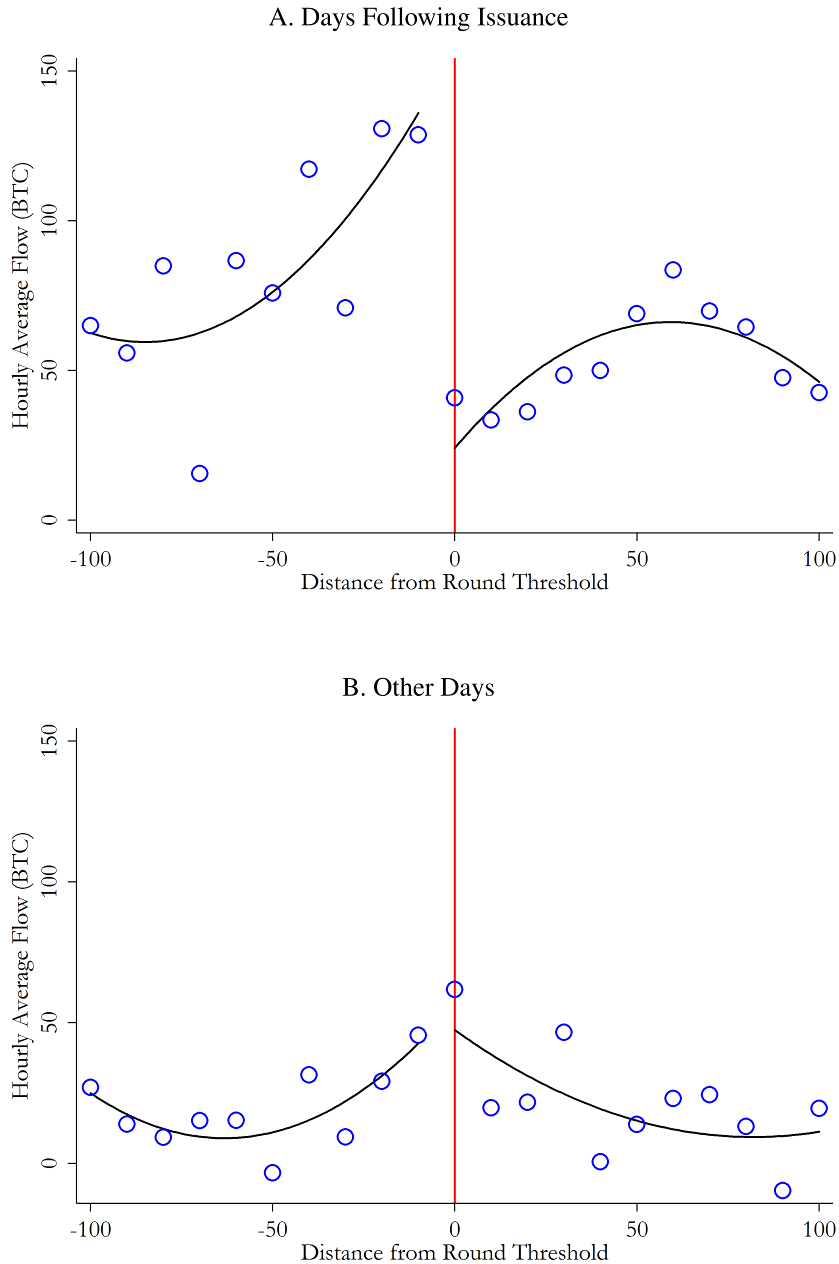



**Figure 9. Flows around Round Number Thresholds.** This figure shows the average net hourly flows of Tether from Bitfinex to two major Tether exchanges, Poloniex and Bittrex, and Bitcoin from these exchanges to Bitfinex around round number thresholds of Bitcoin prices. The Bitcoin prices are based on hourly prices reported by *CoinDesk*. The horizontal axis shows the distance of the price from round thresholds in multiples of $500 at the beginning of each hour, and the vertical axis shows the flow within that 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 function of the price distance to the round thresholds. Panel A shows the results for times when a Tether authorization occurred in the previous 72 hours and panel B for other times. The sample covers from March 1, 2017 to March 31, 2018.

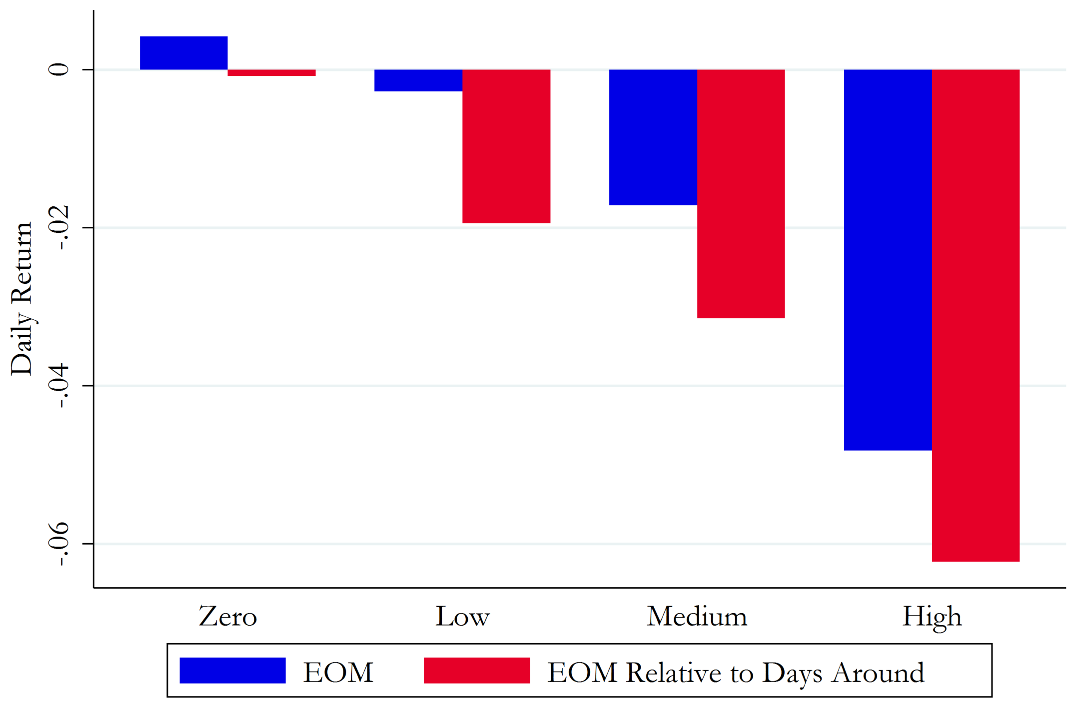



**Figure 10. End-of-the-Month Returns and Quantiles of Tether Issuance.** This figure shows end-of-the-month (EOM) daily Bitcoin returns for different quantiles of monthly Tether issuance. Four quantiles of Tether issuance are defined based on total Bitcoin-denominated Tether issuance each month. All 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. The 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 of the prior four days and subsequent four days. The sample covers from March 2016 to March 2018.

**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 U.S. dollar and Tether 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 billion dollar, from March 1, 2017 to March 31, 2018 using data are from *CoinAPI*. Panel B shows the daily return correlation between major cryptocurrencies. The daily pricing data are from *CoinMarketCap*. Panel C reports the autocorrelation of the major cryptocurrency at 1-hour, 3-hour, and 5-hour intervals. The 3-hour and 5-hour autocorrelations are calculated using hourly returns rolled over 3-hour and 5-hour windows. Standard errors are adjusted for heteroscedasticity and autocorrelation. The intraday pricing data are from *CoinAPI*.

A. Total Volume ($B)

| Coin | Binance | Bitfinex | Bitstamp | Bittrex | Coinbase | Gemini | Huobipro | Kraken | Okex | Poloniex |
|---|---|---|---|---|---|---|---|---|---|---|
| BCC | 0.8 | 0 | - | 1.7 | - | - | - | - | - | - |
| BCH | - | 18.8 | 0.7 | - | 3 | - | 1.5 | 2 | 2.5 | 3.1 |
| BNB | 2.7 | - | - | - | - | - | - | - | - | - |
| BTC | 32.8 | 120.8 | 36.2 | 11.5 | 53.1 | 16.5 | 8.1 | 17.1 | 6.9 | 14.6 |
| DASH | - | - | - | 0.3 | - | - | 1 | 0.3 | 0 | 0.6 |
| DSH | - | 2.7 | - | - | - | - | - | - | - | - |
| EOS | - | 8.1 | - | - | - | - | 2.4 | 0.1 | 0.3 | - |
| ETC | - | 5.6 | - | 0.6 | - | - | 0.9 | 1 | 1.3 | 1.4 |
| ETH | 10.2 | 35.4 | 5.4 | 2.5 | 32.5 | 7.8 | 3.1 | 14.5 | 3.1 | 4.9 |
| LTC | 2.7 | 13.1 | 2.4 | 1 | 24.5 | - | 1.1 | 1.8 | 2.8 | 2.7 |
| NEO | 3.9 | 4.5 | - | 1.5 | - | - | 0.2 | - | 0.2 | - |
| OMG | - | 3.8 | - | 0.5 | - | - | 0.2 | - | 0 | - |
| XMR | - | 2.8 | - | 0.3 | - | - | - | 0.8 | 0 | 0.6 |
| XRP | - | 17.1 | 7.4 | 1.9 | - | - | 1.5 | 3.3 | 0.3 | 2.9 |
| ZEC | - | 2.3 | - | 0.3 | - | - | 0.3 | 0.4 | 0 | 0.7 |

B. Correlations

| | BCC | BCH | BTC | BNB | DASH | DSH | EOS | ETC | ETH | LTC | NEO | OMG | XMR | XRP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BCH | 0.17 | | | | | | | | | | | | | |
| BTC | 0.47 | 0.24 | | | | | | | | | | | | |
| BNB | 0.31 | 0.21 | 0.46 | | | | | | | | | | | |
| DASH | 0.28 | 0.42 | 0.39 | 0.20 | | | | | | | | | | |
| DSH | 0.16 | 0.02 | 0.27 | 0.17 | 0.12 | | | | | | | | | |
| EOS | 0.19 | 0.34 | 0.35 | 0.28 | 0.30 | 0.09 | | | | | | | | |
| ETC | 0.25 | 0.42 | 0.42 | 0.28 | 0.36 | 0.15 | 0.38 | | | | | | | |
| ETH | 0.30 | 0.40 | 0.44 | 0.37 | 0.44 | 0.14 | 0.45 | 0.61 | | | | | | |
| LTC | 0.24 | 0.31 | 0.45 | 0.34 | 0.36 | 0.20 | 0.35 | 0.50 | 0.42 | | | | | |
| NEO | 0.16 | 0.25 | 0.30 | 0.43 | 0.31 | 0.09 | 0.29 | 0.43 | 0.34 | 0.31 | | | | |
| OMG | 0.26 | 0.17 | 0.41 | 0.42 | 0.40 | 0.06 | 0.41 | 0.45 | 0.60 | 0.41 | 0.60 | | | |
| XMR | 0.26 | 0.35 | 0.49 | 0.26 | 0.55 | 0.14 | 0.34 | 0.43 | 0.52 | 0.42 | 0.24 | 0.40 | | |
| XRP | 0.15 | 0.24 | 0.20 | 0.17 | 0.10 | 0.09 | 0.29 | 0.17 | 0.19 | 0.26 | 0.12 | 0.32 | 0.23 | |
| ZEC | 0.22 | 0.41 | 0.38 | 0.34 | 0.58 | 0.15 | 0.42 | 0.49 | 0.52 | 0.36 | 0.34 | 0.45 | 0.54 | 0.27 |

C. Autocorrelations

| Coin | 1-Hour: Coefficient | t-stats | 3-Hour: Coefficient | t-stats | 5-Hour: Coefficient | t-stats |
|---|---|---|---|---|---|---|
| BCC | -0.05 | -1.49 | -0.06 | -1.6 | -0.1 | -2.45 |
| BCH | -0.03 | -1.11 | -0.03 | -0.87 | -0.06 | -1.53 |
| BNB | -0.06 | -1.68 | -0.06 | -1.6 | -0.09 | -1.96 |
| BTC | -0.04 | -2.83 | -0.06 | -3.55 | -0.05 | -2.46 |
| DASH | -0.08 | -3.26 | -0.07 | -2.7 | -0.08 | -2.78 |
| DSH | -0.05 | -2.66 | -0.06 | -2.48 | -0.1 | -3.73 |
| EOS | -0.04 | -1.93 | -0.05 | -2.06 | -0.09 | -3.5 |
| ETC | -0.05 | -2.71 | -0.07 | -3.81 | -0.03 | -1.42 |
| ETH | -0.07 | -1.88 | -0.07 | -2.8 | -0.07 | -2.62 |
| LTC | -0.02 | -0.95 | -0.04 | -1.41 | -0.02 | -0.76 |
| NEO | -0.06 | -2.72 | -0.05 | -1.73 | -0.06 | -2.12 |
| OMG | -0.07 | -3.82 | -0.04 | -1.55 | -0.04 | -1.27 |
| XMR | -0.04 | -1.33 | -0.06 | -2.74 | -0.08 | -2.97 |
| XRP | -0.09 | -3.01 | -0.07 | -2.33 | 0.02 | 0.39 |
| ZEC | -0.07 | -2.54 | -0.05 | -2 | -0.09 | -3.15 |

**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 3-hour Bitcoin returns:

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

where $R_t$ is average hourly Bitcoin return on Bitfinex, Poloniex, and Bittrex at time t and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex. 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) shows the results separately for observations with lagged negative and positive returns. Column (5) shows the results conditioning on both 72 hours after Tether issuance and negative lagged return. Panel B estimates the regression in Column (5) of Panel A for the hourly flow of Bitcoin from Poloniex and Bittrex to other major exchanges, using the flow of coins on Bitcoin blockchain. Standard errors are adjusted for heteroscedasticity and autocorrelation. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Regression of Return on Lagged Flow

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Issue | NoIssue | L.Ret<0 | L.Ret>0 | L.Ret<0_Issue |
| Lag Tether Flow | 4.367* | -0.212 | 2.890* | -1.520 | 8.592** |
| | (2.31) | (-0.28) | (2.24) | (-1.61) | (2.83) |
| L.Ret | -0.0408** | -0.0338*** | -0.0725*** | 0.00789 | -0.0881** |
| | (-3.13) | (-4.00) | (-4.37) | (0.48) | (-3.07) |
| Constant | -1.023 | 3.369** | -1.132 | -0.331 | -8.253* |
| | (-0.40) | (2.96) | (-0.71) | (-0.21) | (-2.29) |
| Observations | 2643 | 6822 | 4456 | 5004 | 1256 |
| Adjusted R2 | .01 | .004 | .014 | .001 | .04 |

B. Bitcoin Flow from Other Exchanges

| | Ret | Ret | Ret | Ret | Ret | Ret |
|---|---|---|---|---|---|---|
| Bitfinex Flow | 8.212** | | | | | 8.111** |
| | (2.78) | | | | | (2.74) |
| Bitstamp Flow | | 6.393 | | | | 3.808 |
| | | (1.39) | | | | (0.87) |
| BTCC Flow | | | -0.00350 | | | -3.882 |
| | | | (-0.00) | | | (-0.60) |
| Kraken Flow | | | | 1.415 | | 0.404 |
| | | | | (0.28) | | (0.09) |
| Gemini Flow | | | | | -2.058 | -3.785 |
| | | | | | (-0.71) | (-1.31) |
| Constant | 1.032 | 6.133 | 6.443 | 6.099 | 6.472* | 1.360 |
| | (0.32) | (1.94) | (1.96) | (1.79) | (2.01) | (0.41) |
| Observations | 1256 | 1256 | 1256 | 1256 | 1256 | 1256 |
| Adjusted R2 | .022 | .002 | -.001 | -.001 | -.001 | .02 |

**Table III. The Effect of Flow of Bitcoin and Tether on Other Cryptocurrencies Return.** This table shows OLS estimates for which the dependent variable is the average 3-hour returns for major cryptocurrencies other than Bitcoin:

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

where $R_t$ is average hourly return on Bitfinex, Poloniex, and Bittrex at time t and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex. 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 shows the results 72 hours after Tether authorization and Panel B for other days. Panel C shows the results when the lagged return is negative and Panel D when lagged return is positive. Panels E shows the results conditioning on both 72 hours after Tether issuance and negative lagged return. Standard errors are adjusted for heteroscedasticity and autocorrelation. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Days Following Issuance

| Coin | Coefficient | t_stat | N |
|---|---|---|---|
| DASH | 8.92 | 3.15 | 1876 |
| ETC | 8.61 | 2.94 | 2568 |
| ETH | 8.41 | 3.51 | 2630 |
| LTC | 8.26 | 2.42 | 2524 |
| XMR | 7.06 | 2.5 | 2268 |
| ZEC | 7.64 | 3.12 | 2447 |

B. Other Days

| Coin | Coefficient | t_stat | N |
|---|---|---|---|
| DASH | .57 | .42 | 3959 |
| ETC | .53 | .48 | 6458 |
| ETH | 1.2 | 1.18 | 6753 |
| LTC | 2.31 | 2.31 | 6415 |
| XMR | .31 | .24 | 5432 |
| ZEC | .63 | .49 | 6117 |

C. Following Negative Returns

| Coin | Coefficient | t_stat | N |
|---|---|---|---|
| DASH | 3.83 | 1.94 | 2691 |
| ETC | 5.36 | 3.04 | 4476 |
| ETH | 4.88 | 3.04 | 4519 |
| LTC | 6.84 | 3 | 4411 |
| XMR | 4.36 | 2.19 | 3653 |
| ZEC | 4.58 | 2.91 | 4254 |

D. Following Positive Returns

| Coin | Coefficient | t_stat | N |
|---|---|---|---|
| DASH | 4.5 | 2.26 | 3111 |
| ETC | .72 | .41 | 4530 |
| ETH | 2.12 | 1.49 | 4857 |
| LTC | 1.4 | .98 | 4524 |
| XMR | .48 | .33 | 4029 |
| ZEC | 1.11 | .64 | 4280 |

E. Following Negative Returns-Issuance

| Coin | Coefficient | t_stat | N |
|---|---|---|---|
| DASH | 10.12 | 3.15 | 870 |
| ETC | 15.53 | 2.94 | 1240 |
| ETH | 12.11 | 3.51 | 1248 |
| LTC | 15.66 | 2.42 | 1213 |
| XMR | 8.78 | 2.5 | 1068 |
| ZEC | 8.93 | 3.12 | 1181 |

**Table IV. Bitcoin Return Reversals.** This table shows OLS estimates for which the dependent variable is the average 3-hour future Bitcoin returns and the independent variable is the average 3-hour lagged returns:

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

Panel A shows the results for the entire sample and Panel B for the prior two months and subsequent two months from the reported presence of the CFTC subpoenas. Standard errors are adjusted for heteroscedasticity and autocorrelation. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. All the Sample

| | Negative Lagged Return | | Positive Lagged Return | |
|---|---|---|---|---|
| | Mar16-Feb17 | Mar17-Mar18 | Mar16-Feb17 | Mar17-Mar18 |
| Lag Ret | 0.00566 | -0.145*** | -0.0137 | -0.00699 |
| | (0.08) | (-4.71) | (-0.37) | (-0.24) |
| Constant | 0.000117 | -0.000226 | 0.000167** | 0.000137 |
| | (1.36) | (-1.55) | (2.92) | (0.98) |
| Observations | 3955 | 4837 | 4805 | 5707 |
| Adjusted R2 | 0 | .012 | 0 | 0 |

B. Before and After the Press Report of CFTC Subpoenas

| | Negative Lagged Return | | Positive Lagged Return | |
|---|---|---|---|---|
| | Before | After | Before | After |
| Lag Ret | -0.220*** | 0.00113 | -0.0146 | 0.0456 |
| | (-3.64) | (0.02) | (-0.23) | (0.55) |
| Constant | -0.000799 | 0.0000776 | -0.000271 | -0.000732 |
| | (-1.38) | (0.15) | (-0.47) | (-1.36) |
| Observations | 705 | 698 | 783 | 688 |
| Adjusted R2 | .026 | -.001 | -.001 | 0 |

**Table V. Flow of Coins around Round Tresholds of Bitcoin Price.** Panel A shows OLS estimates for which the dependent variable is hourly average net flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex. $BelowRoundCutoff_t$ is a dummy variable that takes the value of one if Bitcoin price, at the end of the previous hour, falls into the $50 price bucket below a $500 price multiple and zero if it is in the $50 bucket above such multiple. Panel B estimates a regression of average 3-hour average Bitcoin return on the $BelowRoundCutoff$ dummy. Panel C estimates two stage least squares regression of Bitcoin returns on flow:

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

where in the first stage, $\hat{Flow}_t$ is instrumented using a dummy variable that takes the value of one if 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 issuance and 0 if within the $50 bucket above or in days apart from Tether issuance. Standard errors are adjusted for heteroscedasticity and autocorrelation. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Flow Around Round Thresholds

| | All | Issue | NoIssue |
|---|---|---|---|
| Below Round Cutoff | 17.37* | 58.79*** | 4.699 |
| | (2.36) | (3.71) | (0.58) |
| Constant | 29.09*** | 41.38*** | 23.32*** |
| | (6.24) | (4.83) | (4.21) |
| Observations | 1595 | 464 | 1131 |
| Adjusted $R^2$ | 0.003 | 0.030 | -0.001 |

B. Return Around Round Thresholds

| | Issue | NoIssue | Issue_L.Ret<0 | Issue_L.Ret>0 |
|---|---|---|---|---|
| Below Round Cutoff | 20.61* | -3.629 | 32.87* | 11.91 |
| | (2.42) | (-0.79) | (2.58) | (1.29) |
| Constant | 1.766 | 5.512 | 11.75 | -7.205 |
| | (0.33) | (1.87) | (1.39) | (-1.15) |
| Observations | 464 | 1133 | 214 | 250 |
| Adjusted R2 | .012 | 0 | .025 | .002 |

C. Instrumenting the Flow Using the Round Thresholds

| | All | Issue | L.Ret<0 | Issue_L.Ret<0 |
|---|---|---|---|---|
| Lagged Flow | 26.50* | 35.06* | 45.14** | 48.58* |
| | (2.11) | (2.10) | (2.98) | (2.35) |
| Constant | -4.168 | -12.74 | -7.515 | -11.48 |
| | (-0.88) | (-1.24) | (-1.07) | (-0.74) |
| Observations | 1594 | 464 | 728 | 214 |
| Wald F-statistic | 22.19 | 12.75 | 12.78 | 7.893 |

**Table VI. EOM Bitcoin Returns and the Effect of Tether Issuance.** This table shows 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 the $EOM_t$ takes the value of one on the second to last day of the month at midnight UTC time and $Issuance_t$ is total Bitcoin-denominated Tether issuance in that month scaled by the standard deviation of monthly Tether issuance. Column (5) interacts the EOM dummy with quantiles of issuance as defined in Figure 10. The sample is from March 2016 to March 2018. Standard errors are robust to heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | All | NoIssuance | Issuance | All | All |
| EOM | -0.0230** | -0.000788 | -0.0377*** | -0.00648 | -0.000788 |
| | (-3.24) | (-0.14) | (-3.65) | (-1.36) | (-0.14) |
| Issuance | | | | 0.00146 | |
| | | | | (0.47) | |
| EOM=1 × Issuance | | | | -0.0222** | |
| | | | | (-2.85) | |
| Low × EOM | | | | | -0.0187* |
| | | | | | (-2.27) |
| Med × EOM | | | | | -0.0307** |
| | | | | | (-2.71) |
| High × EOM | | | | | -0.0615* |
| | | | | | (-2.40) |
| Low | | | | | 0.0117* |
| | | | | | (2.08) |
| Med | | | | | 0.00933 |
| | | | | | (1.33) |
| High | | | | | 0.00908 |
| | | | | | (1.07) |
| Constant | 0.0110*** | 0.00501 | 0.0150*** | 0.00995*** | 0.00501 |
| | (4.32) | (1.49) | (4.19) | (3.50) | (1.48) |
| Observations | 225 | 90 | 135 | 225 | 225 |
| Adjusted $R^2$ | 0.035 | -0.011 | 0.078 | 0.064 | 0.060 |

**Table VII. The Relationship between Flows and BTC-USD versus Tether-USD Rate.** This table shows OLS estimates for which the dependent variables are the outflow of Tether from Bitfinex (Panel A) and the inflow of Bitcoin to Bitfinex (Panel B), and the independent variables are multiple lags of BTC-USD and Tether-USD returns:

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

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

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

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 heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Tether Flow

| | Tether Flow | Tether Flow | Tether Flow | Tether Flow | Tether Flow |
|---|---|---|---|---|---|
| L.BTC_USD_Ret | -0.0684*** | -0.0711*** | -0.0726*** | -0.0729*** | -0.0730*** |
| | (-3.78) | (-3.91) | (-4.04) | (-4.07) | (-4.06) |
| L2.BTC_USD_Ret | | -0.0789*** | -0.0801*** | -0.0822*** | -0.0824*** |
| | | (-5.72) | (-5.81) | (-5.95) | (-5.96) |
| L3.BTC_USD_Ret | | | -0.0430** | -0.0450** | -0.0460*** |
| | | | (-3.10) | (-3.24) | (-3.30) |
| L4.BTC_USD_Ret | | | | -0.0488*** | -0.0496*** |
| | | | | (-3.90) | (-3.96) |
| L5.BTC_USD_Ret | | | | | -0.0248 |
| | | | | | (-1.59) |
| L.Tether_USD_Ret | -0.00885 | -0.000419 | 0.00606 | 0.00623 | 0.00801 |
| | (-0.68) | (-0.03) | (0.45) | (0.46) | (0.59) |
| L2.Tether_USD_Ret | | 0.0115 | 0.0268 | 0.0293* | 0.0322* |
| | | (0.86) | (1.87) | (2.04) | (2.22) |
| L3.Tether_USD_Ret | | | 0.0285* | 0.0333* | 0.0381* |
| | | | (2.13) | (2.21) | (2.54) |
| L4.Tether_USD_Ret | | | | 0.00370 | 0.0125 |
| | | | | (0.29) | (0.88) |
| L5.Tether_USD_Ret | | | | | 0.0150 |
| | | | | | (1.26) |
| Constant | 0.0174 | 0.0177 | 0.0180 | 0.0183 | 0.0185 |
| | (1.59) | (1.62) | (1.64) | (1.67) | (1.69) |
| Observations | 8742 | 8739 | 8736 | 8733 | 8730 |
| Adjusted $R^2$ | 0.004 | 0.010 | 0.012 | 0.015 | 0.015 |

B. Bitcoin Flow

| | BTC Flow | BTC Flow | BTC Flow | BTC Flow | BTC Flow |
|---|---|---|---|---|---|
| L.BTC_USD_Ret | -0.1000*** | -0.103*** | -0.106*** | -0.106*** | -0.106*** |
| | (-5.99) | (-6.19) | (-6.43) | (-6.45) | (-6.49) |
| L2.BTC_USD_Ret | | -0.0753*** | -0.0780*** | -0.0795*** | -0.0797*** |
| | | (-4.77) | (-4.94) | (-5.03) | (-5.05) |
| L3.BTC_USD_Ret | | | -0.0635*** | -0.0647*** | -0.0663*** |
| | | | (-4.35) | (-4.41) | (-4.51) |
| L4.BTC_USD_Ret | | | | -0.0387** | -0.0401** |
| | | | | (-2.63) | (-2.73) |
| L5.BTC_USD_Ret | | | | | -0.0344* |
| | | | | | (-2.38) |
| L.Tether_USD_Ret | -0.00972 | -0.00356 | -0.00102 | 0.00185 | 0.00296 |
| | (-0.69) | (-0.24) | (-0.07) | (0.12) | (0.19) |
| L2.Tether_USD_Ret | | 0.00603 | 0.0107 | 0.0168 | 0.0176 |
| | | (0.45) | (0.72) | (1.13) | (1.13) |
| L3.Tether_USD_Ret | | | 0.00123 | 0.0131 | 0.0154 |
| | | | (0.09) | (0.92) | (1.05) |
| L4.Tether_USD_Ret | | | | 0.0203 | 0.0244 |
| | | | | (1.51) | (1.68) |
| L5.Tether_USD_Ret | | | | | 0.00373 |
| | | | | | (0.27) |
| Constant | 0.0218* | 0.0221* | 0.0224* | 0.0226* | 0.0228* |
| | (2.00) | (2.04) | (2.07) | (2.09) | (2.10) |
| Observations | 8744 | 8741 | 8738 | 8735 | 8732 |
| Adjusted $R^2$ | 0.010 | 0.015 | 0.019 | 0.020 | 0.021 |

C. Price Differences Across Exchanges

| | (1) | (2) |
|---|---|---|
| | Tether | BTC |
| Arbitrage Spread | 0.0182 | 0.0246 |
| | (1.17) | (1.58) |
| Average Return | -0.107*** | -0.129*** |
| | (-7.04) | (-8.17) |
| Constant | 0.000799 | 0.0000998 |
| | (0.08) | (0.01) |
| Observations | 9461 | 9463 |
| Adjusted $R^2$ | 0.012 | 0.019 |

**Table VIII. The Relationship between Flow, Bitcoin Returns, and Cross-Exchange Arbitrage.** Columns (1) and (2) estimate OLS regressions of Tether and Bitcoin flows on the difference in 3-hour Bitcoin lagged returns between Bitfinex and Poloniex ($ArbitrageSpread$) and the average of 3-hour Bitcoin lagged returns on Bitfinex and Poloniex ($AverageReturn$):

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

where $AverageReturn_t = \frac{(R_t^{BFX} + R_t^{PLX})}{2}$ and $ArbitrageSpread_t = R_t^{BFX} - R_t^{PLX}$, both standardized by subtracting the mean and dividing by the standard deviation. $R_t^{BFX}$ is hourly Bitcoin return on the Bitfinex exchange and $R_t^{PLX}$ is the hourly Bitcoin return on the Poloniex exchange. Columns (3) and (4) show similar results for the flow between Bitfinex and Bittrex exchanges. The sample period is from March 1, 2017 to March 1, 2018. Standard errors are robust to heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Poloniex_Tether | Poloniex_BTC | Bittrex_Tether | Bittrex_BTC |
| Arbitrage Spread | 0.0617*** | 0.0235 | 0.0468* | 0.0453* |
| | (3.71) | (1.39) | (2.41) | (2.24) |
| Average Return | -0.0802*** | -0.0871*** | -0.0834*** | -0.107*** |
| | (-5.63) | (-6.27) | (-3.85) | (-5.38) |
| Constant | -0.0440*** | -0.0385*** | 0.0890*** | 0.0988*** |
| | (-4.26) | (-3.65) | (6.44) | (7.58) |
| Observations | 7747 | 7750 | 6713 | 6716 |
| Adjusted $R^2$ | 0.013 | 0.010 | 0.009 | 0.014 |

## Internet Appendix

**Figure IA1. Snapshot of a 10-Minute Random Sample of Transactions on the Bitcoin Blockchain.** This figure shows the flow of Bitcoin recorded on the Bitcoin blockchain over a 10-minute random sample in 2017. 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. The direction of the flow is shown by the curvature of the edges, with Bitcoin moving clockwise from a sender to a recipient.

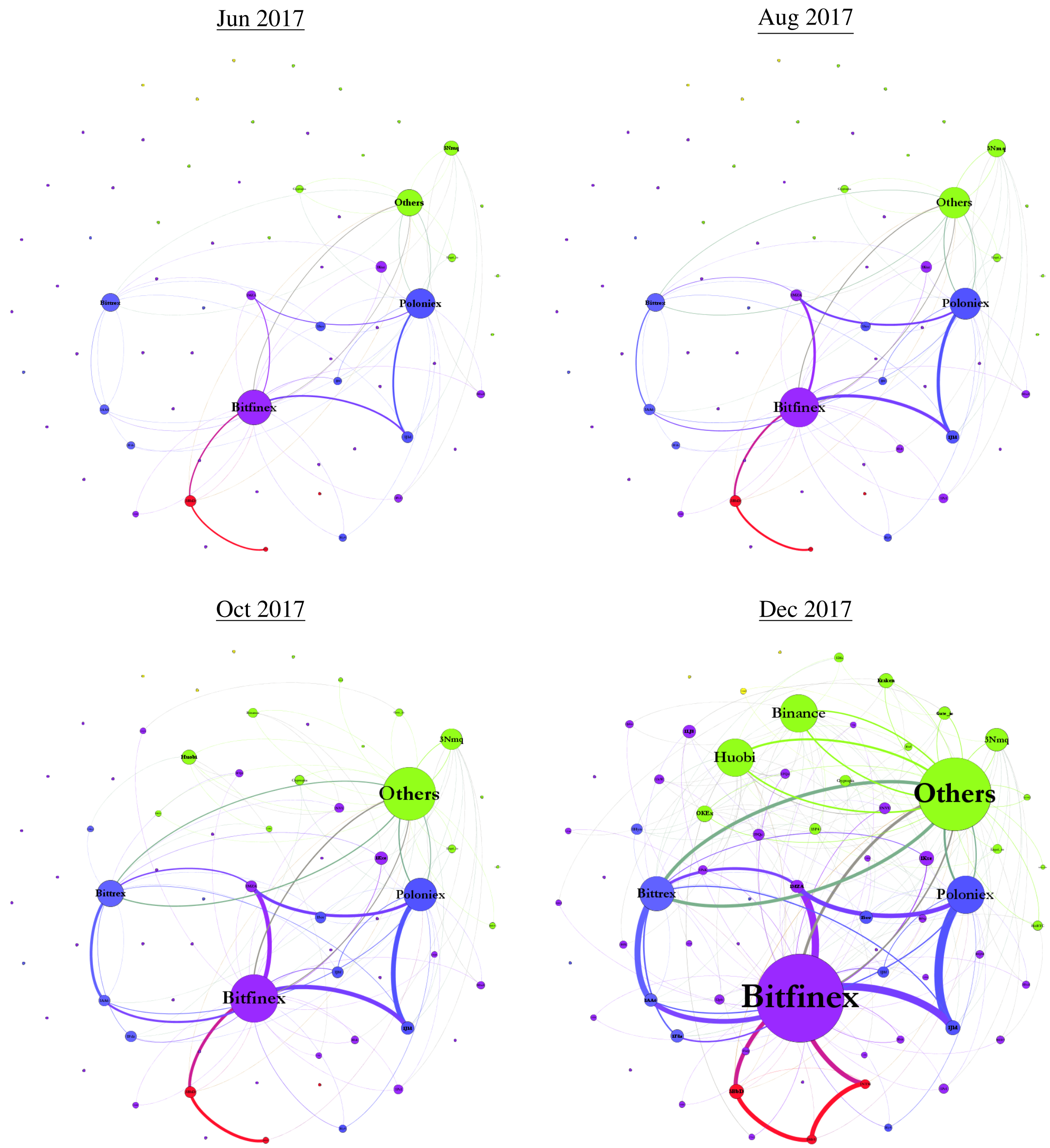



**Figure IA2. Snapshots of Tether Blockchain Over Time.** This figure shows the aggregate flow of Tether between major exchanges and market participants from genesis until different points in time. Tether transactions are captured on the Omni Layer as transactions with the coin ID 31. The data include confirmed transactions with the following action types: Grant Property Tokens, Simple Send, and Send All. Wallet identity of the exchanges on Tether Blockchains 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. Intra-node 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.

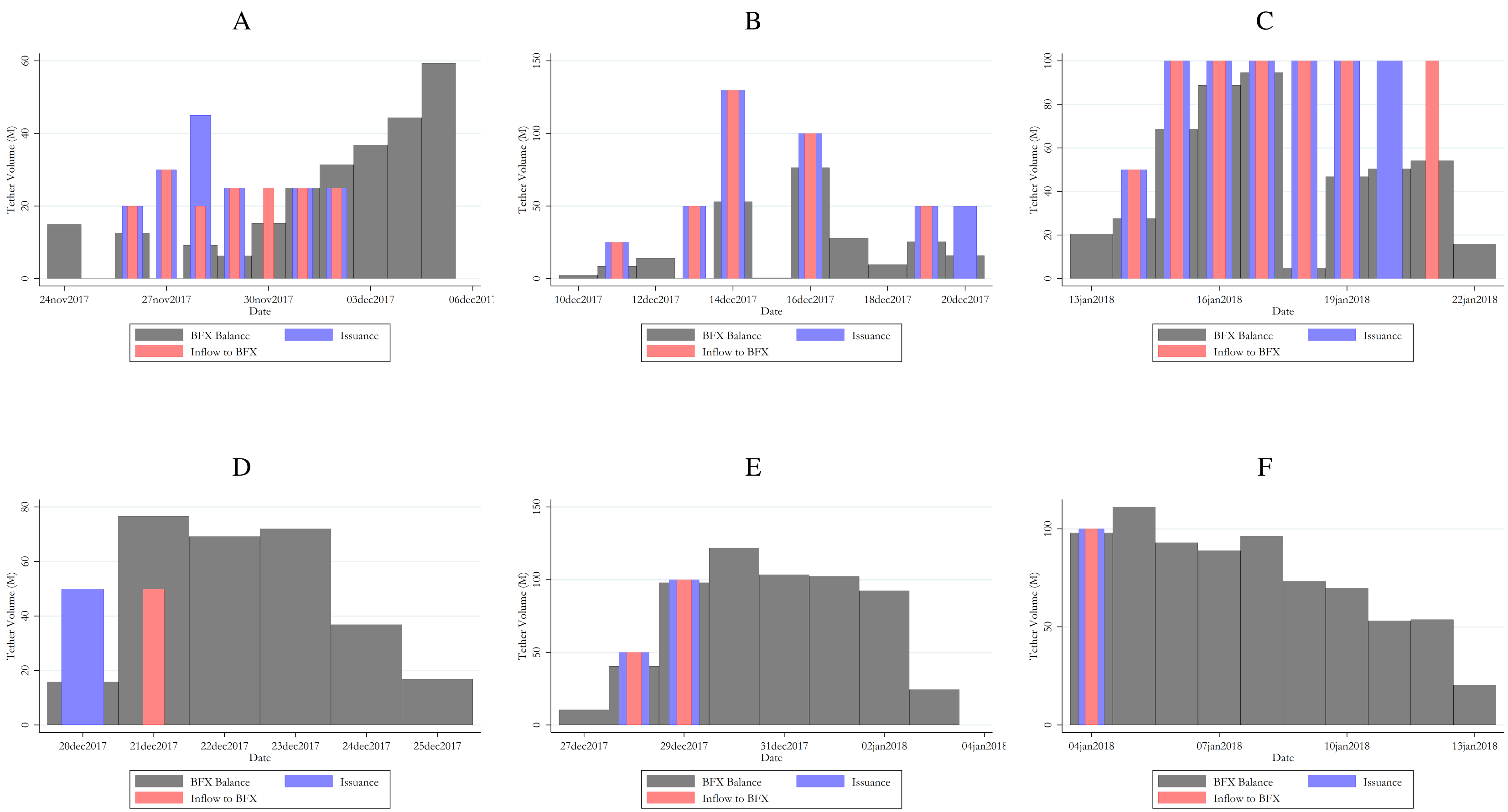



**Figure IA3. Examples of Tether Grants and Changes in Bitfinex Wallet Balance.** This figure shows multiple examples of Tether grants, inflow of Tether to Bitfinex, and Tether balance on Bitfinex over the subsequent days. Large gray bars show the Tether balance on Bitfinex, the medium blue bars show Tether grants, and the red narrow bars show the inflow of Tether to Bitfinex.

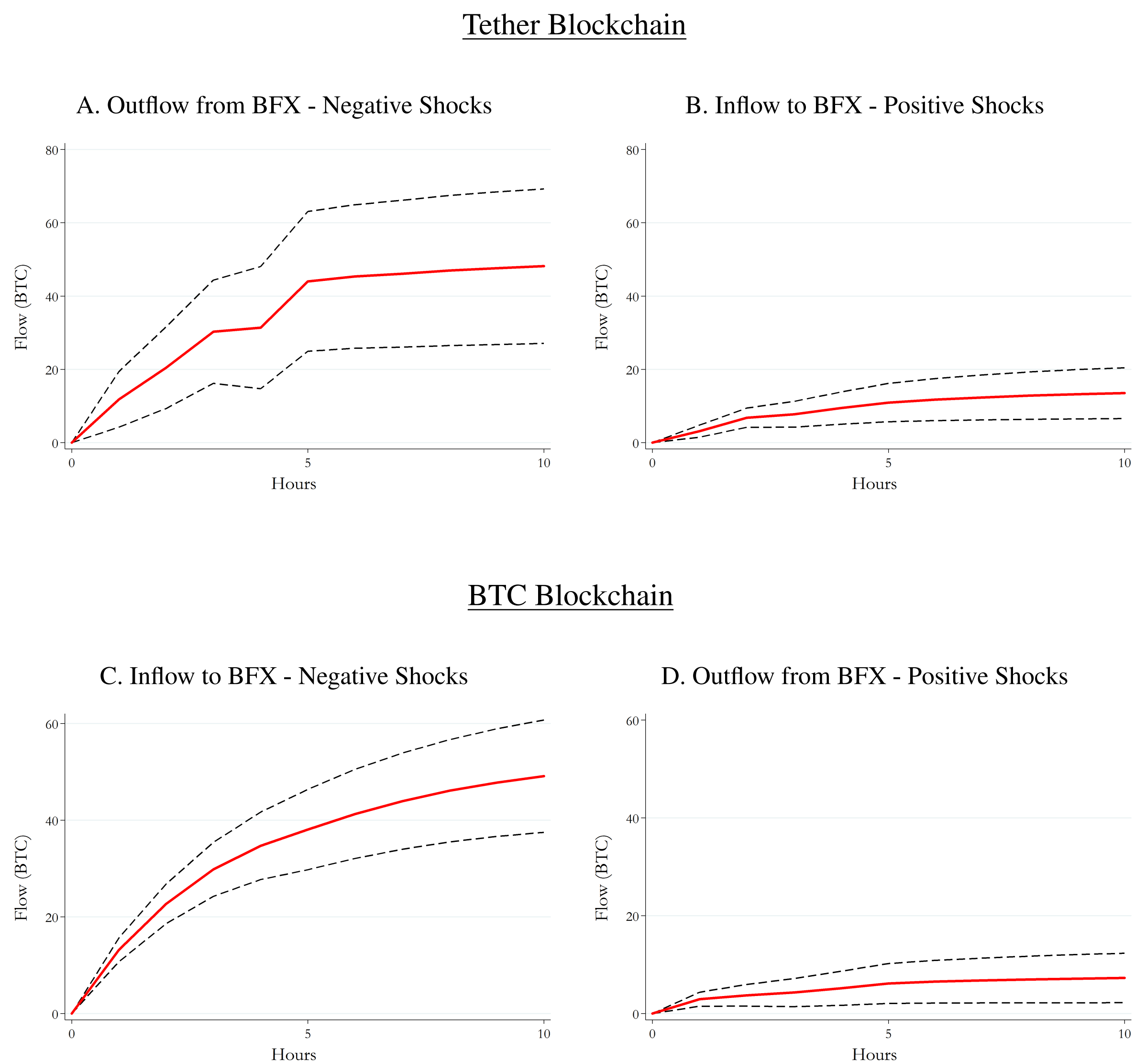



**Figure IA4. Bitcoin and Tether Flows in Response to Shocks to Bitcoin Returns.** This figure shows cumulative impulse response functions describing the change in Bitcoin and Tether flow between Bitfinex and two major Tether exchanges, Poloniex and Bittrex, in response to shocks to Bitcoin returns. The VAR is estimated using hourly data with five lags, and shocks are orthogonalized through a Cholesky factorization. Panels A and C show the outflow of Tether from Bitfinex and the inflow of Bitcoin to Bitfinex in response to one negative standard deviation shock to Bitcoin returns, and Panels B and D show the inflow of Tether to Bitfinex and the outflow of Bitcoin from Bitfinex in response to one positive standard deviation shock to Bitcoin returns. The dashed line shows the 95% confidence interval.

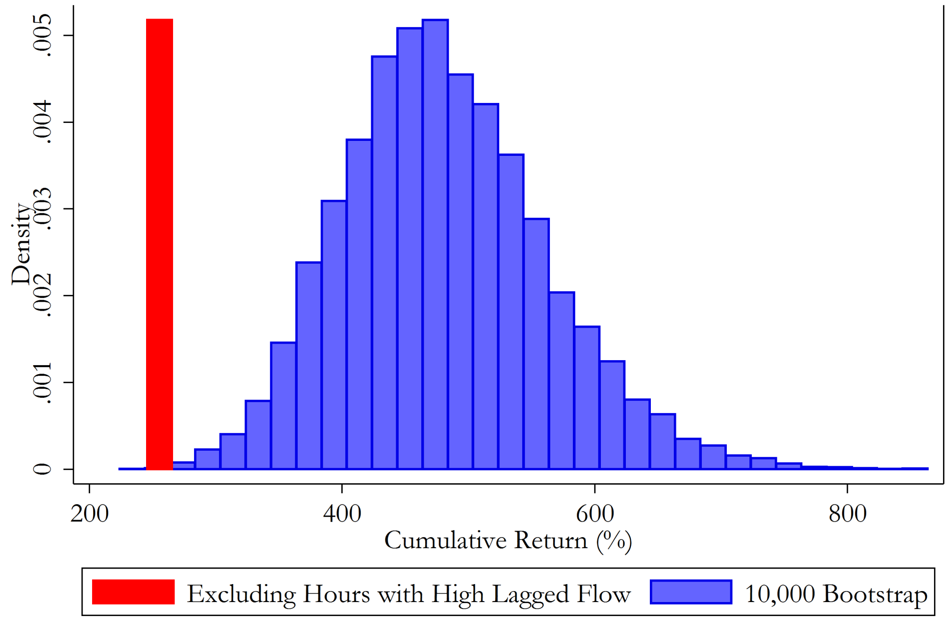



**Figure IA5. Predictive Effect of High-Flow Hours on Aggregate Cryptocurrencies Returns.** This figure shows the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018, excluding 87 high-flow hours of Tether and Bitcoin (the red bar). The high-flow hours are defined as in Figure 7. The blue bars show the distribution of returns if 87 random hours, conditional on Tether issuance in the prior three days and negative returns in the prior hour, are excluded from the sample.

**Table IAI. Example of a Transaction with Multiple Inputs and Outputs on Bitcoin Blockchain.** This table shows the inputs (senders) and outputs (recipients) for the Bitcoin transaction with hash ID of 5c6f2f3b70d57b32a77b220fbbde79913c0caaf8c72f3bb824dc539f135979cd, occurring on March 30, 2018 at 13:44:21 UTC time.

| Sender | Amount_Sent | Recipient | Amount_Received |
|---|---|---|---|
| 1129qSnNqHSTdmfaAUoKCytUAu29xgjgfJ | 0.05899683 | 112B9PzJz4u47A3JEzjpaiVduowD7gS1vP | 0.23028745 |
| 121cUjoRtGKU25pkuZpxc33LBf2LTHFwab | 0.1151668 | 125qULxTDsx4jEjWEoJe3ynyKCUKECVEyt | 0.17216561 |
| 125KBUcrLHuXP8YbCedRr2fbf9KHq7ENz2 | 0.10526526 | 126uZRfEqqnn2gPvXTJiA6Sabf6X6MEwMX | 0.13101183 |
| 125dwAk8He9k9ieGD9gThwofS7SRbN46PF | 0.05936999 | 12AUPDUfDz59cFTEMgb64Bzk7VQwTiyo5d | 0.04331562 |
| 12A4y9dxy1C5jFtR1xsBecY69CCE9dgt8W | 0.04798837 | 12YDZofcxT61JT2SggP8U9jg94xAEjYKsH | 0.25638395 |
| 12Xf5rRKi1VoeMKoumFGEvWQ9pw9g9kx4L | 0.13439911 | 12YfRCsvNRqfTozfV8z27KS4EwsZkvB9fs | 0.21959335 |
| 12bRPtR5FVqe22oGpYqctX8qLd4eBm9Mbt | 0.114555 | 12sNsPZFUVqVGFc8R4jhLM5a19Jj5xWUuZ | 0.2443245 |
| 12d3NBhcGqLGW7PTXnkELuviehY9hyr112 | 0.084468 | 12tEVnfmRPNAQ8G2GVpDzwJL9rcfuYeF12 | 0.27086641 |
| 12go7FrWssrN5oxkacXKidDRT85GCHz1E7 | 0.12131453 | 12zFasV4qHNnpfgh8HQyct5NFRBqtC6bXh | 0.14859831 |
| 12hhsCepfdi9N4ALNi1YgsSu1bk7wBPtTZ | 0.12306828 | 13NhZkG3vqXWCjEj1zm818EPyKXeFsRDMJ | 0.12276955 |
| ... | | ... | |
| 1QBwQZr2URGKfV1Hup7hLRKrb6M16GmAfN | 0.16809483 | 1Pj42QLhPdPYcyn68M1VprZygFF2uVBLLR | 0.16177408 |
| 1QEnxCnWx7RWNLfiMPKQzb4kx1P4fzub9L | 0.15477798 | 1PqGhJA9yCo5enbMkXdx3swgWVoBcqxEmM | 0.10792842 |
| 1QJ2FpabSeb23jGrZ7uJcSJW17wF6zqven | 0.13 | 1PqxkEP1UNvNtV2r7Dc4mYiG9vrymJpDjm | 0.17662456 |
| 1QP8tyFRUdNDngDzno5kFdPS31BhU6mth | 0.10856289 | 1Q1g8XmwLpvsYUf2wLP7J4CzGeAQFqXaw5 | 0.17042204 |
| 1TiyBwNqkALSHiXw8sR7GWabig8FZr1h3 | 0.11509374 | 1Q1h1YQ2QZ8SPFJpS3pVfQbNeHrpLxFrBf | 0.24294307 |
| 1VHMSZxDmGqhNxa9JrVsZM6H1LQ3AoraA | 0.12646174 | 1QB7yyYm2JE4Wur5wEsqQnZBmcNmE9WPRB | 0.21583378 |
| 1act2jbkqnbVCtcr9adqVQHeN6XrsE4F7 | 0.15357679 | 1QJnBEmeCXfdTjiU1MSshPQApao5TVN1vs | 0.11199467 |
| 1ruKkoPZkvgVHfHeyAmgeVoM59qCvA8gF | 0.17539078 | 1S5iCdyaLzpVghTJxq4k9EghzebZE8xpi | 0.20482052 |
| 1whWUapyjrrBozaBkRLaHyk9g1aJRHJPb | 0.13116103 | 1Vg7FnQT9oHbxuZqR7Cs53rsHv835iQAJ | 0.26632879 |
| 1wiAk4JyhjKv1MSRKgh6Gn76ydbZWp9F7 | 0.1373944 | 1XyQj4QBuskv7rqsyw3cadyTcJ3nP4Dy8 | 0.15614583 |
| 1z4rqnRxp5rs3DAUE2PdTAsUPtrG6ep5p | 3.96564064 | 1kmLcU8GxRWSw8UuUGxNu28iGbTHkSqJ6 | 0.15713512 |

**Table IAII. The Relationship between Authorization and Flow of Tether and Bitcoin Volatility and Returns.** This table shows OLS estimates for which the dependent variables are the net aggregate flow of Tether from Bitfinex to Poloniex and Bittrex and the net flow of Bitcoin from Poloniex and Bittrex to Bitfinex:

$$Flow_t = \beta_0 + \beta_1 \frac{1}{3} \sum_{i=1}^{3} R_{t-i} + \beta_2 LaggedVol_t + \epsilon_t$$

where $R_t$ is the hourly Bitcoin returns, and $LaggedVol_t$ is the 3-hour lagged volatility constructed from 5-minute Bitcoin returns. Results are shown separately for hours with positive and negative lagged returns. Standard errors are robust to heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

| | Tether Flow from Bitfinex | | Bitcoin Flow to Bitfinex | |
|---|---|---|---|---|
| | Neg Lagged Ret | Pos Lagged Ret | Neg Lagged Ret | Pos Lagged Ret |
| Lagged Return | -43.05*** | -11.24 | -71.73*** | -6.400 |
| | (-4.36) | (-1.25) | (-7.72) | (-0.91) |
| Lagged Volatility | 16.42* | 29.81*** | 8.079 | 41.77*** |
| | (2.50) | (4.47) | (1.05) | (7.91) |
| Constant | -0.478 | -7.652 | 20.30*** | 1.377 |
| | (-0.10) | (-1.77) | (3.74) | (0.39) |
| Observations | 3648 | 4423 | 3648 | 4424 |
| Adjusted $R^2$ | 0.036 | 0.012 | 0.069 | 0.031 |

**Table IAIII. Flow of Coins around Round Thresholds of Bitcoin Price for Major Exchanges.** This table shows OLS estimates for which the dependent variable is the hourly flow of Bitcoin from Poloniex and Bittrex to other major exchanges, using flow on the Bitcoin blockchain:

$$Flow_t = \beta_0 + \beta_1 BelowRoundCutoff_t + \epsilon_t$$

where $BelowRoundCutoff_t$ is a dummy variable that takes the value of one if Bitcoin price, at the end of the previous hour, falls into the $50 price bucket below a $500 price multiple and zero if it is in the $50 bucket above such multiple. Panel A shows the results for three days after Tether issuance and Panel B for other days. Standard errors are robust to heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Days After Issuance

| | Bitfinex Flow | Bitstamp Flow | BTCC Flow | Kraken Flow | Gemini Flow |
|---|---|---|---|---|---|
| Below the Cutoff | 56.36** | 5.187 | -4.577 | 6.753 | 4.354 |
| | (3.15) | (0.62) | (-0.94) | (0.88) | (0.58) |
| Constant | 46.65*** | 8.612 | 18.48*** | 24.36*** | -1.588 |
| | (4.49) | (1.78) | (5.58) | (6.44) | (-0.50) |
| Observations | 464 | 464 | 464 | 464 | 464 |
| Adjusted $R^2$ | 0.020 | -0.001 | -0.000 | -0.000 | -0.001 |

B. Other Days

| | Bitfinex Flow | Bitstamp Flow | BTCC Flow | Kraken Flow | Gemini Flow |
|---|---|---|---|---|---|
| Below the Cutoff | 1.339 | 3.875 | 2.101 | -0.572 | 1.534 |
| | (0.17) | (0.80) | (0.74) | (-0.14) | (0.44) |
| Constant | 39.88*** | 6.149* | 13.50*** | 27.45*** | 0.933 |
| | (7.82) | (2.00) | (9.42) | (10.55) | (0.46) |
| Observations | 1134 | 1134 | 1134 | 1134 | 1134 |
| Adjusted $R^2$ | -0.001 | -0.000 | -0.000 | -0.001 | -0.001 |

**Table IAIV. The Effect of Tether Issuance on Bitcoin EOM Returns.** This table shows OLS estimates for which the dependent variable is EOM Bitcoin returns and the independent variable is monthly Tether issuance:

$$R_t = \beta_0 + \beta_1 Issuance_t + \epsilon_t$$

where the EOM return is defined as in Figure 10 and $Issuance_t$ is total monthly Bitcoin-denominated Tether issuance, scaled by standard deviation of monthly issuance. Column (1) shows the results for raw EOM returns and Column (2) for raw returns relative to the average return in the prior four days and subsequent four days. The sample is from March 2016 to March 2018. Standard errors are robust to heteroscedasticity. $t$-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

| | (1) | (2) |
|---|---|---|
| | Raw Return | Relative to Days Around |
| Issuance | -0.0208** | -0.0222** |
| | (-2.82) | (-3.14) |
| Constant | 0.00347 | -0.00648 |
| | (0.88) | (-1.66) |
| Observations | 25 | 25 |
| Adjusted $R^2$ | 0.372 | 0.375 |