IS BITCOIN REALLY UN-TETHERED?

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Abstract

This paper investigates whether Tether, a digital currency pegged to the U.S. dollar, influenced Bitcoin and other cryptocurrency prices during the 2017 boom. Using algorithms to analyze blockchain data, we find that purchases with Tether are timed following market downturns and result in sizable increases in Bitcoin prices. The flow is attributable to one entity, clusters below round prices, induces asymmetric autocorrelations in Bitcoin, and suggests insufficient Tether reserves before month-ends. Rather than demand from cash investors, these patterns are most consistent with the supply-based hypothesis of unbacked digital money inflating cryptocurrency prices. *JEL* Codes: G14, G23, G29.

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Innovation, excessive speculation, and dubious behavior are often closely linked. Periods of extreme price increases followed by implosion, commonly known as 'bubbles', are often associated with legitimate inventions, technologies, or opportunities. However, they can be carried to excess. Financial bubbles often coincide with the belief that a rapid gain can be obtained from simply selling the asset to another speculator.[1] Perhaps because of the focus on speculative activity rather than verifiable fundamentals, bubbles have historically been associated with various forms of misinformation and fraud. For example, in the Mississippi Bubble of 1719-1720, promoters engaged in false marketing about the potential of income generating assets, price support by the stock itself, and distribution of paper money that was not fully backed by gold as claimed [Dale (2004) and Kindleberger and Aliber (2011)]. As we will briefly discuss in the next section, famous bubbles such as the 1840s Railroad bubble, roaring 1920s stock market boom, the dot-com bubble, and the 2008 financial crisis contained substantial evidence of misinformation, false accounting, price manipulation, collusion, and fraud, often in sophisticated forms.

Cryptocurrencies grew from nearly nothing to over $300 billion in market capitalization in only a few years and fit the historical narrative of previous bubbles quite well–an innovative technology with extreme speculation surrounding it. To many, Bitcoin and other cryptocurrencies offer the promise of an anonymous, decentralized financial system free from banks and government intervention. The conception of Bitcoin corresponds to the middle of the 2008-2009 financial cri-

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

sis, 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,[2] especially in an age when centralized clearing is subject to concerns of both external hacking and internal manipulation.[3] Ironically, new large entities have gained centralized control over the vast majority of operations in the cryptocurrency world, such as centralized exchanges that handle the majority of transactions and stable coin issuers who can control the supply of money like a central bank. Our study examines the role of the largest stable coin, Tether, on Bitcoin and other cryptocurrency prices. These centralized entities largely operate outside the purview of financial regulators and offer varying levels of limited transparency. Additionally, operating based on digital stable coins rather than fiat currency even further relaxes the necessity for these entities to establish a legitimate fiat banking relationship.[4] 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 stable coin that accounts for

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

[3]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.

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

more Bitcoin transaction volume than the U.S. dollar. Tether is 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,[5] the cryptocurrency exchanges largely reject such concerns and widely use Tether in transactions.

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

Alternatively, under the 'pushed' hypothesis, Bitfinex prints Tether regardless of the demand from cash investors. In this case, additional supply of Tether can create an inflation in price of Bitcoin that is not from a genuine capital flow. In this setting, the Tether creators have several potential motives. First, if the Tether founders, like most early cryptocurrency adopters and exchanges, have large holdings of Bitcoin, they generally profit from the inflation of the cryptocurrency prices. Second, the coordinated supply of Tether creates an opportunity to manipulate cryptocurrencies. When prices are falling, the Tether creators can convert their large Tether supply into Bitcoin in a way that pushes Bitcoin up and then sell some Bitcoin back into dollars in a venue with less price impact to replenish

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

Tether reserves. Finally, if cryptocurrency prices crash, the founders essentially have a put option to default on redeeming Tether, or to potentially experience a 'hack' or insufficient reserves where Tether-related dollars disappear. Both the 'pushed' and 'pulled' alternatives have different testable implications for capital flows and cryptocurrency returns that we can take to the powerful blockchain data.

We begin our exercise by collecting and analyzing both the Tether and Bitcoin blockchain data through a series of algorithms to reduce the complexity of 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 algorithms developed in computer science to cluster groups of related Bitcoin wallets. Large clusters are then labeled through identifying certain member wallets inside each group and tracking the flow of coins between major players in the market.

Figure 1 plots the aggregate flow of Tether among major market participants on the Tether blockchain from its conception in October 6, 2014 until March 31, 2018. The size of the nodes is proportional to the sum of coin inflow and outflow to each node, the thickness of the lines is proportional to the size of flows, and all flow movements are clockwise. Tether is authorized, moved to Bitfinex, and then slowly distributed to other Tether-based exchanges, mainly Poloniex and Bittrex. The graph shows that almost no Tether returns to the Tether issuer to 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.[6] Additionally, we find that the cross-exchange Bitcoin flows on Bitcoin blockchain closely matches the Tether flows on Tether blockchain. This independently verifies our algorithm for categorizing the exchange identities and also captures the direct exchange of Tether for Bitcoin. Additionally, we find that one large player is associated with more than half of the exchange of Tether for Bitcoin at Bitfinex, suggesting that the distribution of Tether into the market is from a large player and not many different investors bringing cash to Bitfinex to purchase Tether.

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

To gauge the aggregate magnitude of the observed price impact, we focus on

[6] Between March 1, 2017 and March 31, 2018, we grouped over 640 thousand wallet addresses as Bitfinex, 720 thousand addresses as Poloniex, and 1.22 million wallet addresses as Bittrex through our clustering algorithm.

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

A further detailed analysis for the single largest player on Bitfinex shows that the 1%, 5%, and 10% of hours with the highest lagged flow of Tether by this one player are associated with 55%, 67.2%, and 79.2% of Bitcoin's price increase over our March 1, 2017 to March 31, 2018 sample period. This pattern is not present for the flows to any other Tether exchanges, and simulations show that these patterns are highly unlikely to be due to chance; this one large player or entity either exhibited clairvoyant market timing or exerted an extremely large price impact on Bitcoin that is not observed in the aggregate flows from other smaller traders. Such a trading pattern by this one player is also large enough to induce a statistically and economically strong reversal in Bitcoin prices following negative returns.

Investors hoping to stabilize and drive up the price of an asset might concen-

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

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

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

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

printing. This pattern is not present in reserve wallets on any other exchanges.

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

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

The rest of the paper 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 the main data sources and explains our methodologies to analyze the blockchain data and flows. Section III analyzes the potential influence of Tether on Bitcoin, and Section IV further tests whether the flows are consistent with pushed or pulled explanations. Section V concludes.

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

A. Speculative Bubbles and the Prevalence of Dubious Market Activity

Periods of excessive price speculation often share the themes of optimism around a new technology, focus on selling to others rather than economic cashflows, and questionable activities. The famous South Sea Bubble of 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 (2002)]. In the Roaring Twenties, investment pools would manipulate a stock price through 'wash-sales,' collusion with stock-exchange specialists, and coordinated publicity from commentators in order to pump a stock at an inflated price to the public [Malkiel (1981)]. The technology or 'dot-com' bubble of 1997 to 2000 also contained strong elements of stock promotion through inflated forecasts from affiliated analysts [Lin and McNichols (1998)], pushing or 'laddering' prices through implicit agreements to purchase more IPO shares in the aftermarket [Griffin, Harris, and Topaloglu (2007a)], and accounting fraud (e.g., Enron and Worldcom). Hedge funds and other institutional investors were the main net buyers of overpriced technology stocks during this period [Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011)].

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

B. Brief History of Bitcoin and Exchange 'Hacks'

On October 31, 2008, the whitepaper "Bitcoin: A Peer-to-Peer Electronic Cash System" was released by Satoshi Nakamoto [Nakamoto (2008)]. The paper outlines a digital currency system where transactions are recorded on a chain of linked blocks, hence “blockchain”, and verified electronically through a decentralized network of users. This decentralized feature avoids the traditional system of government-backed currencies controlled by centralized Federal banks and clearing houses. On January 3, 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] By April 23, 2011, Bitcoin exceeded parity with the U.S. dollar, euro, and British pound with the market cap passing $10 million USD, and by March 28, 2013, the total Bitcoin market cap passed $1 billion USD.

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

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[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.

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

C. *Brief History of Tether*

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

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

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

Panel B of Figure 2 shows transactions of major cryptocurrencies in U.S. dollars as compared to Tether, aggregated across all cryptocurrency exchanges

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

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

[13] See Popper (2017).

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

Those in the blogosphere and the mainstream press began to raise questions regarding Tether in the second half of 2017.[15] In April 2017, Tether lost its banking relationship with a Taiwanese bank linked to Wells Fargo. Since then, Tether has issued over $2 billion Tether without fully disclosing banking details. This could be due to not wanting to subject their bank to public scrutiny and 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. Tether hired a consultant that released an internal memo showing reserves on September 15, 2017.

Immediately after the first draft of this paper, a law firm released a report on sufficient Tether reserves in June 2018.[16] On February 25, 2019 Tether changed

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

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

[16]They have also released EOM snapshot bank statements showing reserves at the EOM. Tether

their definition of Tether backing to read "traditional currency and cash equivalents." In response to legal motions, on April 30, 2019, Bitfinex's former General Counsel admitted that Tether does not have cash reserves equal to 100% of the outstanding Tethers. In a May 15, 2019 court hearing, a Bitfinex attorney also admitted that Tether did invest in instruments beyond cash, including Bitcoin, something clearly at odds with Tether's longstanding claims.

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

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

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

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

D. Main Hypotheses

This section examines two main alternative 'pulled' versus 'pushed' hypotheses[19] about Tether functions: 1) Tether is 'pulled' or driven by legitimate demand from investors who use Tether as a medium of exchange to enter their fiat capital into the crypto space. In this case, the price impact of Tether reflects natural market demand.

2) Tether is 'pushed' through a supply-driven scheme to print an unbacked digital dollar and use it to purchase Bitcoin. In this case, additional supply of Tether can create an inflation in the price of Bitcoin and other cryptocurrencies that is not from a genuine capital flow.

Our first hypothesis is that Tether is driven by 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 traditional deposits. If driven by demand from new investors that hold dollars and wish to convert their dollars to Tether and then into cryptocurrencies, the greater demand may result in a higher market rate for the Tether-USD pair. A lower price of Tether would then be a consequence of weak demand for Tether, and a higher price (perhaps at or above one) could then result as a consequence of strong Tether demand.

H1A: Tether's price relative to the U.S. dollar may increase as a consequence

[19]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 (2007b)].

of strong investor demand. Tether flows should be strongly related to this demand proxied for by 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 correspond to periods when Bitcoin sells at a premium on Bitfinex relative to that exchange.[20]

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 fees, transaction fees, and interest earned from trading in Tether, other possible valuable benefits of such a plan could be as follows.

First, like an inflationary effect of printing money, issuing Tether increases the money supply in the crypto space and can significantly push cryptocurrency prices up by generating an artificial demand. Since most cryptocurrency exchanges and early movers are long in Bitcoin and other cryptocurrencies, they would generally benefit. 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 slowly convert some of their cryptocurrencies to U.S. dollars and retrospectively provide either full or partial dollar reserves for Tether.

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

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

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

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

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

H2A: If Tether issuers are trying to provide stability to the market during downturns, outflows of Tether and purchases of Bitcoin by Bitfinex may follow periods of negative Bitcoin returns.

H2B: If the Tether supply is large enough to have a material price impact on Bitcoin, Bitcoin prices should go up after Tether flows into the market, especially after periods with large authorization of Tether.

H2C: Bitcoin returns may show a return reversal after negative returns, especially during times when Tether flows into the market.

H2D: Since round-number thresholds can be price anchors to set a price floor and are often used as buying signals by investors, flow of Tether might increase if Bitcoin falls below these salient round-number thresholds. This effect should be more pronounced in periods with large Tether authorization.

H2E: If Tether is not fully-backed by dollars at the outset, but the issuers want to signal to investors otherwise by releasing EOM (or other interval) accounting statements, then Tether creators may liquidate the Bitcoins into U.S. dollars to demonstrate sufficient reserves. This could create negative returns in Bitcoin at the EOM, particularly in periods with large Tether issuances.

While these hypotheses need not all follow from the pulled hypothesis, H2A-H2D examine if the flow of Tether into the market is consistent with creating price supports and inflating Bitcoin prices, and H2E examines if the potential price impact is due to unbacked printing of Tether which can have an inflationary effect on Bitcoin. In the next section, we discuss the data and details behind testing the hypotheses.

II. Data, Algorithms, and Flows Between Major Accounts

A. *Data*

The price and the blockchain data obtained for this study amount to over 200 GB from more than ten sources, with *CoinAPI*, *Coinmarketcap.com*, *Blockchain.info*, *Omniexplorer.info*, and *CoinDesk* as our main sources. The in-traday pricing data on major cryptocurrencies are from *CoinAPI*. 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.[21]

[21]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. Daily prices of various coins are

Bitcoin blockchain data are obtained from *Blockchain.info* and cover the period from Bitcoin initiation in January 2009 to March 2018. The blockchain data contain the entire history of Bitcoin transactions between Bitcoin wallets and include variables such as wallet IDs of senders and recipients as a string of 34 characters and numbers, 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. Over the October 2014 to March 2018 period, Tether is issued via the Omni Layer Protocol based on the Bitcoin blockchain, and Tether blockchain data are from *Omniexplorer.info*.

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

Tether exchanges account for a large portion of cryptocurrencies trading volume over our sample period. Table I, Panel A, shows the total trading volume on major exchanges for major cryptocurrencies from March 1, 2017 to March

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obtained from *Coinmarketcap.com*, which calculates the price of each coin by taking the volume-weighted average of prices reported at different exchanges. We also use intraday *CoinDesk* price index, which aggregates prices across major markets. 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.

[22]The Internet Appendix IA.B includes the list of representative addresses that can be used to assign identities of major exchanges.

31, 2018. Tether-based exchanges are marked with a "*." Some exchanges, including Gemini and Coinbase, specialize in a limited number of major coins such as Bitcoin and Ethereum. Others, especially the Tether-related exchanges, 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. As shown in Panel B of Figure 2, a large share of major cryptocurrencies transactions are denominated in Tether.

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

Panel C of Table I shows the autocorrelation of cryptocurrencies at various frequencies. The autocorrelations are generally negative. For example, a 1% change in the lagged 1-hour Bitcoin prices is followed by 6 basis points reversal in the next hour. The reversal is 6 and 5 basis points at 3- and 5-hour intervals.

B. Analyzing Bitcoin Blockchain

The Bitcoin blockchain up to March 31, 2018 is a 170 GB network database of more than 360 million wallet addresses and billions of transactions. It is common for each entity to have multiple wallet addresses, and transactions with multiple senders and recipients are frequent.[23] The complexity of the data can be observed

[23] 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

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 [Androulaki et al. (2013), Meiklejohn et al. (2013), Reid and Harrigan (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 find connected components of this "same-input" relation throughout the entire Bitcoin blockchain and consider each component as a group of wallets controlled by the same entity. We take three more steps. First, if a transaction has multiple recipients, the flow from the sender is allocated proportionally by the number of coins received by each recipient. Second, for each transaction, we exclude the portion of coins that have the same input and output wallets. Finally, we exclude the transaction fees as reflected in the difference between total Bitcoin sent and received in one transaction. The clustered group of wallets that contain exchange addresses are assigned to the identified exchanges. Between March 1, 2017 and March 31, 2018, a group of approximately 640 thousand wallets are labeled as Bitfinex, 720 thousand wallets as Poloniex, and 1.22 million wallets as Bittrex.

Figure 3 shows the flows on the Bitcoin blockchain. First, one can see that

are the recipients.

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

C. 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. The transfer of Tether from Tether authorizer (account labeled as 3MbY) to Tether treasuries (1NTM and 3BbD), all colored in red, is called "authorization," and the transfer out of Tether treasuries, primarily to Bitfinex, is called "issuance." Note that there are barely any flows moving back to the initial Tether printing node, consistent with individuals stating 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 the USD-Tether pair for the majority of 2017.

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

Fourth, most of the Tether flows to and from Bitfinex are through Bittrex and Poloniex. 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, this is the primary channel through which Tether is converted to Bitcoin; however, we also examine flows to other exchanges. To calculate the flows between exchanges, we consider the intermediary wallets who receive Tether from Bitfinex and transfer them all to the same exchange as addresses belonging to that exchange.

Note that since the figure is proportional to the size of the flows, the graph puts substantial emphasis on the end of 2017 and early 2018 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.

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

D. Bitcoin and Tether Net Flows

Flows between two parties on the blockchain are more formally defined as the signed net amount of capital transferred between those entities. Specifically, our

[25]We show this formally in a VAR model in Figure IA3, and examples are shown in Figure IA4.

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. Similar to the flow of Bitcoin, we define the net flow of Tether as below

$$\begin{aligned} NetTetherFlow_t = &(\sum_{t-1}^{t} Tether_{BFX \to PLX} - \sum_{t-1}^{t} Tether_{PLX \to BFX}) \\ &+(\sum_{t-1}^{t} Tether_{BFX \to BTX} - \sum_{t-1}^{t} Tether_{BTX \to BFX}) \end{aligned} \tag{2}$$

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

We also verify that flows identified on the Tether blockchain moving out of Bitfinex and to Poloniex and Bittrex correspond to opposite flows back on the Bitcoin blockchain which come out of Poloniex and Bittrex and into Bitfinex. Figure IA5 shows that the two series are correlated at 0.72 for Poloniex and 0.71 for Bittrex at daily intervals, and that they also have similar magnitudes. The Bitcoin flow between other exchanges, even between other Tether-based exchanges and Bitfinex, have much lower correlations with the Tether flow to Poloniex and Bittrex and a much larger difference in magnitude. We also find a strong relation between inflow of Tether to Poloniex and Bittrex on the blockchain data and reported exchange trading volume on Poloniex and Bittrex that is not present in a placebo test for other Tether-related exchanges.[26]

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

$$Tether/BitcoinFlow = (NetTetherFlow_t + NetTetherFlow_t)/2 \quad (3)$$

After printing, Tether is used to purchase Bitcoin primarily on Poloniex and Bittrex. We examine if the sensitivity of flow of Tether to Bitcoin returns is symmetric in response to positive and negative shocks. Tether is used to purchase Bitcoin when returns are negative, but we do not find considerable Tether flows following price increases (as shown in Figure IA7 and Table IAII).

E. Detailed Deposit Accounts

We drill down on the nature of the Tether flows out of Bitfinex and the corresponding Bitcoin flows back by focusing on the exact deposit addresses used to move these coins. Typically, to electronically detect which user has deposited

[26]The details of our verification method and the results are described in the Internet Appendix IA.A.

funds and to credit these funds to their account, each exchange user receives her own unique deposit wallet address. Interestingly, Panel A of Figure 4 shows that 81% of the Tether flows from Bitfinex to Poloniex and Bittrex are through one large deposit address for each exchange. This account is responsible for 47% of all Tether flows from Bitfinex to all Tether exchanges combined. The first four digits of these addresses are shown as 1J1d for Poloniex and 1AA6 for Bittrex in the figure. Additionally, 52% of the Bitcoin flows back to Bitfinex from all Tether exchanges goes to a single deposit address on Bitfinex, which we label with its first four digits on the Bitcoin blockchain of 1LSg. The relation is described in Figure IA9, which shows how Bitfinex sends Tether out on the Tether blockchain through 1J1d and 1AA6 and receives flows back from 1MZA. On the Bitcoin blockchain, a majority of the Bitcoin deposits from Poloniex and Bittrex to Bitfinex go through 1LSg, and the flows back go to Poloniex and Bittrex through 1DEc and 1PCw.

If the Tether flows to 1J1d and 1AA6 on the Tether blockchain correspond to Bitcoin flows to 1LSg on the Bitcoin blockchain, it suggests that all these wallets are likely controlled by the same entity, which sends the printed Tether into the market in exchange for Bitcoin. To examine this, we compare the Tether flows from Bitfinex to 1J1d and 1AA6 on Poloniex and Bittrex to the Bitcoin flow from Poloniex and Bittrex to the top-100 largest Bitcoin addresses on Bitfinex, including 1LSg. The correlation of Bitcoin flows from Bittrex to 1LSg with Tether flows from Bitfinex to 1AA6 on Bittrex is 0.69. The correlation is 0.64 for 1J1d on Poloniex. Flows to other large deposit accounts on Bitfinex do not come close in terms of the correlation or the magnitude of the flows. The Internet Appendix IA.A (and Figures IA10 and IA11) describes more details about the procedure to identify these wallet addresses that move Tether and Bitcoin between Bitfinex, Poloniex, and Bittrex and verify their relation. Analogous to our flow calculations in Equations (1)), (2), and (3), we calculate the average net Tether/Bitcoin flows to these large and closely tied wallets and label them as "1LSg flows" throughout the paper. We will also compare the effect of flows that are not part of this group of wallets.

III. Are Bitcoin Prices Related to Tether?

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.

A. Examining Flows and Bitcoin Prices

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

We estimate a regression of rolling 3-hour average Bitcoin returns on lagged average net hourly 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, as the effect of flows might not be incorporated in exchange prices immediately. The traceable flows on the blockchains indicate when capital moves to the exchanges, not necessarily when the transactions occur within the exchange. We expect the flow of Tether to an exchange to precede the time when the Tether is used to purchase Bitcoin.[27] For controls we include: past returns to account for the effects of potential return reversals [Lehmann (1990)], daily volatility of hourly returns in the previous 24 hours to account for possible relations between returns and volatility, and lagged returns interacted with volatility to account for the potential of larger return reversals during periods of high volatility [Nagel (2012)].

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

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

To more precisely examine the source of the flow effect, we analyze three different flow components: 1) the net Tether flows out from Bitfinex (and the Bitcoin back) to the closely tied 1LSg address as discussed above, 2) the net Tether flow out from Bitfinex (and the Bitcoin back) to the rest of Poloniex and Bittrex accounts not involving the 1LSg addresses, and 3) the rest of the net Tether flows out from Bitfinex (and the Bitcoin back) to other Tether exchanges including Binance, HitBTC, Huobi, Kraken, and OKEx. Column (1) of Panel B of Table II shows that on days right after Tether printing, for a 100 Bitcoin increase in the 1LSg flow, the 3-hour average future Bitcoin return goes up by 4.24 basis points, controlling for lagged returns, volatility, and their interaction. The results are significant at the five-percent level. There is no significant positive relationship for the rest of the Poloniex and Bittrex flows (flow component 2). The same is true for flows into other Tether exchanges.

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

[28]Table IAIII shows similar results for the relationship between 1LSg flows and other major cryptocurrency prices.

B. Large Flows and Prices

We now specifically focus on the 1% of hours (95 out of 9,504 hours) with the largest Tether/Bitcoin Flow. Panel A of Figure 5 implements an event study of Bitcoin and other cryptocurrency prices around these high-flow events. The large flow hours occur at time -1 to 0 by construction. The results show that returns are large and negative between time -3 and -1. However, after the large flow, the pattern changes starting at time zero. The next hour returns are large at 80 basis points per hour, and returns are positive by 1.23% over the next three hours after the flow. Panel B shows sharp positive returns in the three-hour window after the flows for all six of the other major cryptocurrencies as well. We further examine the spillover in the cross-section of cryptocurrencies by constructing an exchange-level value-weighted return index of all coins other than Bitcoin using all other coin-BTC pairs for all exchanges in the sample. The altcoins listed on Bitfinex, Poloniex, and Bittrex have significantly larger Bitcoin denominated returns than the coins listed on other exchanges in the hours right after the flows (as shown in Table IAIV). Consistent with the effect being driven by Tether flows, the return is not different before the high flow periods.

We examine the results for the largest player, 1LSg. Figure IA12 focuses on the largest 1% of the 1LSg flows and finds that returns are positive by 1.27% over the next three hours, while it was -1.50 over the three hours before. We examine if this behavior is linked to a general increase in blockchain transactions by examining Bitcoin prices around the times with high flows from Bitfinex to non-1LSg Poloniex and Bittrex wallets or to other Tether exchanges, and we find no statistical or economic effect around these times.

Note that the only conditioning variable for these hours is lagged flows, and we do not condition on past returns, but the large negative returns preceding the flows seem to be consistent with the investors using a 'buying-the-dips' strategy. To see if a normally occurring reversal pattern and not the impact of the flows is driving the returns, we find hours in the sample that are the closest match to our 95 high-flow hours in terms of lagged returns in the previous three hours, but we do not condition on high flow of Tether. While the returns from time -3 to 0 are the same by construction, the returns in the three hours after are -0.06% and indistinguishable from zero (as shown in Figure IA13), indicating that the higher returns after time 0 are not due to a general price reversal or 'buying-the-dips' pattern in the market.

C. Is the Price Effect Economically Important?

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

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

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

We now perform the same analysis by focusing only on hours following the top 1% of 1LSg flows. From March 1, 2017 to March 31, 2018, excluding the top 1% of times with high lagged flow of Tether and Bitcoin though 1LSg accounts, the Bitcoin price only rises 216% percent. Hence, only 1% of the hours (95 of 9504) with the strongest 1LSg flows are associated with 55.0% of the rise of Bitcoin in the next hour. When removing the top 5% and 10% of hours, returns are 67.2% and 79.2% lower respectively (as shown in Table IAV). We also perform a bootstrap analysis for this account by replacing these 1% of hours with other randomly selected hours. Figure 7 shows that the simulated distribution of Bitcoin

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

[30] Ethereum, for example, experienced nearly a 2400% return during this period, while if the Tether-related hours were excluded it would have alternatively experienced around a 900% return.

returns averages to 221% and in none of the 10,000 simulations the return is close to the actual return. The return distributions when replacing the hour following the top 5 and 10% of 1LSg flows are also considerably to the left of the actual returns and indicate that the observed patterns are unlikely due to chance.

To test if the high-flow return relationship is a general result of extreme market events reflected in the blockchain data, we also perform simulations in Figure IA14 where we remove the top 1, 5 and 10% of net flows from Bitfinex to other Poloniex and Bittrex addresses. There seems to be weak evidence that the extreme non-1LSg flows have some effects on prices for the top 1% of hours, but not the top 5 and 10%. For the net Tether/Bitcoin flows associated with other main five Tether-based exchanges (Binance, HitBTC, Huobi, Kraken, and OKEx) removing the top 1, 5 or 10% of the flows has no effect on simulated Bitcoin prices.

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

Note that this finding has some caveats. The effect only considers the hourly periods with extreme flows. Measuring such findings over other intervals will be less precise and more difficult, but the flow 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, though it seems feasible that the issuers could sell Bitcoin through channels with considerably less price impact. If the purchased Bitcoin is not permanently liquidated for dollars, then the inflationary effect due to increasing the money supply can be persistent. Overall, although it is difficult to fully assess the exact price impact of Tether, these back-of-the-envelope calculations demonstrate that the effect is plausibly large.

D. Negative Serial Correlation in Bitcoin Prices

The flows of Tether and Bitcoin follow a very specific pattern: accounts on Bitfinex buy 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.

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

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

[32]Table IAVII shows that the results are entirely driven by top hours of 1LSg flows and top

volatility shows that the results cannot be explained by the possibility of larger return reversals during periods of high volatility [Nagel (2012)].

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

IV. Is Tether Pushed or Pulled?

The results in the previous section are consistent with a sizable price impact of Tether. We will further examine possible predictions of the pushed hypothesis (H2D and H2E) as well as variants of the pulled hypothesis to shed light on the nature of this price impact.

A. Currency Flows Around Round Price Thresholds

Following Tversky and Kahneman (1974), there is a large literature demonstrating the importance of price anchoring for a variety of assets including stocks. Shiller (2000) 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 prices to the round-number threshold. Such an anchor could

hours of other flows are not related to the reversal. For example, every 1% drop in Bitcoin prices is followed by 52 basis points reversals in the next hour if accompanied by top 1% of 1LSg flows.

be specifically important for cryptocurrency prices where the underlying value cannot be gauged through fundamentals.

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, upon observing a technical support at the threshold, to purchase as well. This could also be consistent with recent theories that suggest higher participation of users and investors make Bitcoin more appealing to other users/investors due to the network effect [Cong, Li, and Wang (2019b) and Sockin and Xiong (2018)].

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

Table V, Panel A, formally tests whether the Tether/Bitcoin flow is different below and above the round price thresholds. The dependent variable is the net

Tether/Bitcoin flow, and the independent variable is a dummy that takes the value of one if Bitcoin price is in the $50 bandwidth below the round multiples of $500 and zero if in the $50 bandwidth above. The results show that purchasing below the threshold is economically and statistically significant only after authorization.

Panel B of Table V examines the disaggregated flows following authorization and finds that the higher flow below round-number thresholds is driven by the 1LSg accounts with a t-statistic of 3.71. Other accounts at Bittrex and Poloniex as well as other Tether exchanges do not have statistically or economically significant flows below the threshold. Panel C shows that there is also no such pattern in non-authorization periods. Overall, the evidence indicates that the flow below thresholds is driven by the 1LSg account, and only after authorization; the pattern is not typically observed in the market.

We now examine what effect, if any, the inflow of Tether below the threshold might exert on Bitcoin returns. Panel A of Table VI estimates a regression of average 3-hour future returns on the lagged round-number threshold dummy. On days following Tether authorization, when prices are below the round threshold, the future hourly return is 20.61 basis points higher on average. The return effect is only present in periods of both authorization and negative lagged returns.

Note that it is possible that the Bitfinex-related wallets are trading around round-number thresholds simply 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 [Bhattacharya, Holden, and Jacobsen (2012)]. The large purchasing by 1LSg accounts provides a coherent explanation as to how prices can be pushed above the thresholds. Additionally, if other traders see such large purchasing, they might join the buying either due to triggered technical trading indicators or through the perception of a stronger network effect [Cong, Li, and Wang (2019b) and Sockin and Xiong (2018)].

We next use the discontinuity around round-number thresholds as an instrument to identify the effect of Tether on Bitcoin prices by estimating a fuzzy regression discontinuity design. 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 authorization. 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. The exclusion restriction is supported by the fact that on days apart from Tether authorization, neither the flows nor the future Bitcoin returns are different below and above the thresholds, and that flows associated with no other accounts are different below and above the thresholds.

Panel B of Table VI estimates a two-stage least squares regression of 3-hour future Bitcoin returns on the lagged net Bitcoin/Tether flow, where the flow is instrumented using the cutoff dummy. The reported Wald F-statistics show that the first stage regressions are strong, suggesting a strong instrument. The second stage regression indicates that for 100 Bitcoin purchased by Bitfinex, the average hourly Bitcoin return in the next 3 hours goes up by 26.42 basis points. The effect is 33.88 basis points if the sample is limited to days after authorization, and 45.34 basis points after authorization and lagged negative returns. The effect is insignificant for periods after authorization but with positive lagged returns. In Panel C we perform the same analysis except instrumenting for the 1LSg flows rather than the aggregate Poloniex and Bittrex flows, but we also control for the flows associated with other accounts on Poloniex and Bittrex as well as on other exchanges. The results are economically larger with a 100 Bitcoin flow by 1LSg associated with an average hourly Bitcoin return in the next 3 hours of 65.44 basis points after authorization. This result highlights a very strong effect of 1LSg flows on Bitcoin prices, especially on days after Tether authorization.

B. *Demand from Investors with Fiat Currency?*

B.1. End-of-the-Month Returns

The previous sections establish that flow of Tether explains a sizable increase and predictable trading patterns in Bitcoin prices. These patterns are potentially consistent with fiat purchases of Tether through Bitfinex, but the purchases and trading would need to be driven by one large player who moved over two billion dollars into Tether through the Bitfinex exchange. Alternatively, if the printed Tether is not backed by dollars and does not reflect the inflow of real capital into the crypto space, such increases in Bitcoin prices can largely reflect an inflation caused by printing unbacked money. In this section, we examine the backing of Tether by borrowing from the intermediary asset pricing literature, specifically Du, Tepper, and Verdelhan (2018) and He and Krishnamurthy (2018), 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.[33] If Tether does not maintain a full reserve daily

[33] As announced on https://tether.to/tether-update/, audits were made publicly available on Tether.to. Tether stated that they planned to be audited by a non-Chinese firm, but it eventually canceled the audit due to "the excruciatingly detailed procedures." It was stated by Bitfinex's

but does seek to release audit statements at the EOM to signal a full reserve to investors, there could be a negative selling pressure on Bitcoin to convert it to USD reserves before the EOM as hypothesized in H2E. The EOM selling effect should be related to the Tether issuance. Moreover, if cash needs to be raised through liquidating other major cryptocurrencies, as they also showed large price increase around Tether flows, they should show an EOM effect as well, which we examine by constructing value-weighted returns of the top five cryptocurrency returns.

Figure 9 depicts Bitcoin daily returns at EOM by dividing the months in the sample into four quantiles based on their monthly Tether issuance.[34] The blue bars show the raw EOM returns, and the red bars benchmark the EOM returns by subtracting the average return in four days before and four days after. There is a clear 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.

However, we caveat the relation by noting that there are only 25 months in our sample, and the two months with the largest Tether issuance, December 2017 and January 2018, exhibit a strong end-of-the-month effect. Because of the relatively

chief technology officer in an interview about lack of audit on Tether that "[w]hat we want to do is not [audit] the bank balances as of now, but we want to demonstrate to the community that we had the money *at the end of every single month*, since a reasonable date like January 2017 and on."

[34]Cryptocurrencies officially trade on UTC timestamp and daily prices close at midnight UTC time, when business 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.

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

Table VII further examines this result. Column (1) shows that the EOM return is 2.3% less than returns in the four days before and after the EOM. Columns (2) and (3) indicate that there is no effect in months without Tether issuance, but the EOM return is 3.8% lower in months with Tether issuance (t-statistic of 3.65). Finally, Column (4) interacts the EOM dummy with the magnitude of the monthly Tether issuance and shows that for a one-standard deviation higher Tether issuance, the EOM return is 2.2% more negative. Column (5) statistically tests the plot in Figure 9 and shows that relative to months with zero issuance, months with low, medium, and high issuance have a negative EOM return of 1.9%, 3.1%, and 6.1% respectively, all statistically significant. As a sensitivity check in Columns (6-8), we exclude the top two months of flow. As expected, the results are weaker but still statistically and economically significant.

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

As a one-period example not at EOM, we also noticed that Tether released a

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

limited audit of a snapshot of their cash balance as of September 15, 2017. Tether later fired the auditor. Prices dropped 25% from September 12, 2017 to the audit day of September 15, 2017 (as shown in Figure IA15).

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

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

B.2. Flows and the 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. If the demand for Tether mainly comes from investors who hold dollars and seek to invest in Bitcoin, the greater demand could translate into a higher market rate for the Tether-USD pair. Kraken was the most active market-based venue for exchanging Tether for dollars in 2017, although the market volume of the pair was less than 1% of the Bitcoin-Tether volume. The rate on Kraken often stays close to one over our sample period from March 1, 2017 to March 31, 2018 but has a standard deviation of 2%. If part of the demand for Tether spills over to Kraken, one would expect changes in the Tether-USD rate to be related to the flow of Tether.

Panel A of Table VIII 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. Similarly, Panel B examines Bitcoin flow and shows that the corresponding flow of Bitcoin back is highly sensitive to BTC-USD rates but bears no relationship with the Tether-USD pair. We further examine this relationship by constructing different proxies for the Tether price using value-weighted and equally-weighted Tether-USD rates across all available exchanges as well as constructing a synthetic rate using Bitcoin prices on Bitfinex versus dollar exchanges. The results using these proxies instead of the Kraken Tether-USD rate are similar (Tables IAXI, IAXII, and IAXIII). We also examine results for the 1LSg account and other accounts on Tether exchanges and find similar results (as shown in Table IAXIV).

Another possibility is that the overall price difference between Tether and USD exchanges is driving the flow. 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 between Tether and USD exchanges. We then estimate a regression of Tether and Bitcoin flows on the spread and the average returns. Panel C of Table VIII shows that the flows are not sensitive to the spreads. Moreover, Panel C of Table IAXIV shows that the flows to 1LSg and other Poloniex and Bittrex accounts have no relationships with the spread, however, the flows to Binance and Huobi are positively related to the spread. This finding suggests that when the BTC-Tether pair trades at a higher discount relative to BTC-USD, capital flow to Binance and Huobi increases to buy Bitcoin at a lower price. This indicates that Tether is used in arbitrage activities, but the 1LSg activities are not driven by these arbitrage proxies.

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

C. *Flows and Bitcoin Prices across Exchanges*

Tether may facilitate cross-exchange arbitrage among Tether exchanges. In particular, imagine that Bitcoin prices increase on Bitfinex, but Bitcoin prices on Poloniex have a delay to adjust. Traders can respond to the spread by sending Tether to Poloniex and buying undervalued Bitcoins. This cross-exchange arbitrage also necessitates a flow of Tether back to Bitfinex when Bitfinex prices are lower than Poloniex prices. However, as shown in Figure 1, this reverse flow pattern is not commonly observed. On the other hand, the flow of printed Tether through Bitfinex might also cause prices to inflate first on Bitfinex before the Tether moves to other exchanges.

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

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

V. Conclusion

Periods of rapid price appreciation are historically associated with innovation and growth but also with nefarious activities that lead to misallocation of capital. The 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 and understand the role of central monetary entities in a cryptocurrency world. We examine whether the growth of the largest pegged cryptocurrency, Tether, is primarily driven by investor demand or is supplied to investors as a scheme to inflate cryptocurrency prices.

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

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

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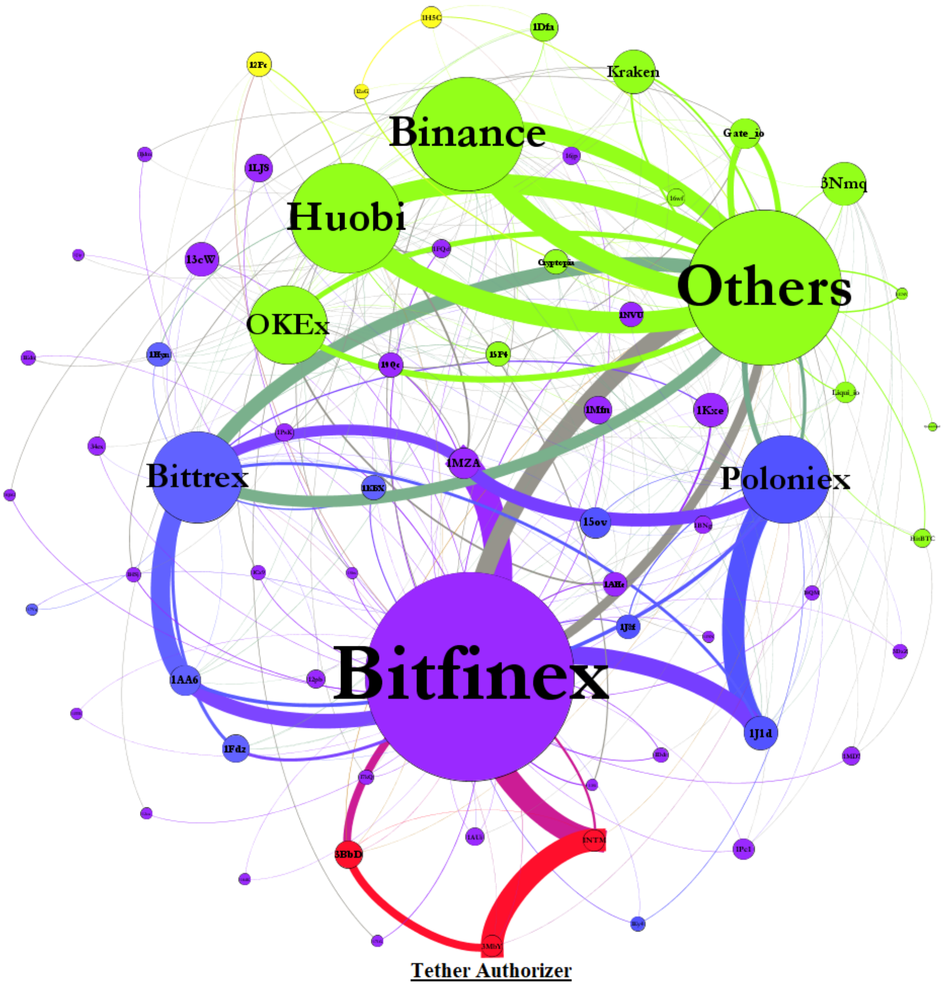
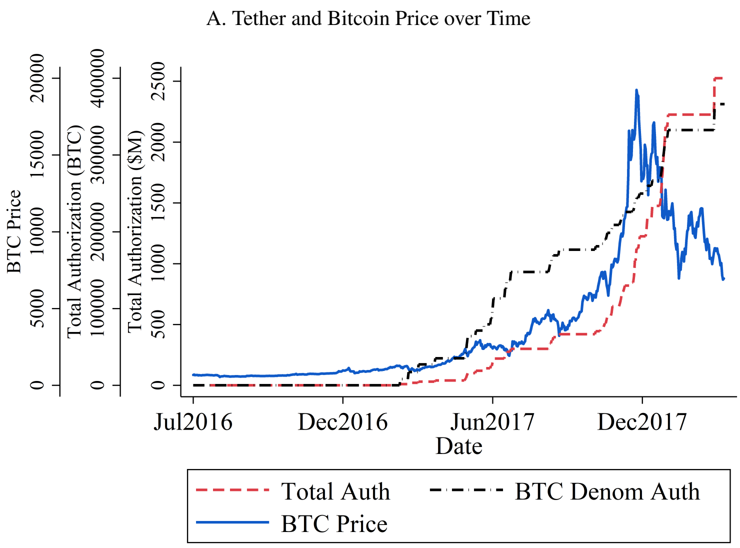


Figure 1. Aggregate Flow of Tether between Major Addresses. This figure shows the aggregate flow of Tether between major exchanges and market participants from Tether genesis block to March 31, 2018. Tether transactions are captured on the Omni Layer as transactions with the coin ID 31. The data include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



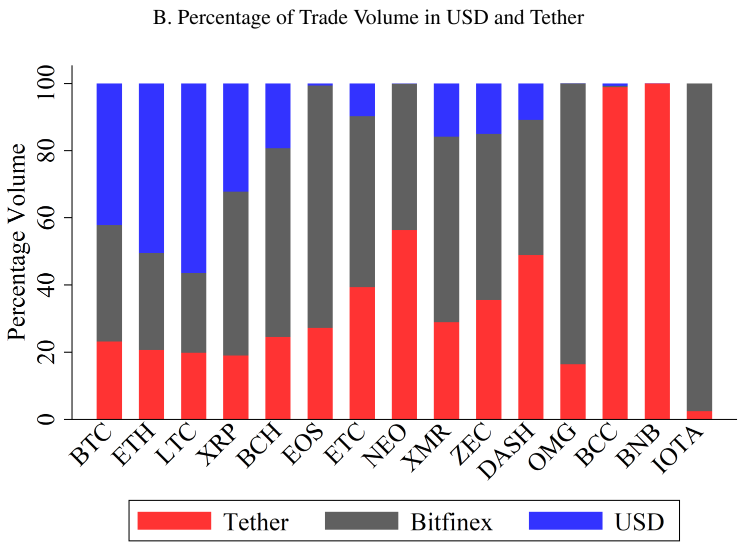


Figure 2. Tether Authorization and Bitcoin Price over Time and Trade Volume in Dollar and Tether. Panel A shows the cumulative authorization of Tether and Bitcoin price over time. The red dashed line shows cumulative authorization in million Tether tokens. The black dashed line shows Tether cumulative authorization denominated in contemporaneous Bitcoin price. The blue line shows Bitcoin price. Authorization is defined as transactions with transaction type "Grant Property Tokens" on Tether blockchain. 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 aggregate trade volume across exchanges reported in *CoinAPI* data over the same period. The blue bars show the percentage of volume traded against USD, the red bars show the percentage against Tether, and the gray bars show the percentage against USD/Tether on the Bitfinex exchange.

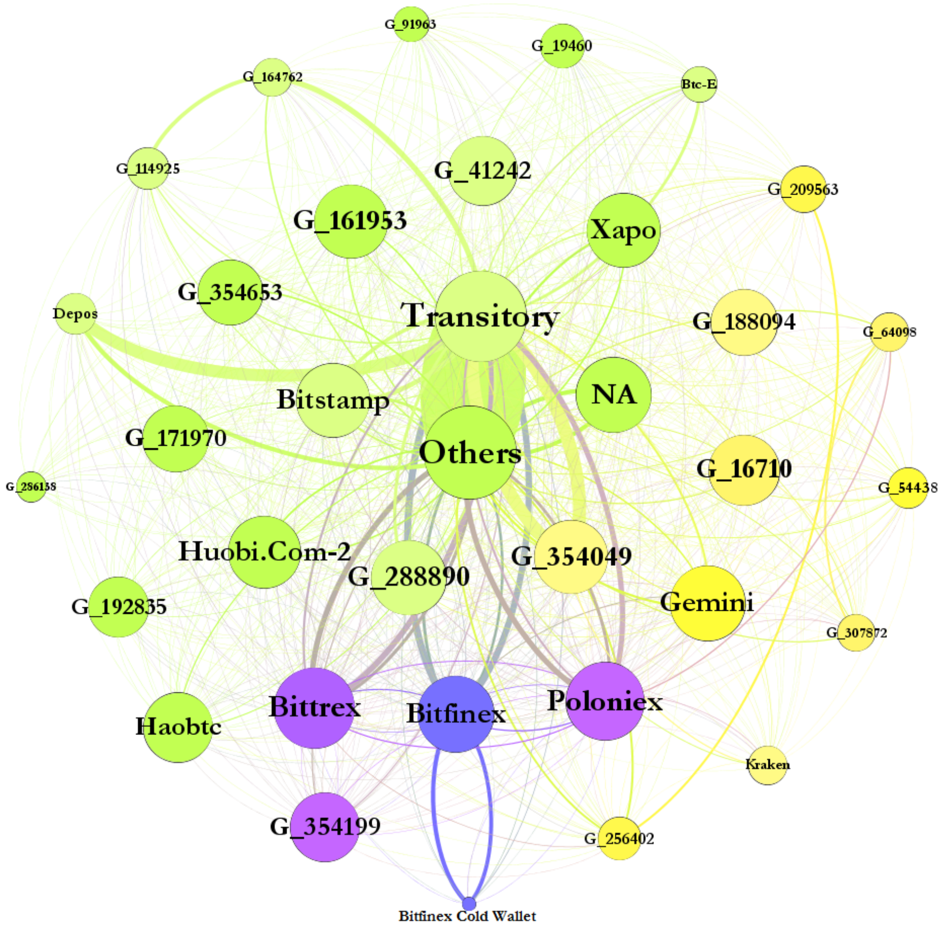


Figure 3. Aggregate Flow of Bitcoin between Major Addresses. This figure shows the aggregate flow of Bitcoin between major exchanges and market participants from March 1, 2017 to March 31, 2018. Groups of addresses are clustered by finding the connected component of the same input relation on the Bitcoin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

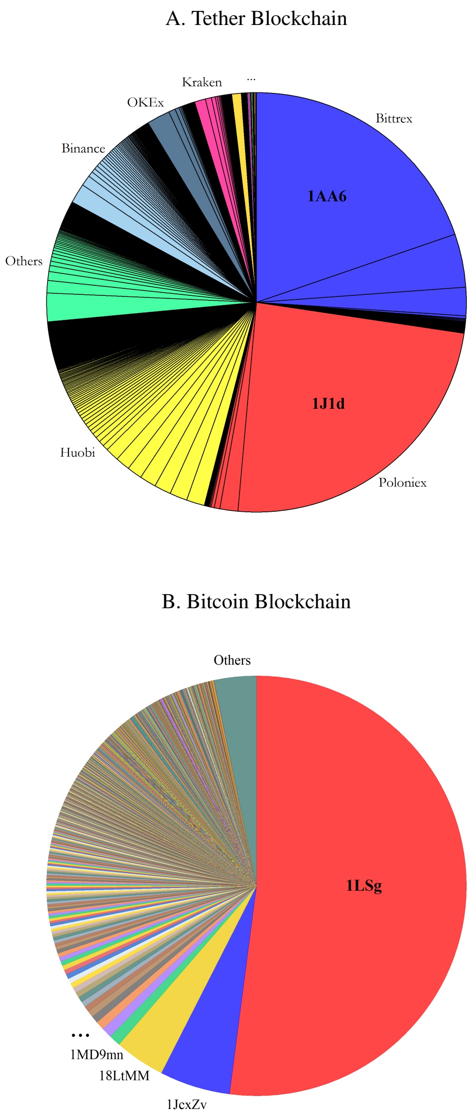


Figure 4. Top Accounts Associated with the Flow of Tether from and Bitcoin to Bitfinex. Panel A shows the largest recipients of Tether from Bitfinex recorded on Tether blockchain between March 1, 2017 to March 31, 2018. Exchange wallet identities are obtained from the Tether rich list. Moreover, intermediary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

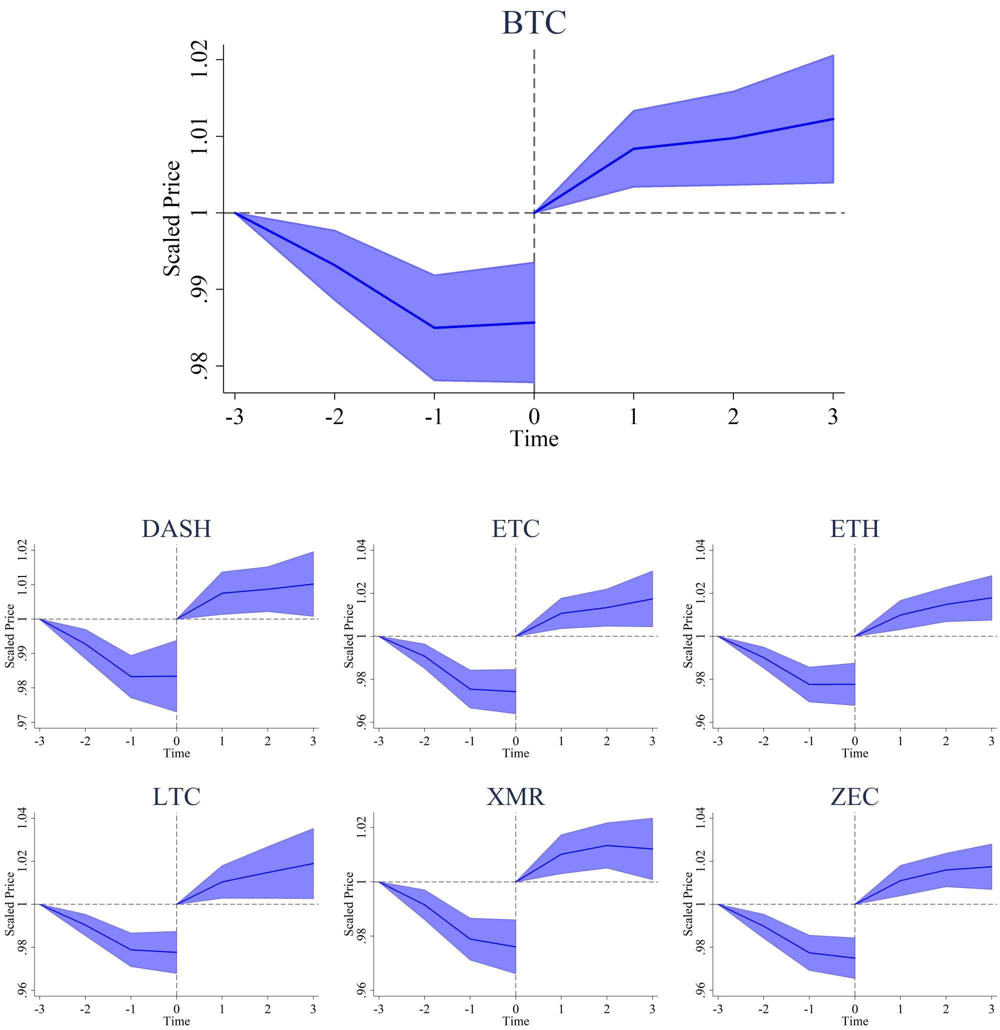


Figure 5. Prices of Bitcoin and Other Cryptocurrencies around High-Flow Events. Panel A shows Bitcoin prices three hours before and after the top 1% of high-flow hours to Poloniex and Bittrex. Prices are scaled to one at time -3 before the event and at time zero after the event. Scaled prices are averaged across the events. The high-flow events are defined as top 1% of hours with high net average flows of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin back from Poloniex and Bittrex to Bitfinex in the prior hour, meaning high flows occur between time -1 and time 0. Panel B shows similar results for other major cryptocurrencies.

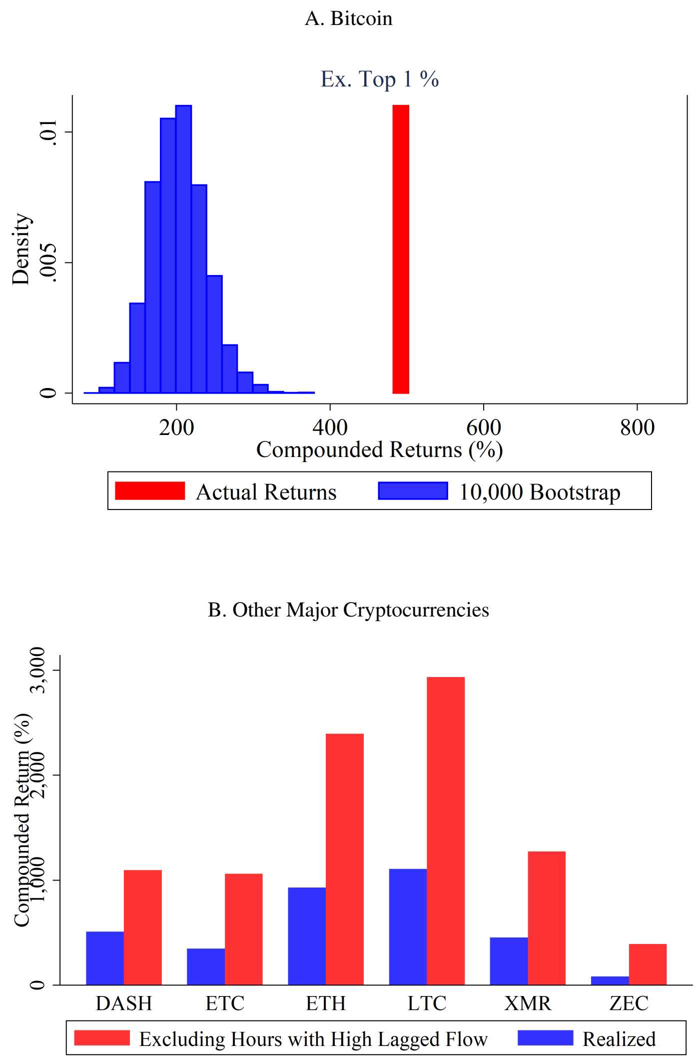


Figure 6. Predictive Effect of High-Flow Hours on Cryptocurrencies Returns. The red bar in Panel A shows the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018. The blue bars show the distribution of the returns if the top 1% hours with high lagged flow of Tether and Bitcoin are replaced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

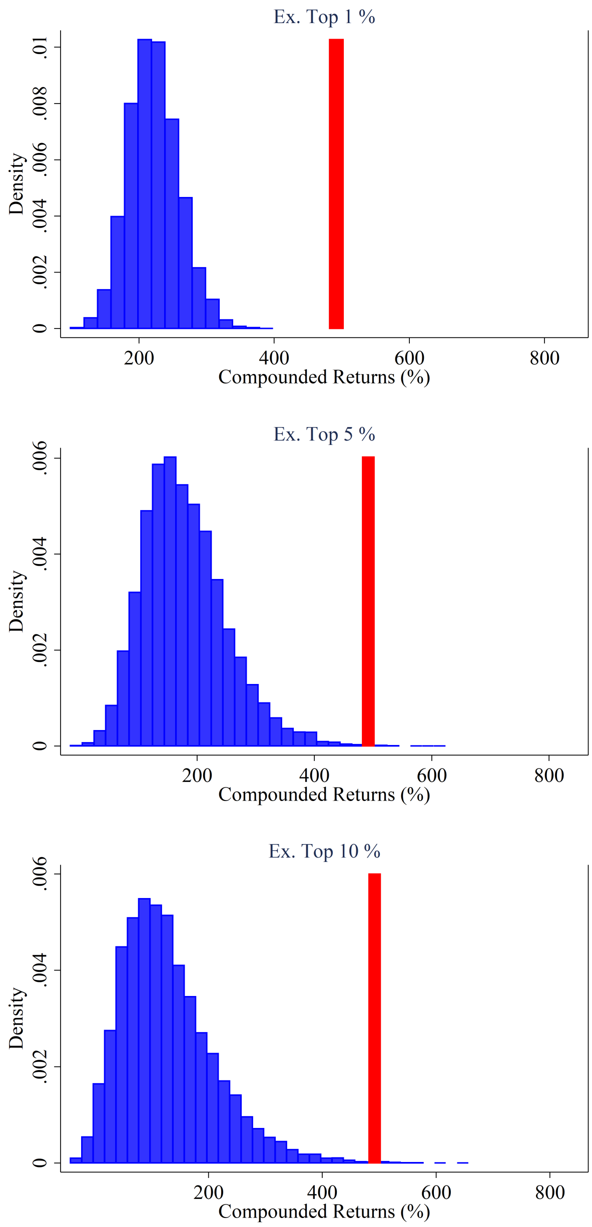


Figure 7. Predictive Effect of 1LSg High-Flow Hours on Bitcoin Returns. The red bars show the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018. The blue bars show the distribution of the returns if the top hours with high lagged 1LSg flow are replaced with a random sample of returns in other hours, bootstrapped 10,000 times. The high 1LSg flow hours are the top 1% of hours with high 1LSg flows as defined in the Internet Appendix IA.A. The return distribution in the top panel replaces top 1% of high lagged 1LSg flow hours with a random sample of returns in other hours, and the middle and bottom panels replace top 5 and 10% respectively.

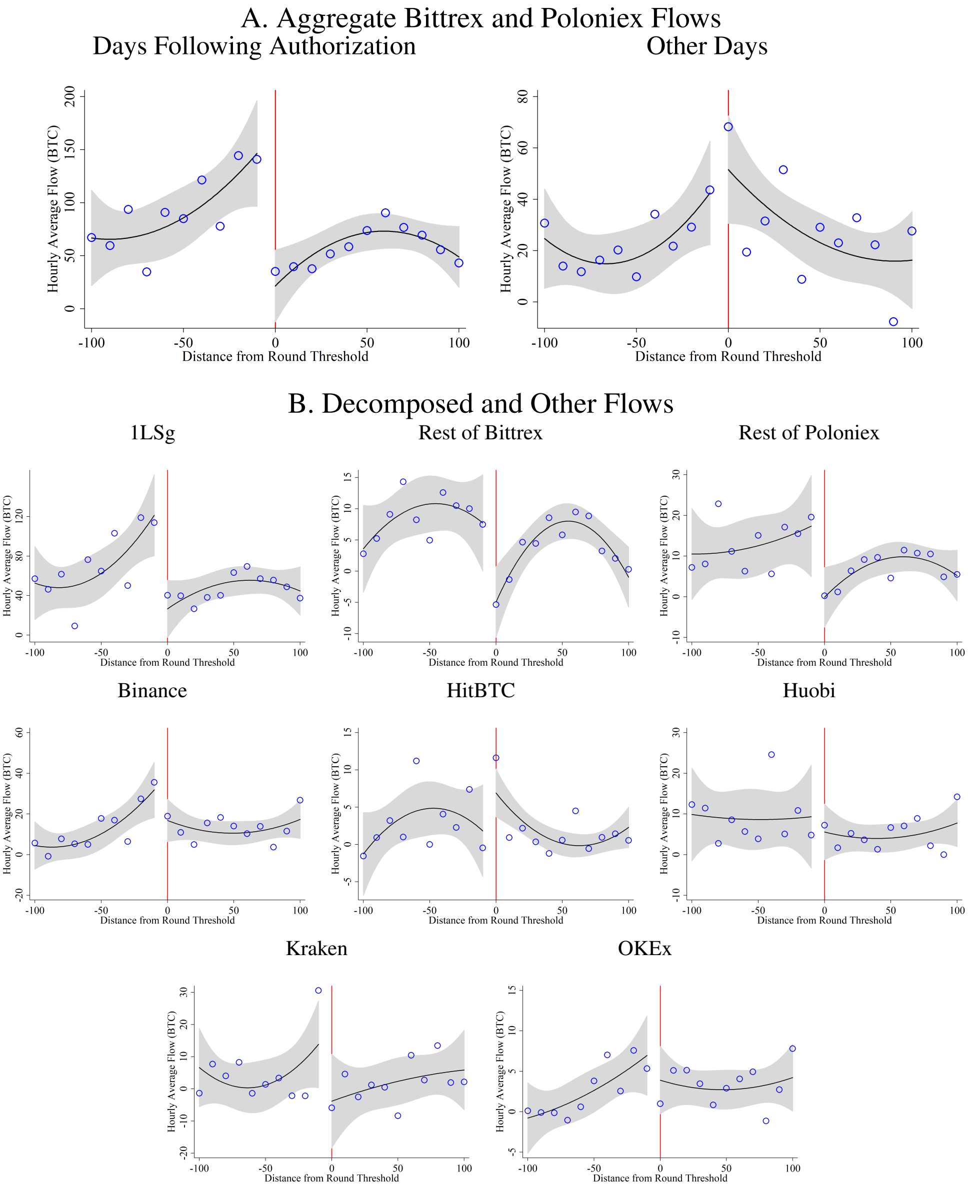


Figure 8. Flows around Round Number Thresholds. This figure shows the average net hourly flows of Tether from Bitfinex to two major Tether exchanges, Poloniex and Bittrex, and Bitcoin from these exchanges to Bitfinex around round number thresholds of Bitcoin prices. The Bitcoin prices are based on hourly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

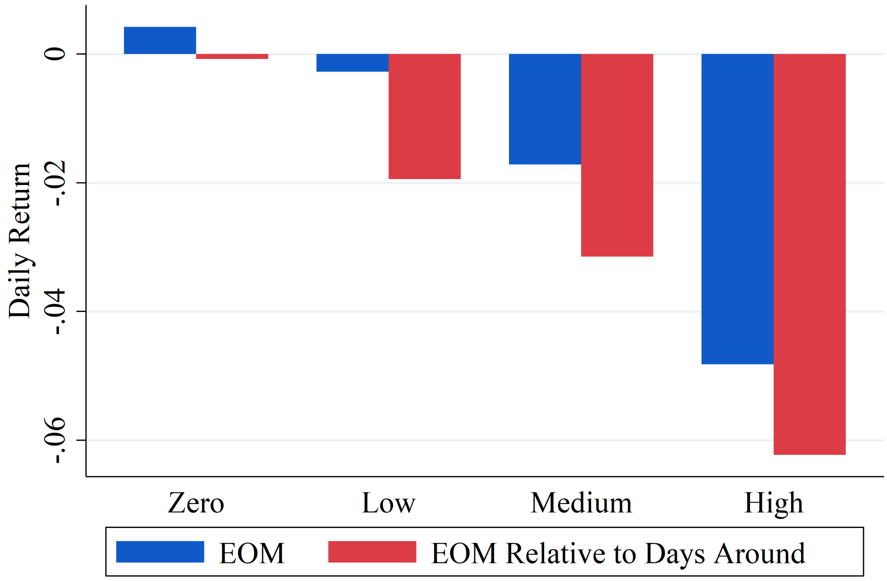


Figure 9. End-of-the-Month Returns and Quantiles of Tether Issuance. This figure shows end-of-the-month (EOM) daily Bitcoin returns for different quantiles of monthly Tether issuance. Four quantiles of Tether issuance are defined based on total Bitcoin-denominated Tether issuance each month. The issuance is calculated as the aggregate monthly Bitcoin-denominated flow of Tether from the Tether treasury to Bitfinex. All months with zero issuance are included in one group, and the other months are divided into three quantiles. The EOM return is defined as the daily return on the second to last day of the month closing at midnight UTC time. 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 USD and Tether across exchanges reported in *CoinAPI* data between March 1, 2017 and March 31, 2018, and the top exchanges are those with the highest aggregate volume for these major cryptocurrencies. Panel A shows the total volume for each cryptocurrency on each exchange in billions of dollars from March 1, 2017 to March 31, 2018 using data from *CoinAPI*. Tether-based exchanges are marked with a star. 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 using price data from the most liquid exchange for each altcoin between March 1, 2017 and March 31, 2018. 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)

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

B. Correlations

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

C. Autocorrelations

Coin	1-Hour: Coefficient	t-stats	3-Hour: Coefficient	t-stats	5-Hour: Coefficient	t-stats
BCC	-0.127	-3.960	-0.166	-6.412	-0.260	-6.800
BCH	-0.039	-1.459	-0.033	-1.136	-0.064	-1.870
BNB	-0.000	-0.827	0.002	1.476	0.004	3.850
BTC	-0.063	-4.089	-0.072	-4.414	-0.062	-2.985
DASH	-0.073	-4.124	-0.052	-2.822	-0.065	-3.540
EOS	-0.075	-2.448	-0.052	-1.376	-0.072	-1.300
ETC	-0.054	-3.182	-0.071	-3.807	-0.031	-1.383
ETH	-0.053	-3.069	-0.043	-2.154	-0.042	-1.780
IOTA	-0.202	-6.775	-0.241	-6.820	-0.224	-6.022
LTC	-0.009	-0.341	-0.047	-1.356	-0.018	-0.476
NEO	-0.081	-3.657	-0.064	-2.341	-0.069	-2.263
OMG	-0.068	-3.745	-0.039	-1.677	-0.039	-1.319
XMR	-0.075	-3.243	-0.067	-3.391	-0.066	-2.877
XRP	-0.104	-3.348	-0.042	-1.374	0.049	1.035
ZEC	-0.077	-3.782	-0.063	-2.446	-0.098	-3.387

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:

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

where R_t is the hourly return of an equally-weighted price index aggregating Bitcoin prices on Tether exchanges Bitfinex, Poloniex, Bittrex, Binance, HitBTC, Huobi, and OKEx and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex. The control variables include lagged returns, volatility calculated using hourly returns in the previous 24 hours, and the interaction of lagged returns and volatility. Column (1) shows the results for times when a Tether authorization occurred in the previous 72 hours and Column (2) for other times. Columns (3) and (4) show the results separately for observations with lagged negative and positive returns. Column (5) shows the results conditioning on both 72 hours after Tether authorization and negative lagged return. Panel B estimates the same regression where the flow is decomposed into a component associated with 1LSg accounts and a component for the flows to other Poloniex and Bittrex accounts (described in detail in Appendix IA.A). It also controls for the net average flows of Tether and Bitcoin to other Tether recipient exchanges, Binance, HitBTC, Huobi, Kraken, and OKEx. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Regression of Return on Lagged Flow

	(1) Auth	(2) NoAuth	(3) L.Ret<0	(4) L.Ret>0	(5) L.Ret<0_Auth
Lag PLX BTX Flow	3.855*	-0.354	2.694*	-1.100	8.134**
	(2.30)	(-0.48)	(2.18)	(-1.20)	(2.93)
LagRet	-0.00600	-0.00985	0.0634*	-0.0518	0.0897
	(-0.18)	(-0.57)	(1.97)	(-1.72)	(1.46)
Volatility	103.9	97.00	-52.33	-70.32	-102.3
	(1.17)	(1.38)	(-0.67)	(-0.89)	(-0.70)
Volatility*Lag Ret	-0.343	-0.289	-1.443***	0.609	-1.660**
	(-0.94)	(-1.14)	(-3.40)	(1.58)	(-2.85)
Constant	-8.071	-1.387	4.261	5.105	2.062
	(-1.44)	(-0.46)	(1.26)	(1.50)	(0.24)
Observations	2645	6856	4488	5009	1258
Adjusted R2	0.012	0.005	0.020	0.001	0.045

B. Regression of Return on Lagged Decomposed Flow

	(1) Auth	(2) NoAuth	(3) L.Ret<0	(4) L.Ret>0	(5) L.Ret<0_Auth
Lag 1LSg Flow	4.240*	-0.484	2.379*	-1.300	8.206***
	(2.37)	(-0.57)	(1.97)	(-1.24)	(3.61)
Lag Other PLX BTX Flow	5.531	-0.513	4.602	-0.372	12.22
	(1.20)	(-0.26)	(1.23)	(-0.16)	(1.32)
Lag Other Flow	-6.483*	1.599	-0.514	0.322	-8.328*
	(-2.36)	(1.43)	(-0.34)	(0.25)	(-2.38)
LagRet	-0.00562	-0.0108	0.0650*	-0.0523	0.0958
	(-0.17)	(-0.63)	(2.01)	(-1.73)	(1.57)
Volatility	121.7	94.23	-51.05	-71.01	-84.21
	(1.36)	(1.33)	(-0.65)	(-0.90)	(-0.57)
Volatility*Lag Ret	-0.346	-0.281	-1.457***	0.613	-1.717**
	(-0.95)	(-1.10)	(-3.42)	(1.59)	(-2.95)
Constant	-8.621	-1.334	4.203	5.108	1.784
	(-1.53)	(-0.44)	(1.24)	(1.50)	(0.21)
Observations	2645	6856	4488	5009	1258
Adjusted R2	0.014	0.005	0.020	0.001	0.049

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

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

where R_t is hourly return using price data from the most liquid exchange for each cryptocurrency between March 1, 2017 and March 31, 2018 and $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex. The control variables include lagged returns, volatility calculated using hourly returns in the previous 24 hours, and the interaction of lagged returns and volatility. Major cryptocurrencies are selected based on the criteria in Table I, conditional on being listed on at least one of the major Tether exchanges as of the beginning of March 2017. Panel A 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 authorization 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 Authorization

Coin	Coefficient	t_stat	N
DASH	6.16	3.26	2645
ETC	7.54	3.00	2645
ETH	6.29	3.10	2645
LTC	6.17	1.83	2645
XMR	4.80	2.19	2645
ZEC	5.65	2.46	2645

B. Other Days

Coin	Coefficient	t_stat	N
DASH	0.59	0.61	6833
ETC	-0.57	-0.52	6833
ETH	0.54	0.58	6833
LTC	1.32	1.27	6833
XMR	0.13	0.12	6833
ZEC	0.50	0.38	6833

C. Following Negative Returns

Coin	Coefficient	t_stat	N
DASH	2.92	1.69	3992
ETC	2.38	1.93	4679
ETH	2.36	1.70	4544
LTC	3.74	2.57	4668
XMR	2.74	1.69	4614
ZEC	3.12	2.00	4785

D. Following Positive Returns

Coin	Coefficient	t_stat	N
DASH	3.47	2.26	3985
ETC	1.92	0.99	4732
ETH	1.65	1.27	4878
LTC	1.99	0.94	4581
XMR	0.59	0.48	4752
ZEC	1.26	0.73	4577

E. Following Negative Returns-Authorization

Coin	Coefficient	t_stat	N
DASH	10.19	3.26	1063
ETC	8.84	3.00	1271
ETH	8.86	3.10	1246
LTC	8.54	1.83	1293
XMR	7.44	2.19	1244
ZEC	7.89	2.46	1293

Table IV. Bitcoin Return Reversals and 1LSg Flow. This table shows OLS estimates for autocorrelation of Bitcoin returns:

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

where R_t is the hourly return of an equally-weighted price index aggregating Bitcoin prices on Tether exchanges, $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex, and the control variables include lagged returns, volatility calculated using hourly returns in the previous 24 hours, and the interaction of lagged returns and volatility. Panel A shows the results for aggregate net flows to Poloniex and Bittrex and Panel B decomposes the flows into 1LSg flows and the rest of Poloniex and Bittrex accounts and controls for the flows into other Tether exchanges, Binance, HitBTC, Huobi, Kraken, and OKEx. The flow variables are standardized by subtracting the mean and dividing by the standard deviation. Panel C estimates a similar regression for dummy variables that take the value of one for top 1%, 5%, and 10% of hours with high lagged flows and volatility. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Using Aggregate Flows to PLX and BTX

	All Sample	Neg Lagged Return	Pos Lagged Return
Lag Ret	-0.0198	0.0004	-0.0420
	(-0.62)	(0.01)	(-0.69)
Lag Flow	0.0003	-0.0002	0.0001
	(1.68)	(-0.53)	(0.34)
Lag Flow × Lag Ret	-0.0326**	-0.0669**	-0.0073
	(-2.73)	(-2.67)	(-0.36)
Lag Volatility	0.0093	0.0060	0.0100
	(1.38)	(0.49)	(0.88)
Lag Volatility × Lag Ret	-0.3961	-0.5918	-0.2719
	(-0.98)	(-0.85)	(-0.37)
Constant	-0.0002	-0.0000	-0.0001
	(-0.67)	(-0.07)	(-0.29)
Observations	9503	4488	5011
R^2	0.008	0.012	0.002
Adjusted R^2	0.007	0.011	0.001

B. Using Decomposed Flows

	All Sample	Neg Lagged Return	Pos Lagged Return
Lag Ret	-0.0125	0.0166	-0.0320
	(-0.38)	(0.27)	(-0.52)
Lag 1LSg Flow	0.0003	-0.0001	-0.0000
	(1.71)	(-0.19)	(-0.02)
Lag 1LSg Flow × Lag Ret	-0.0280*	-0.0545*	0.0050
	(-2.23)	(-2.17)	(0.22)
Lag Volatility	0.0094	0.0060	0.0110
	(1.40)	(0.49)	(0.97)
Lag Volatility × Lag Ret	-0.4986	-0.7798	-0.4123
	(-1.20)	(-1.11)	(-0.55)
Lag PLX BTX Flow × Lag Ret	-0.0200	-0.0272	-0.0153
	(-1.61)	(-1.41)	(-0.95)
Lag Other Flow × Lag Ret	0.0255	0.0404	0.0094
	(1.81)	(1.63)	(0.56)
Constant	-0.0002	0.0000	-0.0002
	(-0.71)	(0.01)	(-0.42)
Observations	9503	4488	5011
R^2	0.009	0.014	0.003
Adjusted R^2	0.008	0.012	0.001

C. Using the Top Percentile Flow and Volatility (Lagged Neg Returns)

	Top 1%	Top 5%	Top 10%
Lag Ret	-0.0583	-0.0169	-0.0299
	(-1.90)	(-0.49)	(-0.78)
Lag High Flows	0.0041	0.0003	-0.0011
	(0.72)	(0.19)	(-0.85)
Lag High Flows=1 × Lag Ret	-0.6091*	-0.2720*	-0.1756
	(-2.56)	(-2.53)	(-1.93)
Lag High Vol	0.0167*	-0.0018	0.0008
	(2.53)	(-0.73)	(0.51)
Lag High Vol=1 × Lag Ret	0.2014	-0.1192	-0.0183
	(1.09)	(-1.42)	(-0.26)
Constant	-0.0000	0.0003	0.0002
	(-0.04)	(1.07)	(0.70)
Observations	4488	4488	4488
R^2	0.024	0.014	0.008
Adjusted R^2	0.023	0.013	0.007

Table V. Flow of Coins around Round Thresholds 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 hour, falls into the $50 price bucket below a $500 price multiple and zero if it is in the $50 bucket above such a multiple.

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

Panel B estimates the same regression for the net average flows into 1LSg accounts, the rest of Poloniex and Bittrex accounts, and the other Tether exchanges, Binance, HitBTC, Huobi, Kraken, and OKEx. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Flow Around Round Thresholds

	All	Auth	NoAuth
Below Round Cutoff	14.75*	60.83***	0.221
	(2.02)	(3.52)	(0.03)
Constant	36.26***	45.55***	31.93***
	(8.52)	(5.19)	(6.78)
Observations	1603	464	1139
Adjusted R^2	0.002	0.028	-0.001

B. Flows to Different Exchanges - Days Following Authorization

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

C. Flows to Different Exchanges - Other Days

	1LSg	Oth BTX	Oth PLX	Binance	HitBTC	Huobi	Kraken	OKEx
Below Round Cutoff	5.815	-2.825	-2.768	-1.085	-0.835	-0.476	0.207	2.043
	(0.89)	(-1.33)	(-1.47)	(-0.47)	(-1.23)	(-0.12)	(0.17)	(0.71)
Constant	19.93***	4.982***	7.015***	3.442*	0.761*	4.123	-0.00519	-0.542
	(4.99)	(3.43)	(5.43)	(2.01)	(2.29)	(1.32)	(-0.01)	(-0.22)
Observations	1139	1139	1139	731	1139	1139	1139	483
Adjusted R^2	-0.000	0.001	0.001	-0.001	0.001	-0.001	-0.001	-0.001

Table VI. Effect of Flow on Returns around Round Thresholds of Bitcoin Price. Panel A estimates a regression of average 3-hour Bitcoin returns on the $BelowRoundCutoff$ dummy. Panel B reports the results for the second stage estimates from a two-stage least squares regression of Bitcoin returns on flows:

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

where in the first stage, $\hat{Flow}_t$ is instrumented using a dummy variable that takes the value of 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 authorization and zero if within the $50 bucket above or in days apart from Tether authorization. Panel C shows the same results as in Panel B but where the flows are decomposed into 1LSg and the rest of Poloniex and Bittrex, and it also controls for aggregate net flows to other Tether exchanges, Binance, HitBTC, Huobi, Kraken, and OKEx. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Return Around Round Thresholds

	Auth	NoAuth	Auth_L.Ret<0	Auth_L.Ret>0
Below Round Cutoff	20.61*	-3.397	32.87*	11.91
	(2.42)	(-0.74)	(2.58)	(1.29)
Constant	1.765	5.466	11.75	-7.205
	(0.33)	(1.87)	(1.39)	(-1.15)
Observations	464	1138	214	250
Adjusted R2	0.012	0.000	0.025	0.002

B. Instrumenting the Flow Using the Round Thresholds

	All	Auth	Auth_L.Ret<0	Auth_L.Ret>0
Flow	26.42*	33.88*	45.34*	22.92
	(2.06)	(2.05)	(2.37)	(0.97)
Constant	-5.724	-13.67	-10.75	-16.81
	(-1.05)	(-1.27)	(-0.72)	(-1.23)
Observations	1602	464	214	250
Wald F-statistic	19.44	12.03	8.217	5.264

C. Instrumenting the 1LSg Flow Using the Round Thresholds

	All	Auth	Auth_L.Ret<0	Auth_L.Ret>0
1LSg Flow	38.52*	65.44*	89.35	47.27
	(2.09)	(2.03)	(1.79)	(1.11)
Oth PLX/BTX Flow	-21.19	-52.65	-76.91	-47.82
	(-1.78)	(-1.45)	(-1.08)	(-1.26)
Oth Flow	-10.18	-38.09*	-35.38	-40.03
	(-1.92)	(-2.10)	(-1.73)	(-1.21)
Constant	-3.364	-10.28	-8.653	-11.08
	(-0.75)	(-1.01)	(-0.53)	(-0.99)
Observations	1602	464	214	250
Wald F-statistic	19.49	7.639	3.291	4.277

Table VII. 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 the aggregate monthly Bitcoin-denominated flow of Tether from the Tether treasury to Bitfinex scaled by its standard deviation. Column (5) interacts the EOM dummy with quantiles of issuance as defined in Figure 9. The sample is from March 2016 to March 2018. Columns (6), (7), and (8) report the results excluding the two months with extreme issuance, December 2017 and January 2018. Panel B estimates the results using the returns on a value-weighted portfolio of top five cryptocurrencies. Each day in the sample, the top five cryptocurrencies are selected based on the average market cap in the previous week reported on *CoinMarketCap*. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. Bitcoin Returns

	Entire Sample					Excluding 2017-12 and 2018-01		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	NoIssuance	Issuance	All	All	Issuance	All	All
EOM	-0.0230**	-0.000788	-0.0377***	-0.00669	-0.000788	-0.0251***	-0.00869	-0.000788
	(-3.24)	(-0.14)	(-3.65)	(-1.41)	(-0.14)	(-4.70)	(-1.84)	(-0.14)
Issuance				0.00123			0.00546	
				(0.39)			(1.63)	
EOM=1 × Issuance				-0.0222**			-0.0107*	
				(-2.85)			(-2.04)	
Low × EOM					-0.0187*			-0.0187*
					(-2.27)			(-2.27)
Med × EOM					-0.0307**			-0.0307**
					(-2.71)			(-2.70)
High × EOM					-0.0615*			-0.0232*
					(-2.40)			(-1.98)
Low					0.0117*			0.0117*
					(2.08)			(2.08)
Med					0.00933			0.00933
					(1.33)			(1.32)
High					0.00908			0.0126
					(1.07)			(1.57)
Constant	0.0110***	0.00501	0.0150***	0.0101***	0.00501	0.0160***	0.00824**	0.00501
	(4.32)	(1.49)	(4.19)	(3.58)	(1.48)	(4.78)	(2.92)	(1.47)
Observations	225	90	135	225	225	117	207	207
Adjusted R^2	0.035	-0.011	0.078	0.065	0.060	0.048	0.024	0.023

B. Top-5 Value-Weighted Returns

	Entire Sample					Excluding 2017-12 and 2018-01		
	(1) All	(2) NoIssuance	(3) Issuance	(4) All	(5) All	(6) Issuance	(7) All	(8) All
EOM	-0.0216**	0.00107	-0.0367***	-0.00188	0.00107	-0.0241***	-0.00301	0.00107
	(-3.19)	(0.25)	(-3.68)	(-0.46)	(0.25)	(-4.05)	(-0.79)	(0.25)
Issuance				0.00179			0.00460	
				(0.53)			(1.53)	
EOM=1 × Issuance				-0.0269***			-0.0186***	
				(-4.45)			(-3.41)	
Low × EOM					-0.0175*			-0.0175*
					(-2.41)			(-2.40)
Med × EOM					-0.0196*			-0.0196*
					(-2.07)			(-2.07)
High × EOM					-0.0762***			-0.0474***
					(-3.99)			(-3.63)
Low					0.0119*			0.0119*
					(2.34)			(2.34)
Med					0.00990			0.00990
					(1.35)			(1.35)
High					0.0106			0.0100
					(1.31)			(1.39)
Constant	0.0101***	0.00367	0.0145***	0.00884**	0.00367	0.0143***	0.00719**	0.00367
	(4.08)	(1.18)	(4.06)	(3.16)	(1.18)	(4.35)	(2.69)	(1.17)
Observations	225	90	135	225	225	117	207	207
Adjusted R^2	0.033	-0.011	0.076	0.083	0.084	0.045	0.030	0.030

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

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

where $R_t^{BTC-USD}$ is the hourly return of Bitcoin prices in U.S. dollars 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:

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

where $AverageReturn_t = \frac{(R_t^{USD} + R_t^{Tether})}{2}$ and $ArbitrageSpread_t = R_t^{USD} - R_t^{Tether}$. All variables are standardized by subtracting the mean and dividing by the standard deviation. Standard errors are robust to 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.Tether_USD_Ret	-0.0082	-0.0016	0.0019	0.0018	0.0047
	(-0.77)	(-0.13)	(0.16)	(0.14)	(0.36)
L2.Tether_USD_Ret		0.0080	0.0160	0.0180	0.0232
		(0.59)	(1.11)	(1.21)	(1.42)
L3.Tether_USD_Ret			0.0138	0.0176	0.0257
			(1.23)	(1.32)	(1.71)
L4.Tether_USD_Ret				0.0024	0.0172
				(0.20)	(1.05)
L5.Tether_USD_Ret					0.0272
					(1.50)
L.BTC_USD_Ret	-0.0448**	-0.0472***	-0.0482***	-0.0489***	-0.0490***
	(-3.14)	(-3.31)	(-3.40)	(-3.44)	(-3.45)
L2.BTC_USD_Ret		-0.0688***	-0.0698***	-0.0715***	-0.0719***
		(-4.80)	(-4.84)	(-4.96)	(-4.95)
L3.BTC_USD_Ret			-0.0299*	-0.0316**	-0.0325**
			(-2.56)	(-2.70)	(-2.73)
L4.BTC_USD_Ret				-0.0419**	-0.0426**
				(-3.05)	(-3.12)
L5.BTC_USD_Ret					-0.0263
					(-1.85)
Constant	-0.0034	-0.0032	-0.0031	-0.0030	-0.0029
	(-0.31)	(-0.29)	(-0.28)	(-0.27)	(-0.27)
Observations	8750	8749	8748	8747	8746
Adjusted R^2	0.002	0.006	0.007	0.008	0.009

B. Bitcoin Flow

	BTC Flow	BTC Flow	BTC Flow	BTC Flow	BTC Flow
L.Tether_USD_Ret	-0.0047	0.0029	0.0033	0.0061	0.0075
	(-0.34)	(0.21)	(0.23)	(0.42)	(0.51)
L2.Tether_USD_Ret		0.0098	0.0085	0.0150	0.0167
		(0.74)	(0.58)	(1.02)	(1.10)
L3.Tether_USD_Ret			-0.0139	-0.0012	0.0021
			(-1.04)	(-0.08)	(0.14)
L4.Tether_USD_Ret				0.0212	0.0271
				(1.62)	(1.93)
L5.Tether_USD_Ret					0.0084
					(0.64)
L.BTC_USD_Ret	-0.1066***	-0.1093***	-0.1126***	-0.1133***	-0.1134***
	(-6.72)	(-6.91)	(-7.18)	(-7.24)	(-7.27)
L2.BTC_USD_Ret		-0.0775***	-0.0808***	-0.0825***	-0.0829***
		(-4.97)	(-5.20)	(-5.30)	(-5.33)
L3.BTC_USD_Ret			-0.0734***	-0.0750***	-0.0761***
			(-4.76)	(-4.85)	(-4.92)
L4.BTC_USD_Ret				-0.0450**	-0.0460**
				(-3.09)	(-3.17)
L5.BTC_USD_Ret					-0.0280
					(-1.91)
Constant	0.0154	0.0158	0.0160	0.0162	0.0163
	(1.43)	(1.47)	(1.49)	(1.51)	(1.52)
Observations	8750	8749	8748	8747	8746
Adjusted R^2	0.011	0.017	0.022	0.024	0.025

C. Price Differences Between USD and Tether Exchanges

	(1) Tether	(2) BTC
Arbitrage Spread	0.0032	0.0163
	(0.22)	(1.08)
Average Return	-0.0823***	-0.1372***
	(-5.77)	(-8.37)
Constant	-0.0000	0.0001
	(-0.00)	(0.01)
Observations	9501	9501
Adjusted R^2	0.007	0.020

Internet Appendix for "Is Bitcoin Really Un-Tethered?"

John M. Griffin and Amin Shams*

Internet Appendix IA.A. Identifying and Verifying the Wallet Labeling Procedure

This appendix explains our labeling and verification algorithm for wallets on Tether blockchain and their corresponding clusters of wallets on the Bitcoin blockchain.

A. Identifying Exchanges

For the Tether Blockchain, the identities of major Tether entities are identified based on the Tether rich list reported by Tether Limited.[1] At each point in time, the rich list reports the top-50 wallets in terms of balance and the exchange identity that the rich wallets belong to. Because the list changes over time, we go back through Internet Archive and collect the identity of any known wallet in the top-50 addresses at any point in time.

For the Bitcoin blockchain, after we cluster wallets that are likely to be controlled by the same entities based on the algorithm explained in Page 15, we take two steps to assign valid labels to major clusters and verify this labeling process: first, we use extensive public data on the identities of representative wallet addresses within a given cluster, and second, we verify the accuracy of these labels by matching and correlating the flow of Bitcoin between these labeled clusters with the flow of Tether between corresponding Tether players whose identities are extracted from the Tether rich list. We explain these two steps in details below.

We extensively searched public forums such as Reddit and BitcoinTalk for the wallets associated with our major exchanges. For example, we have found several wallet addresses that are associated with Bitfinex. When we match these wallets with our clusters, we find that all of these wallets belong to the same cluster, so we label that cluster including all these wallet addresses as Bitfinex. We do the same procedure and are able to label most major exchanges. Note that the readers can label these exchanges by finding the identity of any small subset of the wallets in their associated cluster and would not need all the wallet addresses. Nevertheless, to make the procedure completely replicable and verifiable for future research,

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[1]The richlist can be found here: https://wallet.tether.to/richlist

Internet Appendix IA.B provides a list of representative Bitcoin addresses that can be matched with the clustered wallets to identify major exchanges.

B. Cross-Verifying Tether and Bitcoin Flows

Next, to verify our labeling accuracy, we compare the correlation and magnitude of the Bitcoin flows between major exchanges labeled through our algorithm with the Tether flows between exchanges labeled based on the Tether rich list. If Tether is mainly used to purchase Bitcoin, we should see a correlated flow mimicking the exchange of Tether for Bitcoin across the two blockchains. We proceed in several steps.

1) We compute the daily Tether flows from Bitfinex to Poloniex and Bitfinex to Bittrex.

2) We compute the daily Bitcoin flows between any two given top-twenty exchanges in terms of trading volume that we could label using public data. These exchanges are Binance, Bitfinex, Bitflyer, Bitstamp, Bittrex, BTC38, BTC-e, Btc-Trade, CHBTC, Coinbase, EXMO, Gemini, HitBTC, Huobi, Korbit, Kraken, OKCoin, OKEx, Poloniex, and QuadrigaCX. The list includes both major Tether-based exchanges and fiat-based exchanges.

3) We match the Tether flows from Bitfinex to Poloniex and Bitfinex to Bittrex on the Tether blockchain ($TetherFlow_t^{BFX \rightarrow PLX}$ and $TetherFlow_t^{BFX \rightarrow BTX}$ respectively) to the daily pairwise Bitcoin flows between any of the two exchanges, $BTCFlow_t^{X \rightarrow Y}$, where X and Y could be any of the exchanges in the list of top-twenty exchanges above.

4) We examine the correlation and the difference in the magnitude of Tether and Bitcoin flows when our labeled X and Y exchanges match the exact correspondent exchanges on the Tether rich list versus when they have different identities.

Figure IA5, top-left panel shows the distribution of the computed correlations between the Tether flows from Bitfinex to Poloniex and the Bitcoin flows between any two labeled exchanges on the Bitcoin blockchain. The black bar shows that the correlation stands out for Bitcoin flow between our labeled "Poloniex" and "Bitfinex" wallets ($BTCFlow_t^{(X=PLX \rightarrow Y=BFX)}$). Note that the blue bars include Bitcoin flows from major Tether-based exchanges such as Binance, OKEx, and even Bittrex, but the correlation for the labeled Poloniex wallet is an outlier. The top-right panel shows similar results for Bittrex. Results are similar if we use different time-intervals, such as 12 or 3-hour periods.

The middle-left panel shows the distribution of the adjusted R^2s for the regression below:

$$BTCFlow_t^{X \rightarrow Y} = \alpha + \beta TetherFlow_t^{BFX \rightarrow PLX} + \varepsilon_t$$

where X and Y could be any two given top-twenty exchanges. The black bar shows that the adjusted R^2 is higher than 0.5 for $BTCFlow_t^{(X=PLX \rightarrow Y=BFX)}$, but significantly lower and close to zero for majority of other exchange pairs.

While the results above show the high correlation between the flow of Tether and the flow of Bitcoin for our clustered wallets, another test for validation of our clustering algorithm is to compare the magnitude of the Tether and Bitcoin flows. The bottom-left panel shows the distribution of the coefficient β above. The closer this coefficient to one, the closer the magnitude of the flows of Bitcoin and Tether. The graph shows that the coefficient is again an outlier when $X = Poloniex$ and $Y = Bitfinex$, which suggests that the magnitude of the flows is closest when our labels are used as opposed to when we scramble the labels.

Overall, the labeled wallets have by far the highest correlation and explanatory power in the time-series regression, but also the magnitude of the transferred Bitcoin flow is the closest to the amount of Tether transferred when we use our labeled wallets.

C. Cross-Verifying Tether Flows with Exchange Volume

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. Figure IA6 shows that the inflow of Tether to Poloniex is highly correlated with the Poloniex exchange volume for Bitcoin-Tether pair. When the exchange volume on Poloniex is regressed on the inflow of Tether to Poloneix, the adjusted R^2 is 0.30 as shown in the top-left panel of Figure IA6. (The R^2 is 0.48 using daily data) We then estimate placebo regressions with the same explanatory variable (Tether inflow to Poloniex) but we use Binance exchange volume as the dependent variable. The second panel shows that the adjusted R^2 is only 0.02. Similarly, the other panels show that while there is a general positive relationship, the adjusted R^2s are significantly smaller and close to zero when we replace the exchange trading volume of Poloniex and Bittrex with that of other Tether exchanges. The R^2s from regression of Binance, HitBTC, Huobi, Kraken, and OKEx exchange volume on Tether inflow to Poloniex are 0.02, 0.01, 0.00, 0.00, and 0.00 respectively. That last panel shows that even the R^2 from regression of Bittrex volume on Tether inflow to Poloniex is very small at 0.01.

For Bittrex, the regression of Bittrex volume on Bittrex Tether inflow yields an adjusted R^2 of 0.23 (0.48 when using daily data). However, the adjusted R^2s from the placebo regressions of Binance, HitBTC, Huobi, Kraken, and OKEx exchange volume on Bittrex Tether inflow are close to zero at 0.02, 0.05, 0.00, 0.00, and 0.00 respectively. The R^2 from regression of Poloniex volume on Tether inflow to Bittrex is 0.06. The results demonstrate that the strong linear relation is only present when we match Poloniex and Bittrex flows to their respective exchanges and not simply due to time-varying volatility or overall trading volume.

D. Identifying the Main Players

This appendix describes how we drill down on the nature of the flows out of Bitfinex and the corresponding Bitcoin flows back by focusing on the exact deposit addresses used to move the coins. Typically, to electronically detect which user has deposited funds and to credit these funds to her account, each exchange user receives her own unique deposit wallet address. As shown in Panel A of Figure 4, 90% of the Tether flows from Bitfinex to Poloniex go to a single deposit address, 1J1dCYzS5EerUuJCJ6iJYVPytCMVLXrgM9, which we label as 1J1d. Moreover, 72% of the Tether flows from Bitfinex to Bittrex go to 1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW (hereon 1AA6). Additionally, the Bitcoin blockchain data reveals that 66% of the Bitcoin flowing from Poloniex and Bittrex to Bitfinex goes to the single Bitfinex deposit address that we label as 1LSg throughout the paper:

1LSgEKji3ZoGdvzBgkcJMej74iBd38fySb

We examine if the Tether flow to 1J1d and 1AA6 on Tether blockchain corresponds to the Bitcoin flow from Poloniex and Bittrex to 1LSg. We compare the Tether flow to 1J1d and 1AA6 to the Bitcoin flow from Poloniex and Bittrex to the top-100 largest Bitcoin addresses on Bitfinex, including 1LSg. The correlation between Bitcoin flows from Poloniex to 1LSg on Bitfinex and Tether flows from Bitfinex to 1J1d on Poloniex is 0.69. Similarly, the correlation between Bitcoin flows from Bittrex to 1LSg and Tether flows from Bitfinex to 1AA6 on Bittrex is 0.64. This strongly suggests that the flows on these wallets are linked. We calculate similar correlations between Tether flows from Bitfinex to 1J1d and 1AA6 ($TetherFlow_t^{BFX \xrightarrow{1J1d} PLX}$ and $TetherFlow_t^{BFX \xrightarrow{1AA6} BTX}$ respectively) to the daily Bitcoin flows from Poloniex and Bittrex to any other top-100 deposit addresses on Bitfinex. The blue bars in the top panel of Figure IA10 show that other large deposit accounts on Bitfinex show significantly lower flow correlations with the Tether flows into 1J1d and 1AA6.

Moreover, the second and third row panels shows the distribution of the adjusted R^2s and the β coefficients for the regressions below:

$$BTCFlow_t^{PLX \xrightarrow{X} BFX} = \alpha + \beta TetherFlow_t^{BFX \xrightarrow{1J1d} PLX} + \varepsilon_t,$$

and

$$BTCFlow_t^{BTX \xrightarrow{Y} BFX} = \alpha + \beta TetherFlow_t^{BFX \xrightarrow{1AA6} BTX} + \varepsilon_t$$

where $BTC_{i \xrightarrow{k} j}$ shows the amount of Bitcoins transferred from exchange i to exchange j through deposit address k and $Tether_{i \xrightarrow{k} j}$ shows the amount of Tether transferred from exchange i to exchange j through deposit address k. X can be any of the top-100 Bitfinex recipients of Bitcoin from Poloniex, and Y can be any of the top-100 Bitfinex recipients of Bitcoin from Bittrex. The black bar shows the adjusted R^2s are by far the largest for $X = 1LSg$ for Poloniex and $Y = 1LSg$ for Bittrex, suggesting that the 1LSg deposit address on the Bitfinex exchange has the closest tie to the two Tether deposit addresses on Poloniex and Bittrex, 1J1d and 1AA6. Finally, the bottom panels examine the distribution of the coefficient β above and confirms that the magnitude of the daily Tether flows to 1J1d and 1AA6 is most similar in size to the magnitude of the Bitcoin back to 1LSg. These results suggest that it is very likely that 1J1d Poloniex Tether wallet, 1AA6 Bittrex Tether wallet, and 1LSg Bitfinex Bitcoin wallet are controlled by the same entity/individual to exchange Tether for Bitcoin. For simplicity, we label their activity as 1LSg throughout the paper.

To examine the net Tether and Bitcoin flows, we subtract the Tether flows back from Poloniex and Bittrex to Bitfinex and the Bitcoin flows back from Bitfinex to Poloniex and Bittrex. We find that the flows back are also mainly handled through a large deposit address. Tether wallet 1MZA-ayfFJ9Kki2csoYjFVRKHFFSkdoMLtX moves most of the Tether from both Poloniex and Bittrex back to Bifinex. We label this wallet as 1MZA. Moreover, two Bitcoin deposit addresses 1DEc on Poloniex and 1PCw on Bittrex account for the largest Bitcoin flows back from Bitfinex to Poloniex and Bittrex respectively. We estimate similar results for these flows backward in Figure IA11. The results show that these wallets are likely to be controlled by the same entity.

The table below summarizes the wallets we identify as associated with the main movement of coins between Bitfinex, Poloniex, and Bittrex. The relationship between these wallets is further illustrated in Figure IA9.

Blockchain	Sender	Recipient	Deposit Address
Tether	Bitfinex	Poloniex	1J1d
Tether	Bitfinex	Bittrex	1AA6
Bitcoin	Poloniex and Bittrex	Bitfinex	1LSg
Tether	Poloniex and Bittrex	Bitfinex	1MZA
Bitcoin	Bitfinex	Poloniex	1DEc
Bitcoin	Bitfinex	Bittrex	1PCw

E. Formal Definition of the Flows

The net average flows associated with these wallets is formally defined as the signed net amount of capital transferred between these wallets. We label this value as “1LSg flow” throughout the paper and define it formally analogous to our flow calculations in Equations (1)), (2), and (3):

$$NetBTCFlow_t^{1LSg} = (\sum_{t-1}^{t} BTC_{PLX \xrightarrow{1LSg} BFX} - \sum_{t-1}^{t} BTC_{BFX \xrightarrow{1DEc} PLX}) + (\sum_{t-1}^{t} BTC_{BTX \xrightarrow{1LSg} BFX} - \sum_{t-1}^{t} BTC_{BFX \xrightarrow{1PCw} BTX}) \tag{4}$$

where $BTC_{i \xrightarrow{k} j}$ shows the amount of coins transferred from exchange i to exchange j through deposit address k 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. Similar to the flow of Bitcoin, we define the net flow of Tether as below

$$NetTetherFlow_t^{1LSg} = (\sum_{t-1}^{t} Tether_{BFX \xrightarrow{1J1d} PLX} - \sum_{t-1}^{t} Tether_{PLX \xrightarrow{1MZA} BFX}) + (\sum_{t-1}^{t} Tether_{BFX \xrightarrow{1AA6} BTX} - \sum_{t-1}^{t} Tether_{BTX \xrightarrow{1MZA} BFX}) \tag{5}$$

where $Tether_{i \xrightarrow{k} j}$ shows the amount of coins transferred from exchange i to exchange j through deposit address k between hours $t-1$ and t. The "1LSg flow" is defined as below:

$$1LSgFlow = (NetTetherFlow_t^{1LSg} + NetTetherFlow_t^{1LSg})/2 \tag{6}$$

Throughout the paper, we decompose the aggregate flows to Poloniex and Bittrex into those through the 1LSg channel and those through other non-1LSg accounts on Poloniex and Bittrex:

$$Other\_PLX/BTX\_Flow_t = Tether/BitcoinFlow_t - 1LSgFlow_t \tag{7}$$

where $Tether/BitcoinFlow$ is the aggregate flow to Poloniex and Bittrex defined in Equation (3).

Finally, the net average flows of Bitcoin and Tether between Bitfinex and five other Tether exchanges including Binance, HitBTC, Huobi, Kraken, and OKEx are calculated in a similar fashion as for Poloniex and Bittrex consistent with Equations (1), (2), and (3).

Internet Appendix IA.B. Representative Addresses to Identify Wallet Clusters Associated with Major Exchanges.

Exchange	Address1	Address2
Bitfinex	1Kr6QSydW9bFQG1mXiPNNu6WpJGmUa9i1g	3D2oetdNuZUqQHPJmcMDDHYoqkyNVsFk9r
Binance	1NDyJtNTjmwk5xPNhjgAMu4HDHigtobu1s	16ftSEQ4ctQFDtVZiUBusQUjRrGhM3JYwe
Bitflyer	3JEAszztBTBtsGgxT75mX1QMmvp3FbtLZy	3A4U175prUGEn3B1gUDkz32u8fnF9Nx3Ly
Bitstamp	32RQLBAMSndugVSjA9kyeV4AjzfXXJQ2gp	36mwH1Jg3AMVsEQqVaDSe9YFBTGebaHR1A
Bittrex	13vHWR3iLsHeYwT42RnuKYNBoVPrKKZgRv	1N52wHoVR79PMDishab2XmRHsbekCdGquK
Btc38	16fSNxBHxyP8RMYzVU7oYyhscUFNqRkV29	1EKYZAkJQD1mBws7Fo6vgCBcm2dbTAC9DX
Btce	18gSAdDXKRatd8aGFBpBotchCq1gBQw9Jm	16uD5AfFSRPw96FgSejamvu9vYMHjFbMSQ
Btctrade	1NvvccV8poyNmYgGC1Jt14uhpd5tq5QTr5	17sBKe2PazSfzB485yhcNtsU6rLrDcSzCK
Cbase	16DjTmFX52LqTMRkozuPrsubhFjkV5VEye	1MMdVUrmE8896QE1sWF54qE9tjYxhZcNzp
Chbtc	1LpxLRyBXMXZxRYeyo1YJAZ273dFT4DhVa	1NGMdbQWau5Vdbq9Loh3z5LHPdrWAYAgRE
Exmo	19W5TDzh7MzWHLgCKKKCf6qjUc8Qm4htnZ	1KAqexqZ4FVUhG2qmmXZvccbp5MMrxzuvC
Gemini	1J37CY8hcdUXQ1KfBhMCsUVafa8XjDsdCn	1NYAd6fA2dc5xowuweFUSDRqRTEzDwk28
Hitbtc	3JjPf13Rd8g6WAyvg8yiPnrsdjJt1NP4FC	1EEqRvnS7XqMoXDcaGL7bLS3hzZi1qUZm1
Huobi	19iVyH1qUxgywY8LJSbpV4VavjZmyuEyxV	1Po4J4SNyJuGnMGYJfGTXLEvGgAZKiddr7
Korbit	16jce8CbnyF2dYkBzrXKEdeG2wGMwShkPq	1Jw2vULvXpdFjzTVsKWw21CzFwZhBAjjTk
Kraken	1Kd6zLb9iAjcrgq8HzWnoWNVLYYWjp3swA	1A7znRYE24Z6K8MCAKXLmEvuS5ixzvUrjH
Okcoin	143Feqwz3WmAaYUBcani9GGEmzyFAes8tP	19QC9XoMVWxP43TkzkSKZhtcY4oZFqWb1d
Okex	37Tm3Qz8Zw2VJrheUUhArDAoq58S6YrS3g	3Dqq4kUPr7jDqfqPMBfm54Bz5BcQwG1Wmb
Poloniex	17A16QmavnUfCW11DAApiJxp7ARnxN5pGX	12cgpFdJViXbwHbhrA3TuW1EGnL25Zqc3P
Quadrigacx	3Betb5uAZzEX9MU4U2wPYSbRfUtYxtwaj6	3A7h7kZJCLYLBuqTiibjnw5GZfkRJtKzzv

Internet Appendix IA.C. Timing and Characteristics of Currency Movements

This appendix 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. As described in Figure 1, the transfer of Tether from Tether authorizer (account labeled as 3MbY) to Tether treasuries (1NTM and 3BbD), all colored in red, is called Tether "authorization." There are cases where Tether moves quickly in and out of Bitfinex right after authorization, but it is also common to see a delay of a few days between Tether authorization and the flow of coins from Bitfinex to other Tether exchanges, mainly Poloniex and Bittrex. 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.[2] 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:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_5 y_{t-5} + \varepsilon_t \tag{8}$$

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 ε_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. Throughout the paper 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.

[2] Examples are shown in the Internet Appendix Figure IA3.

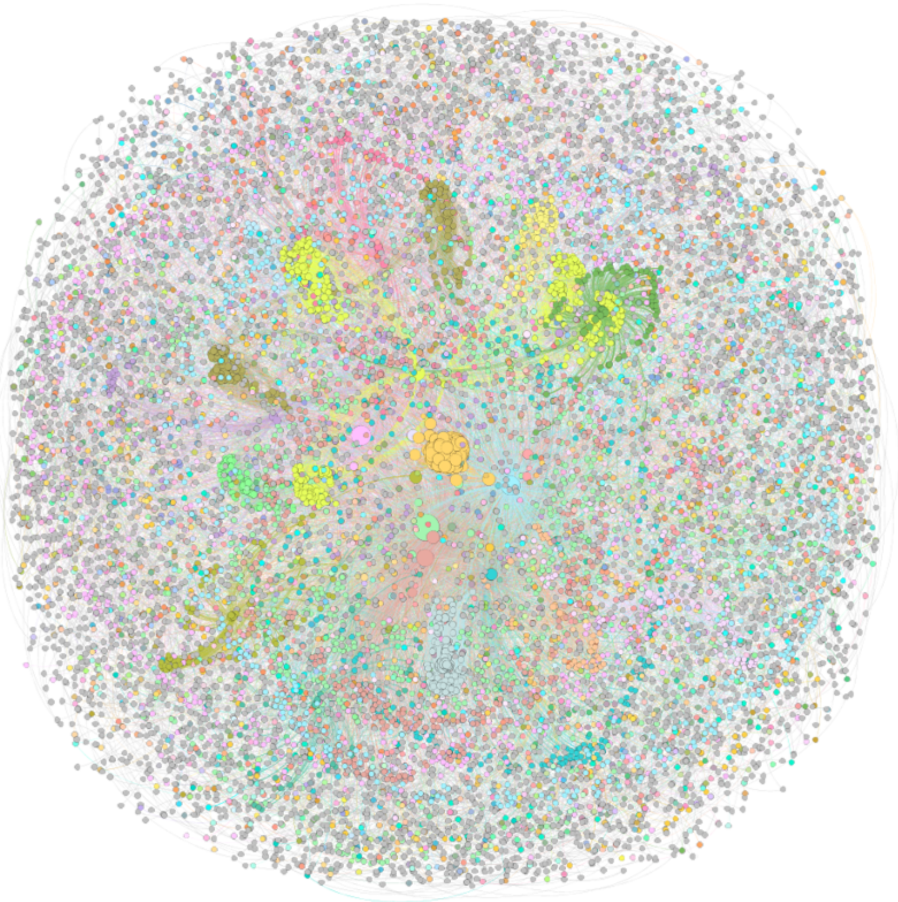


Figure IA1. Snapshot of a 10-Minute Random Sample of Transactions on the Bitcoin Blockchain. This figure shows the flow of Bitcoin recorded on the Bitcoin blockchain over a 10-minute random sample in 2017. The thickness of the edges is proportional to the magnitude of the flow between two nodes, and 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.

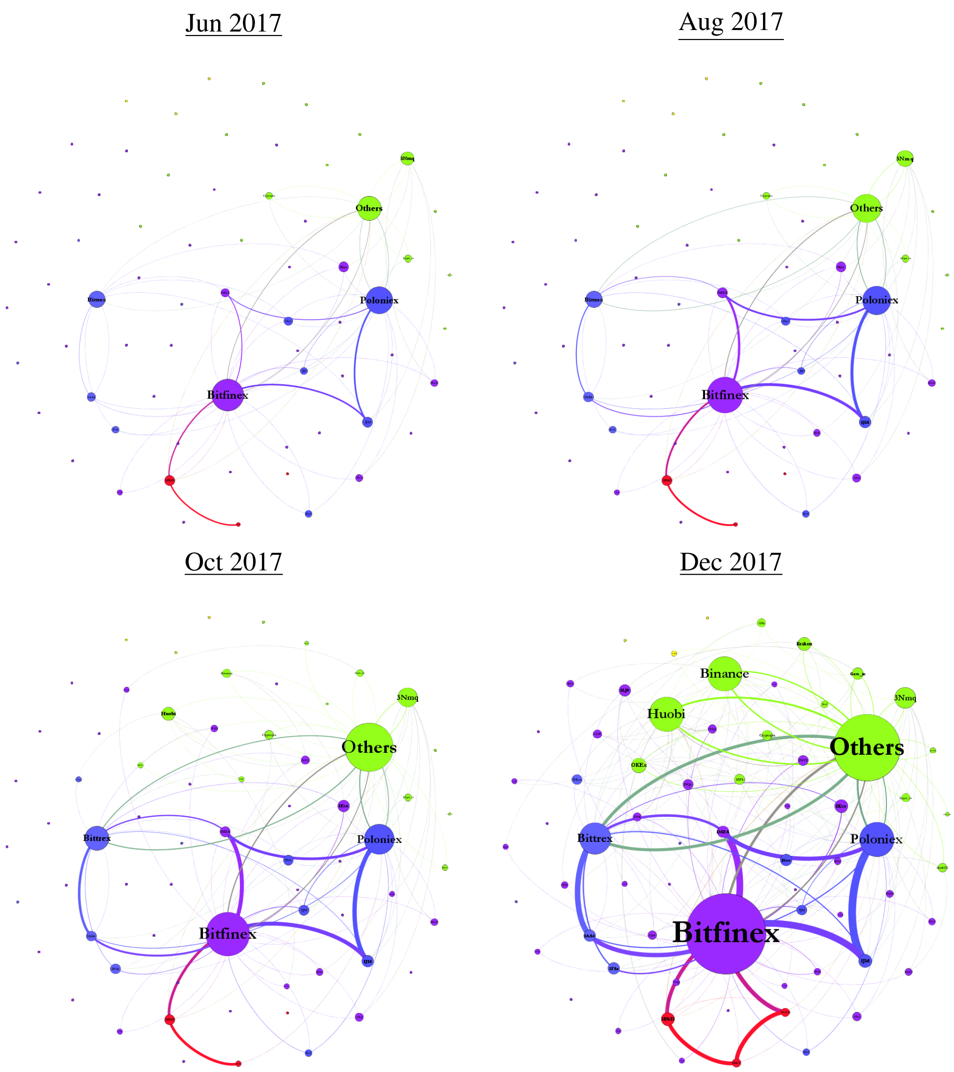
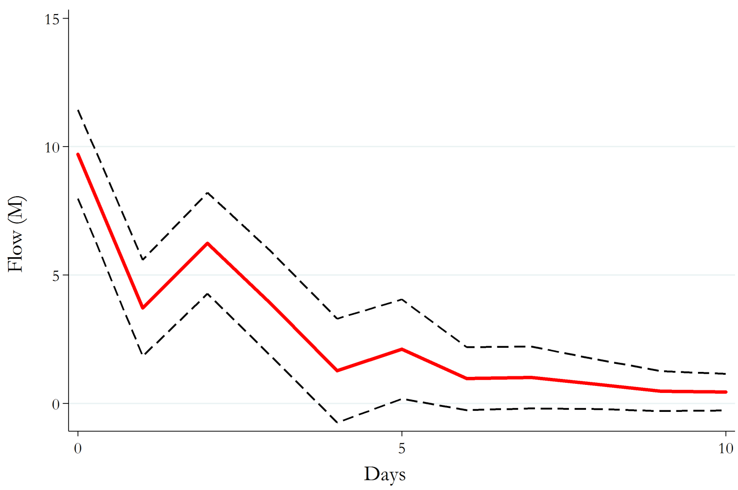


Figure IA2. Snapshots of Tether Blockchain Over Time. This figure shows the aggregate flow of Tether between major exchanges and market participants from genesis until different points in time. Tether transactions are captured on the Omni Layer as transactions with the coin ID 31. The data include confirmed 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.

A. Inflow to Bitfinex



B. Outflow from Bitfinex

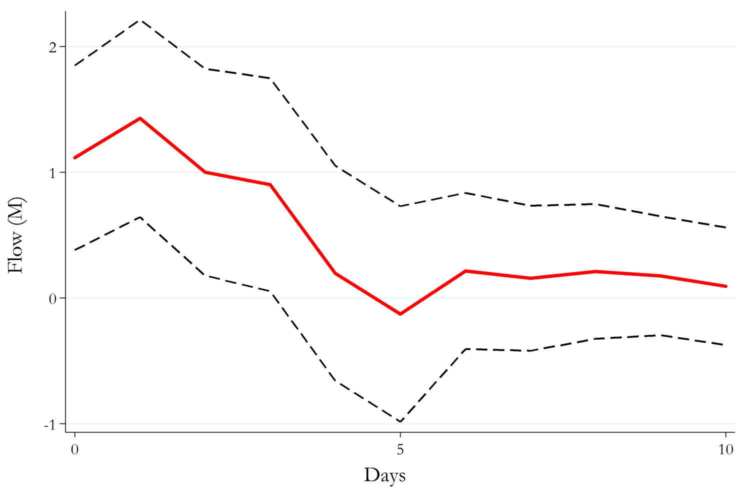


Figure IA3. Flow of Tether to Bitfinex, Poloniex, and Bittrex after Printing Tether. This figure plots impulse response functions describing the change in Tether flow between major exchanges in response to a one standard deviation shock to Tether authorization. Panel A shows the inflow from the Tether treasury to Bitfinex for ten days after Tether authorization. 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 with ordering of authorization of Tether before the flow of Tether from the Tether treasury to Bitfinex and from Bitfinex to other Tether exchanges. The dashed line shows the 95% confidence interval.

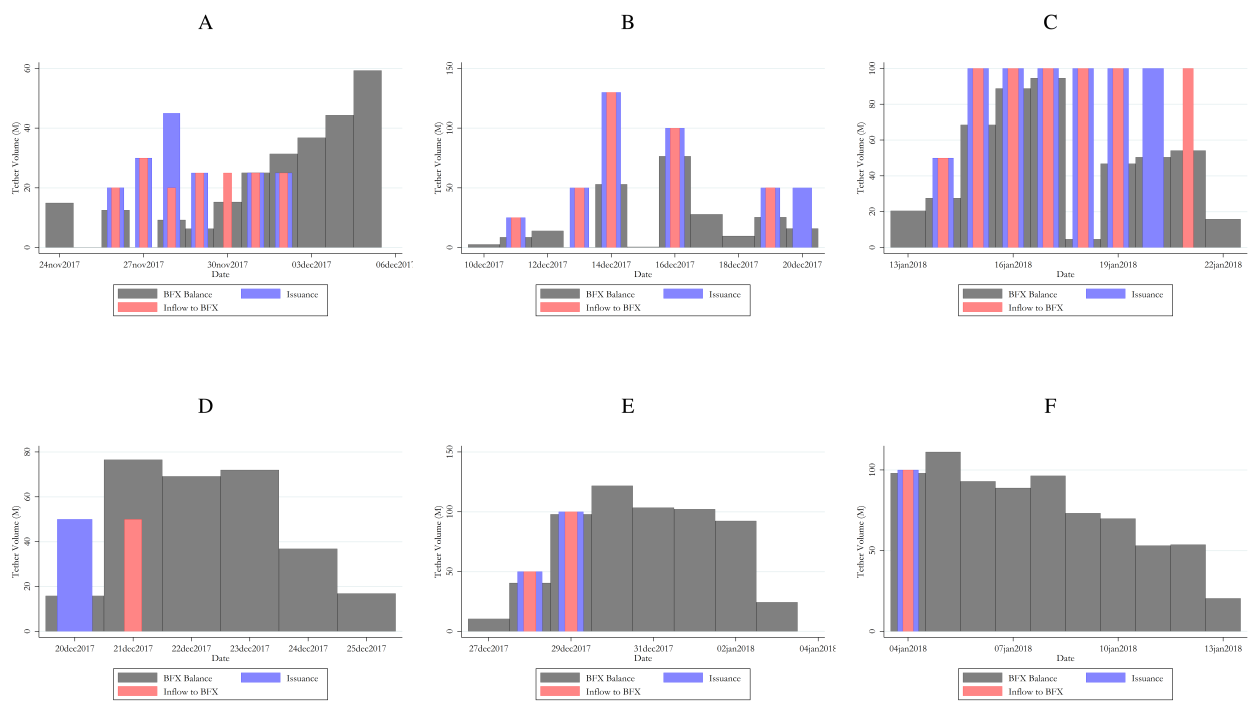


Figure IA4. Examples of Tether Grants and Changes in Bitfinex Wallet Balance. This figure shows multiple examples of Tether grants, inflow of Tether to Bitfinex, and Tether balance on Bitfinex over the subsequent days. Large gray bars show the Tether balance on Bitfinex, the medium blue bars show Tether grants, and the red narrow bars show the inflow of Tether to Bitfinex.

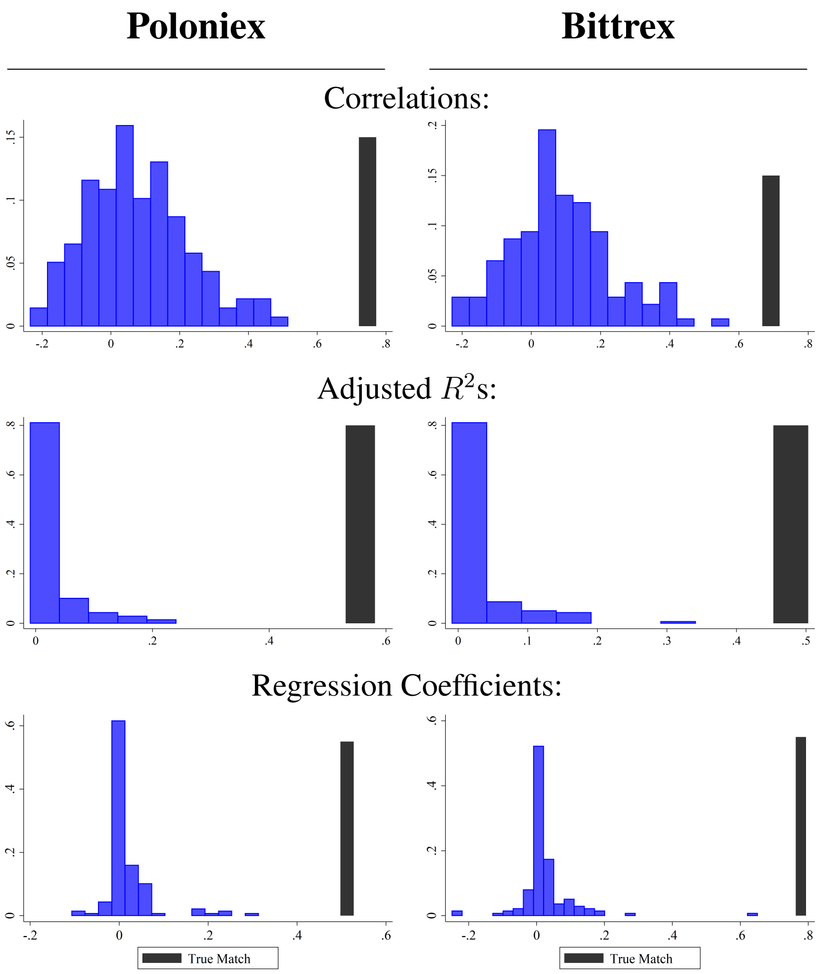


Figure IA5. The Accuracy of the Labeling Procedure. This figure compares the daily Tether flows from Bitfinex to Poloniex and Bitfinex to Bittrex identified using wallet identities on the Tether rich list with Bitcoin flows between exchanges identified using the clustering algorithm in this paper. The Tether flows $TetherFlow_t^{BFX\to PLX}$ and $TetherFlow_t^{BFX\to BTX}$ are compared with Bitcoin flows between any two given top-twenty exchanges in terms of trading volume, $BTCFlow_t^{X\to Y}$, where X and Y could be any of Binance, Bitfinex, Bitflyer, Bitstamp, Bittrex, BTC38, BTC-e, BtcTrade, CHBTC, Coinbase, EXMO, Gemini, HitBTC, Huobi, Korbit, Kraken, OKCoin, OKEx, Poloniex, and QuadrigaCX. The top-left panel shows the distribution of correlations between $TetherFlow_t^{BFX\to PLX}$ and Bitcoin flows between any two exchanges. The black bar shows the correlation when the correct label is used ($BTCFlow_t^{PLX\to BFX}$), and the blue bars show the distribution of correlation with other inter-exchange Bitcoin flows. The middle and bottom panels show the distribution of adjusted R^2s and regression coefficients for the regression of $BTCFlow_t^{X\to Y}$ on $TetherFlow_t^{BFX\to PLX}$ where X and Y can be any of the exchanges listed above. The black bars show the true match using the algorithm in this paper. The right panels show similar results for Bittrex.

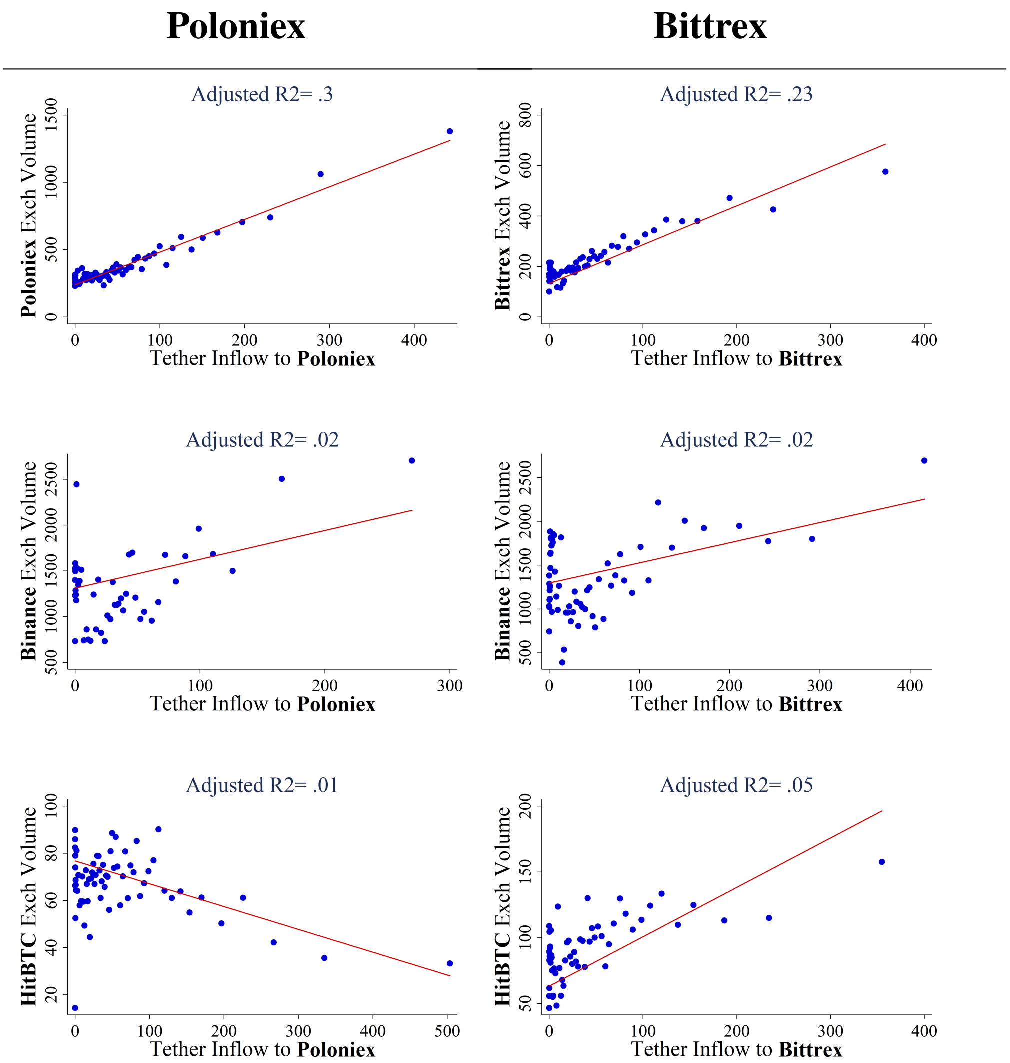
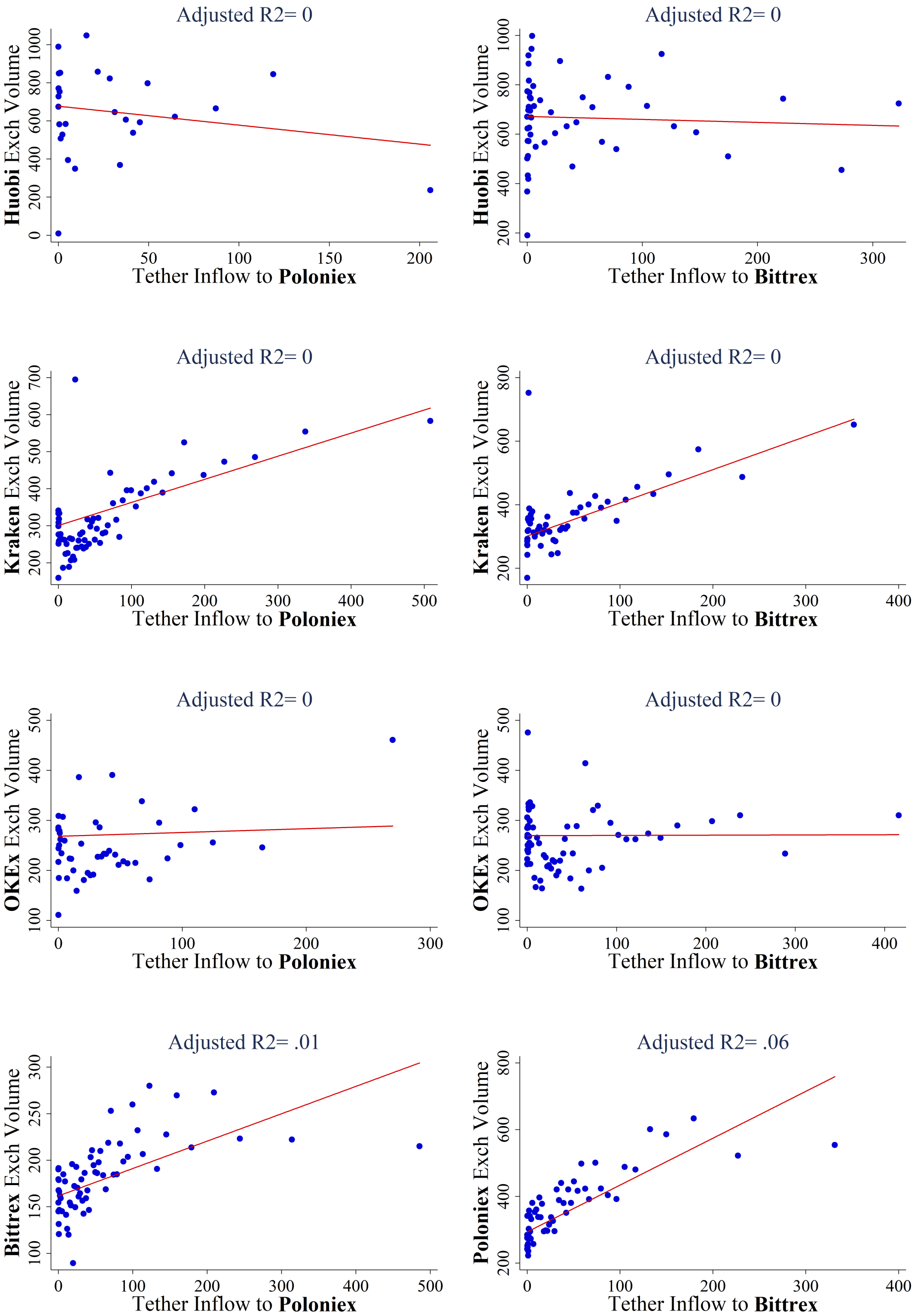
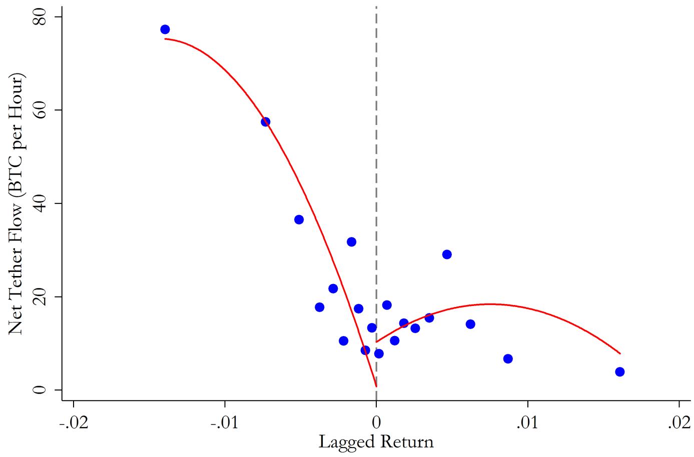


Figure IA6. Flow of Tether to Poloniex and Bittrex and Trading Volume on Tether Exchanges. This figure shows the binscatter plots of 3-hour moving average trade volume on Tether exchanges Poloniex, Bittrex, Binance, HitBTC, Huobi, Kraken, and OKEx as a function of Tether inflow to Poloniex and Bittrex. The reported $R2$s correspond to the regression of exchange volume on Tether flows. The left panels report the results for Tether flows to Poloniex and the right panels for Bittrex. The sample period is from March 1, 2017 to March 31, 2018.


Adjusted R2= 0
Huobi Exch Volume
Tether Inflow to Poloniex
Adjusted R2= 0
Huobi Exch Volume
Tether Inflow to Bittrex
Adjusted R2= 0
Kraken Exch Volume
Tether Inflow to Poloniex
Adjusted R2= 0
Kraken Exch Volume
Tether Inflow to Bittrex
Adjusted R2= 0
OKEx Exch Volume
Tether Inflow to Poloniex
Adjusted R2= 0
OKEx Exch Volume
Tether Inflow to Bittrex
Adjusted R2= .01
Bittrex Exch Volume
Tether Inflow to Poloniex
Adjusted R2= .06
Poloniex Exch Volume
Tether Inflow to Bittrex

A. Tether Flow



B. Bitcoin Flow

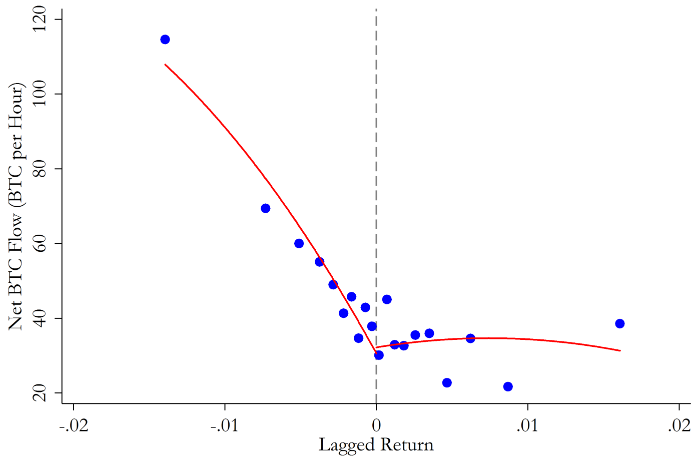


Figure IA7. Net Flow of Bitcoin and Tether for Quantiles of Lagged Return. This figure shows net hourly flow of Bitcoin and Tether between Bitfinex and two major Tether exchanges, Poloniex and Bittrex, as a function of lagged 3-hour average return. The sample period is from March 1, 2017 to March 31, 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.

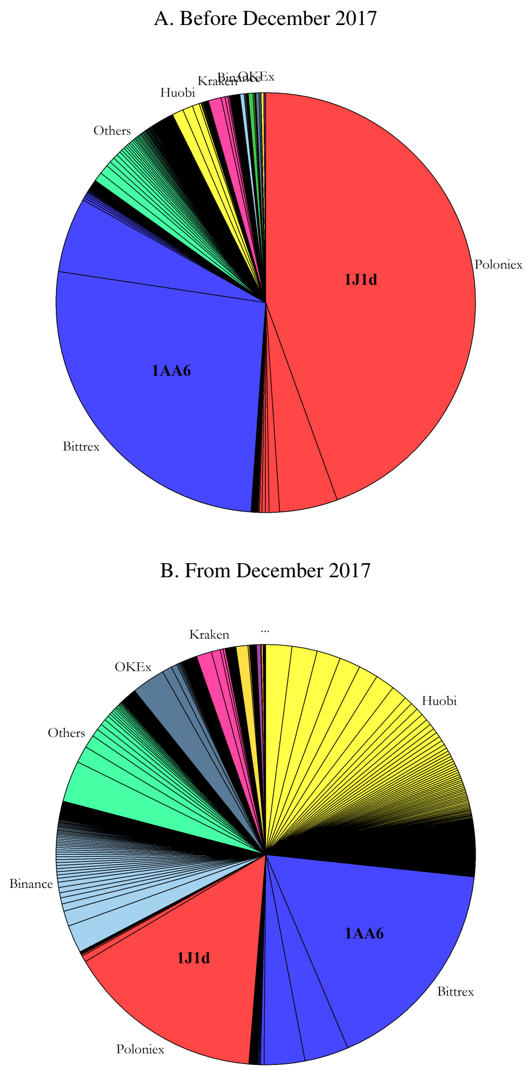


Figure IA8. Top Accounts Associated with the Flow of Tether from Bitfinex. This figure shows largest recipients of Tether from Bitfinex recorded on Tether blockchain between March 1, 2017 to March 31, 2018. Exchange wallet identities are obtained from the Tether rich list. Moreover, intermediary wallets that receive Tether from Bitfinex but send all to wallets of a particular exchange are labeled as that exchange. Exchanges are distinguished by colors, and the partitions show unique wallets within each exchange. The two largest recipients of Tether from Bitfinex on Bittrex and Poloniex are labeled by the first four characters of their wallet ID as 1AA6 and 1J1d. Panel A shows the results for before December 1, 2017, and Panel B for after.

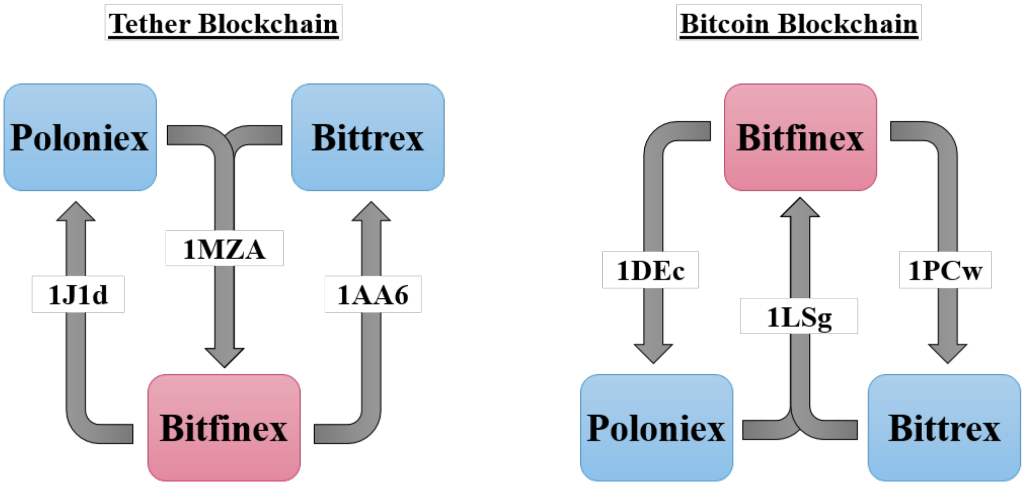


Figure IA9. Top Addresses Associated with Flow of Tether and Bitcoin between Bitfinex, Poloniex, and Bittrex. This figure shows the relationship between top addresses associated with the flows of Tether and Bitcoin between Bitfinex, Poloniex, and Bittrex. Tether wallets 1J1d and 1AA6 are the top recipients of Tether directly from Bitfinex on Poloniex and Bittrex. Bitcoin wallet 1LSg is the largest deposit address for Bitcoin on Bitfinex between March 1, 2017 and March 31, 2018. The link between these wallets is described in the Internet Appendix IA.A. Part of the Tether received by Poloniex and Bittrex goes back to Bitfinex through 1MZA Tether wallet, and in exchange, Bitcoin is sent back to Poloniex and Bittrex through 1DEc and 1PCw.

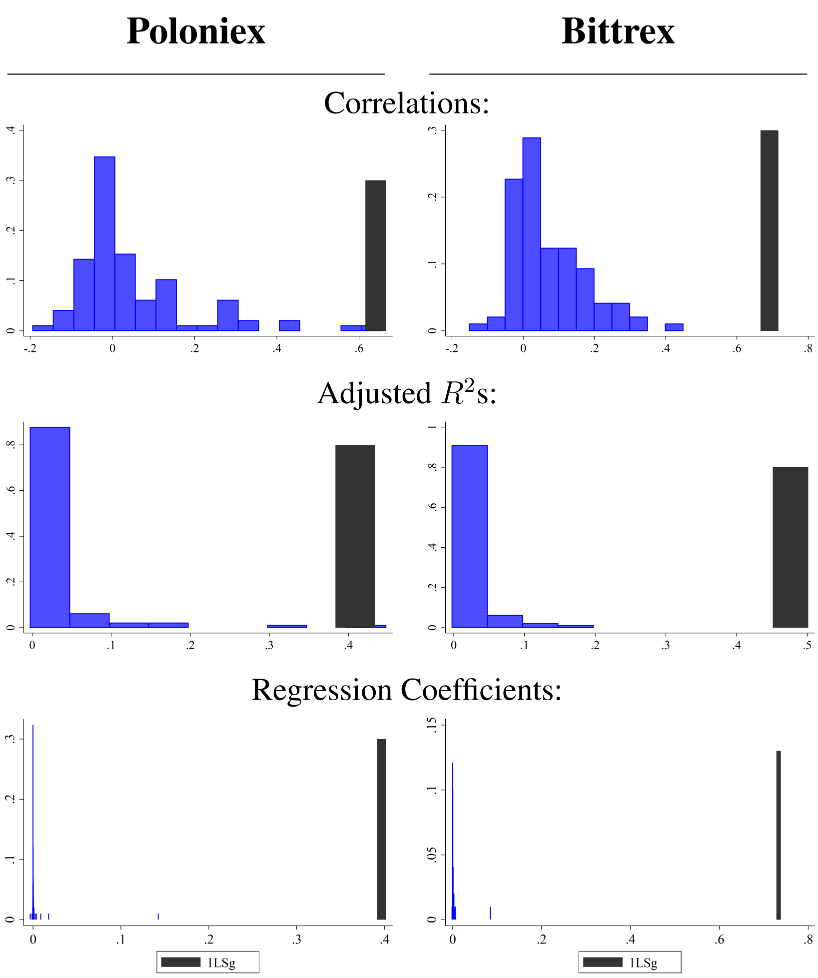


Figure IA10. The Accuracy of the Labeling Procedure for 1LSg Accounts. This figure compares the daily Tether flows from Bitfinex to 1J1d on Poloniex and Bitfinex to 1AA6 on Bittrex with Bitcoin flows back from Poloniex and Bittrex to top-100 Bitfinex Bitcoin recipient wallets from Poloniex and Bittrex. The Tether flows $TetherFlow_t^{BFX \xrightarrow{1J1d} PLX}$ and $TetherFlow_t^{BFX \xrightarrow{1AA6} BTX}$ are compared with daily Bitcoin flows $BTCFlow_t^{PLX \xrightarrow{X} BFX}$ and $BTCFlow_t^{BTX \xrightarrow{Y} BFX}$, where X can be any of the top-100 Bitfinex recipients of Bitcoin from Poloniex, and Y can be any of the top-100 Bitfinex recipients of Bitcoin from Bittrex. The black bar on the top-left panel shows the correlations between $TetherFlow_t^{BFX \xrightarrow{1J1d} PLX}$ and $BTCFlow_t^{PLX \xrightarrow{1LSg} BFX}$ and the blue bars show the distribution of correlations between $TetherFlow_t^{BFX \xrightarrow{1J1d} PLX}$ and Bitcoin flows from Poloniex to any other top 100 Bitfinex recipients of Bitcoin from Poloniex. The middle and bottom panels show the distribution of adjusted R^2s and regression coefficients for the regression of $BTCFlow_t^{PLX \xrightarrow{X} BFX}$ on $TetherFlow_t^{BFX \xrightarrow{1J1d} PLX}$ where X can be any of the top-100 Bitfinex recipients of Bitcoin from Poloniex. The black bars show the results for $X = 1LSg$. The right panels show similar results for Bittrex.

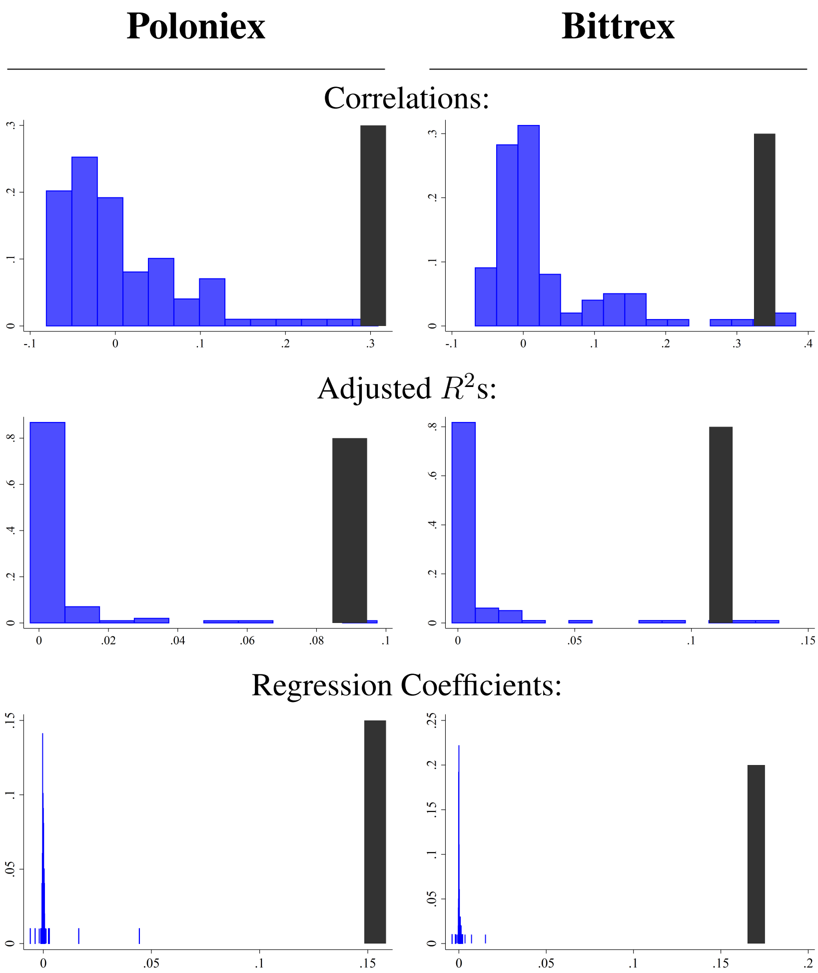


Figure IA11. The Accuracy of the Labeling Procedure for 1LSg Accounts for Flows Backward. This figure compares the daily Tether flows from Poloniex and Bittrex back to Bitfinex through 1MZA account with Bitcoin flows from Bitfinex to top-100 Poloniex and top-100 Bittrex Bitcoin recipient wallets. The left panels compare the Tether flows $TetherFlow_t^{PLX \xrightarrow{1MZA} BFX}$ with daily Bitcoin flows from Bitfinex to deposit addresses on Poloniex, $BTCFlow_t^{BFX \xrightarrow{X} PLX}$, where X can be any of the top-100 Poloniex recipients of Bitcoin from Bitfinex. The black bar on the top-left panel shows the correlations between $TetherFlow_t^{PLX \xrightarrow{1MZA} BFX}$ and $BTCFlow_t^{BFX \xrightarrow{1DEc} PLX}$ and the blue bars show the distribution of correlations with Bitcoin flows from Bitfinex to any other top 100 Poloniex recipients of Bitcoin. The middle and bottom panels show the distribution of adjusted R^2s and regression coefficients for the regression of $BTCFlow_t^{BFX \xrightarrow{X} PLX}$ on $TetherFlow_t^{PLX \xrightarrow{1MZA} BFX}$ where X can be any of the top-100 Poloniex recipients of Bitcoin from Bitfinex. The black bars show the results for $X = 1DEc$. The right panels show similar results for 1PCw wallet on Bittrex.

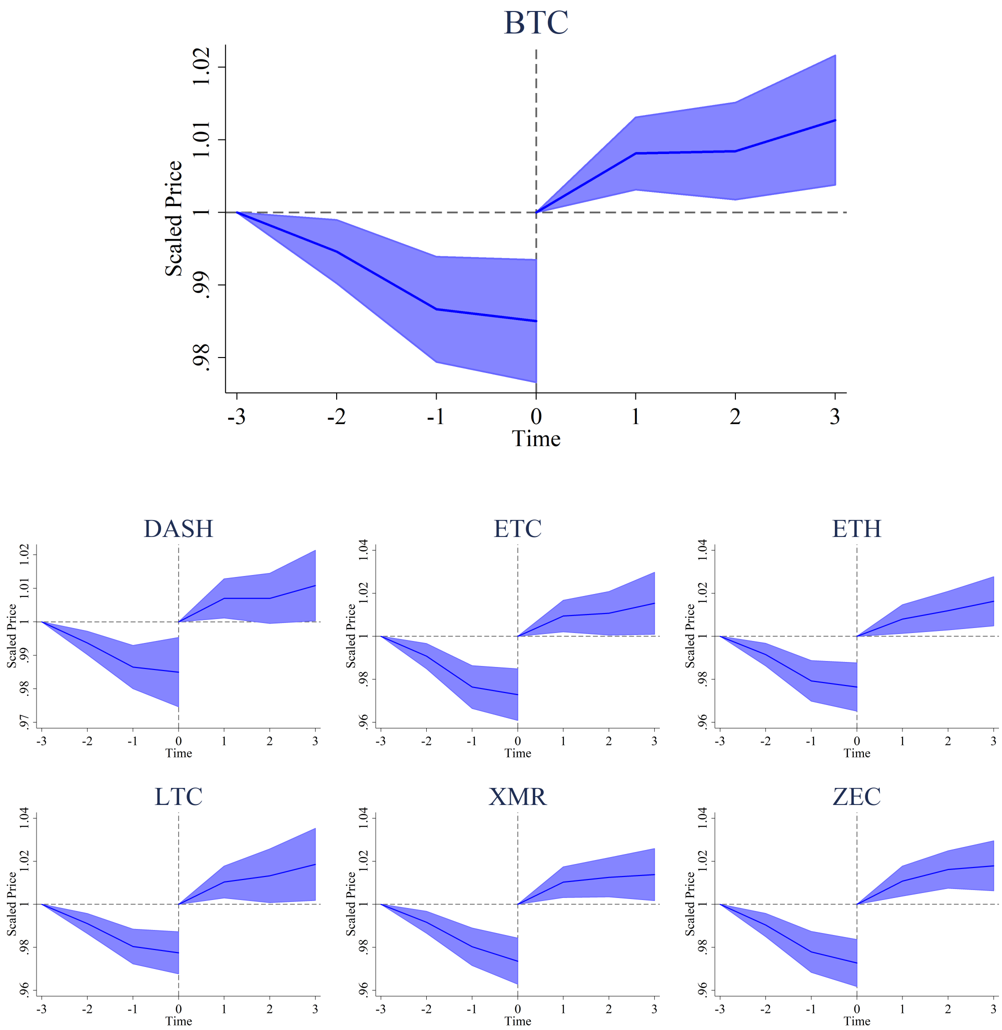


Figure IA12. Prices of Bitcoin and Other Cryptocurrencies around High 1LSg Flow Events. Panel A shows Bitcoin prices three hours before and after the top 1% of high 1LSg flow hours. Prices are scaled to one at time -3 before the event and at time zero after the event. Scaled prices are averaged across the events. The high 1LSg flows occur between time -1 and time 0 and are defined as in Figure 7. Panel B shows similar results for other major cryptocurrencies. The sample period is from March 1, 2017 to March 31, 2018.

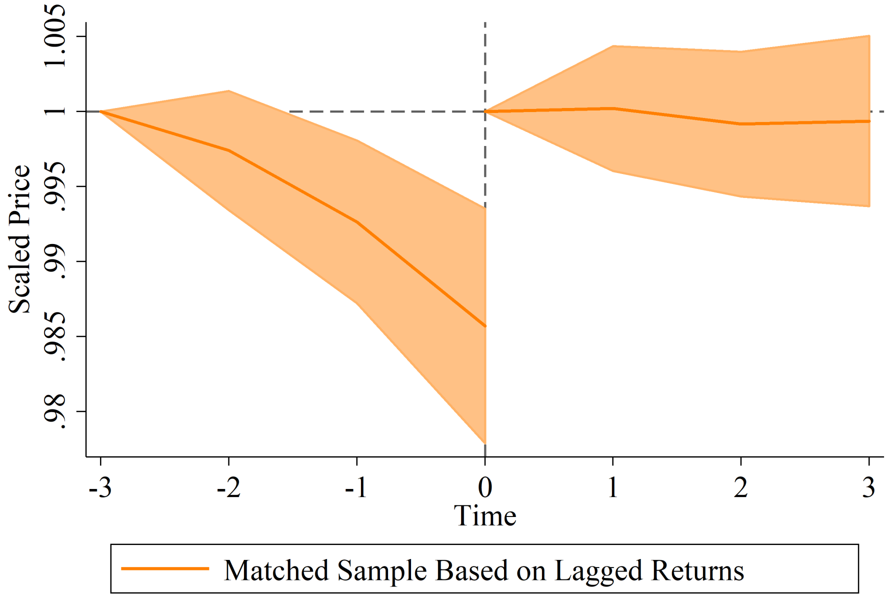


Figure IA13. Bitcoin Prices around Events Matched with High-Flow Hours Based on Lagged Returns. This figure shows Bitcoin prices three hours before and after the hours that are closest matches to the high-flow hours to Poloniex and Bittrex in terms of the compounded returns between times -3 to 0. Prices are scaled to one at time -3 before the event and at time zero after the event. Scaled prices are averaged across the events. The high flows hours are defined as in Figure 5. The sample period is from March 1, 2017 to March 31, 2018.

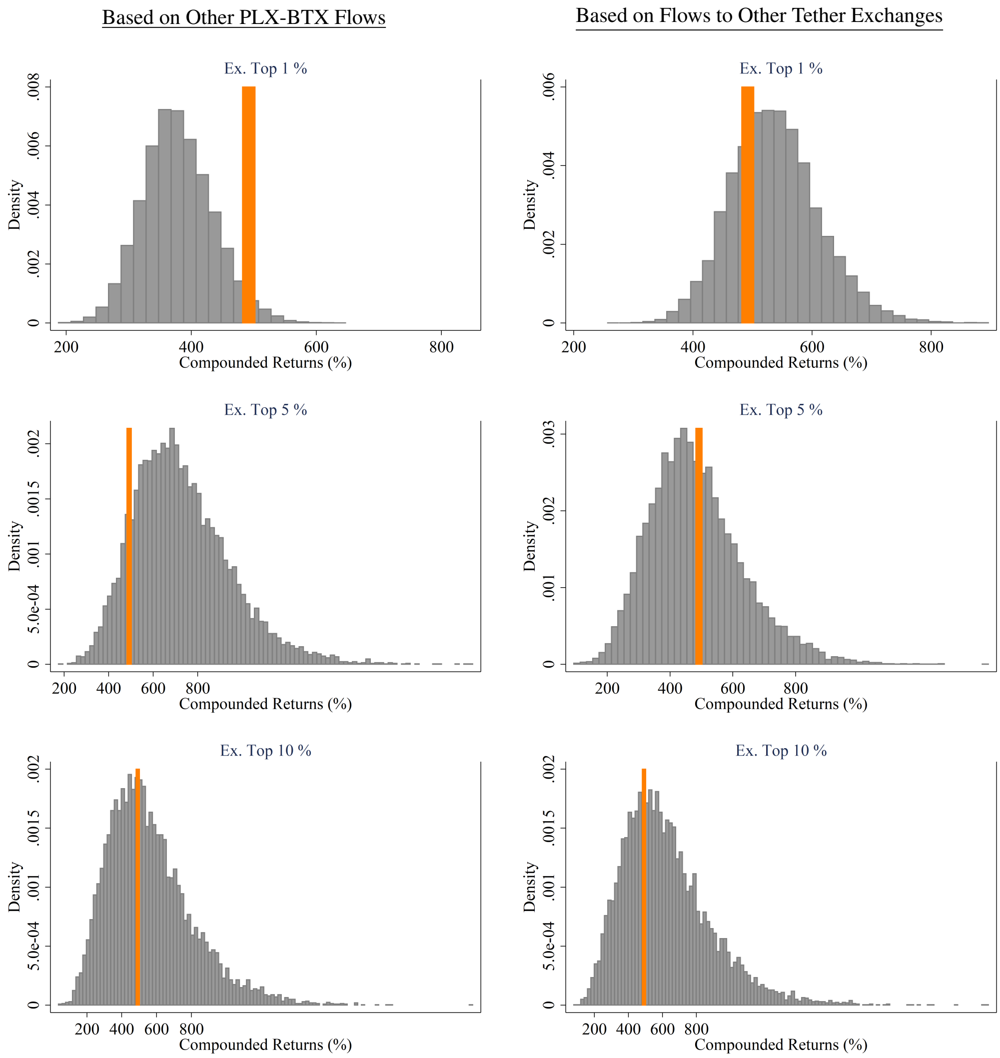


Figure IA14. Relationship Between High-Lagged-Flow Hours to Other Accounts and Bitcoin Returns. The orange bars show the buy-and-hold return of Bitcoin from March 1, 2017 to March 31, 2018. The gray bars in the left panels show the distribution of the returns if the top hours with high lagged net flows from Bitfinex to other Poloniex and Bittrex wallets (non-1LSg) are replaced with a random sample of returns in other hours, bootstrapped 10,000 times. The gray bars in the right panels show the distribution of the returns if the top hours with high lagged net aggregate flow from Bitfinex to all other Tether exchanges are replaced with a random sample of returns in other hours, bootstrapped 10,000 times. The return distribution in the top panel replaces top 1% of high lagged flow hours with a random sample of returns in other hours, and the middle and bottom panels replace top 5 and 10% respectively.

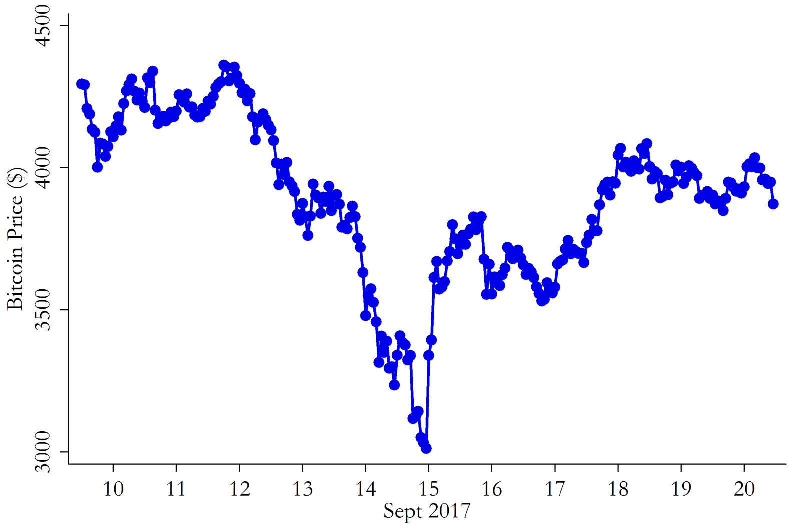


Figure IA15. Bitcoin Prices Around September 15, 2017. This figure shows hourly Bitcoin prices around September 15, 2017, as of which Tether released a limited audit of the cash balance. Tether later fired the auditor because of “the excruciatingly detailed procedures" it was undertaking.

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 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 24-hour lagged volatility constructed from hourly 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	-48.34***	-1.150	-65.56***	-2.228
	(-5.67)	(-0.12)	(-9.68)	(-0.36)
Lagged Volatility	6.610***	1.358	2.074*	3.987***
	(4.44)	(1.24)	(2.02)	(4.77)
Constant	-27.56***	6.278	9.353*	8.450*
	(-3.98)	(0.99)	(1.98)	(2.14)
Observations	4352	5149	4352	5149
Adjusted R^2	0.024	-0.000	0.065	0.008

Table IAIII. The Effect of 1LSg Flow on Other Cryptocurrency Returns. This table shows OLS estimates for which the dependent variable is the average 3-hour returns for major cryptocurrencies other than Bitcoin:

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

where R_t is hourly return using price data from the most liquid exchange for each cryptocurrency between March 1, 2017 and March 31, 2018 and $Flow_t$ is the net hourly 1LSg flow. The control variables include lagged returns, volatility calculated using hourly returns in the previous 24 hours, and the interaction of lagged returns and volatility. Major cryptocurrencies are selected based on the criteria in Table I, conditional on being listed on at least one of the major Tether exchanges as of the beginning of March 2017. Panel A 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 authorization 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 Authorization

Coin	Coefficient	t_stat	N
DASH	7.40	3.44	2645
ETC	8.29	2.84	2645
ETH	6.33	2.74	2645
LTC	6.26	1.78	2645
XMR	5.09	2.01	2645
ZEC	6.39	2.54	2645

B. Other Days

Coin	Coefficient	t_stat	N
DASH	0.65	0.60	6833
ETC	-0.57	-0.45	6833
ETH	0.58	0.53	6833
LTC	1.73	1.49	6833
XMR	0.48	0.37	6833
ZEC	0.42	0.29	6833

C. Following Negative Returns

Coin	Coefficient	t_stat	N
DASH	3.27	1.77	3992
ETC	2.78	1.98	4679
ETH	2.02	1.38	4544
LTC	3.67	2.46	4668
XMR	3.03	1.74	4614
ZEC	3.14	1.88	4785

D. Following Positive Returns

Coin	Coefficient	t_stat	N
DASH	4.11	2.50	3985
ETC	1.38	0.63	4732
ETH	1.78	1.18	4878
LTC	2.52	1.12	4581
XMR	0.58	0.42	4752
ZEC	1.32	0.69	4577

E. Following Negative Returns-Authorization

Coin	Coefficient	t_stat	N
DASH	11.01	3.44	1063
ETC	10.34	2.84	1271
ETH	9.40	2.74	1246
LTC	8.68	1.78	1293
XMR	8.23	2.01	1244
ZEC	8.38	2.54	1293

Table IAIV. Cross-section of Exchange Returns Around High-Flow Hours. This table examines the cross-section of cryptocurrencies exchanges returns around the high-flow hours. For any given exchange with pricing data on *CoinAPI*, an hourly exchange-level return index is calculated using all altcoin-BTC pairs listed on that exchange. Returns are calculated using prices denominated in Bitcoin and are value-weighted across coins by prior two weeks trading volume. The sample includes three hours before and three hours after the high lagged flow hours, and the high flow occurs between time -1 and time 0. $BFX/PLX/BTX$ is a dummy variables that takes the value of one for Bitfinex, Poloniex, and Bittrex exchanges and zero otherwise. The regression controls for time and exchange fixed effects. Column (2) shows the results when the returns are weighted by logarithm of prior two weeks trading volume, and Columns (3) and (4) show the results when high-flow hours are defined based on 1LSg flows. The sample period is from March 1, 2017 to March 31, 2018. Standard errors are adjusted for heteroscedasticity. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001

	Using Aggregate Flows		Using 1LSg Flows	
	(1)	(2)	(3)	(4)
	Returns	Returns	Returns	Returns
T=-2	0.042	0.043	0.037	0.039
	(1.06)	(1.03)	(0.75)	(0.82)
T=-1	0.026	0.058	0.075	0.094
	(0.44)	(0.96)	(1.12)	(1.37)
T=0	-0.015	-0.013	0.042	0.036
	(-0.25)	(-0.23)	(0.53)	(0.46)
T=1	-0.009	0.003	0.028	0.032
	(-0.11)	(0.04)	(0.33)	(0.41)
T=2	0.010	0.025	0.078	0.067
	(0.17)	(0.48)	(1.04)	(1.01)
T=3	-0.003	0.013	0.011	0.023
	(-0.05)	(0.25)	(0.15)	(0.41)
BFX/PLX/BTX*T=-2	-0.079	-0.090	0.025	-0.010
	(-0.72)	(-0.75)	(0.16)	(-0.07)
BFX/PLX/BTX*T=-1	0.192	-0.012	0.039	-0.133
	(1.32)	(-0.06)	(0.24)	(-0.66)
BFX/PLX/BTX*T=0	0.368*	0.355***	0.286**	0.302**
	(2.62)	(3.62)	(2.79)	(3.14)
BFX/PLX/BTX*T=1	0.473**	0.388**	0.434**	0.356**
	(3.42)	(3.02)	(3.37)	(2.82)
BFX/PLX/BTX*T=2	0.323*	0.211	0.293*	0.252
	(2.34)	(1.45)	(2.06)	(1.71)
BFX/PLX/BTX*T=3	0.368*	0.247	0.370*	0.249
	(2.03)	(1.89)	(2.24)	(1.74)
Constant	-0.146***	-0.163***	-0.185***	-0.202***
	(-4.21)	(-5.22)	(-4.00)	(-4.83)
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes
Observations	9828	9828	10395	10395

Table IAV. Bitcoin Compounded Returns Excluding Hours with High Lagged Flows. This table shows the compounded Bitcoin returns from March 1, 2017 to March 31, 2018, excluding the top 1%, 5%, and 10% of hours with highest flows in the previous hour. The first three columns show the returns excluding these hours, and the second three columns show the percentage decline relative to the actual Bitcoin buy-and-hold returns during the same period. The first row shows the returns when excluding top hours with high net average flows for aggregate Poloniex and Bittrex accounts, the second row shows the results for 1LSg flows, the third row for the rest of Poloniex and Bittrex accounts, and the last row for net flows to other Tether-based exchanges.

	Compounded Returns			**Decline Relative to Actual Returns**		
Flow	Ex. 1%	Ex. 5%	Ex. 10%	Ex. 1%	Ex. 5%	Ex. 10%
Agg. PLX BTX	198.6%	138.3%	217.7%	58.8%	71.3%	54.8%
1LSg	216.8%	158.2%	100.1%	55.0%	67.2%	79.2%
Oth. PLX BTX	369.3%	623.5%	419.1%	23.4%	-29.4%	13.0%
Others	522.8%	421.5%	460.9%	-8.5%	12.5%	4.4%

Table IAVI. Bitcoin Return Reversals and 1LSg Flow. This table shows OLS estimates for autocorrelation of Bitcoin returns:

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

where R_t is the hourly return of an equally-weighted price index aggregating Bitcoin prices on Tether exchanges, $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and Bitcoin from Poloniex and Bittrex to Bitfinex, and the control variables include lagged returns, volatility calculated using hourly returns in the previous 24 hours, and the interaction of lagged returns and volatility. The flow variables are standardized by subtracting the mean and dividing by the standard deviation. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

	All Sample	Neg Lagged Return	Pos Lagged Return
Lag Ret	-0.0180	-0.0058	-0.0462
	(-0.56)	(-0.10)	(-0.76)
Lag Flow	-0.0003	-0.0011*	0.0003
	(-0.85)	(-2.17)	(0.69)
Lag Flow × Lag Ret	-0.0326**	-0.0463	-0.0015
	(-2.76)	(-1.53)	(-0.07)
Lag Volatility	0.0086	0.0053	0.0101
	(1.28)	(0.44)	(0.89)
Lag Volatility × Lag Ret	-0.4175	-0.5584	-0.2354
	(-1.03)	(-0.80)	(-0.32)
Lag Flow × Lag Volatility	0.0094	0.0175	-0.0046
	(1.39)	(1.47)	(-0.49)
Constant	-0.0002	-0.0001	-0.0001
	(-0.67)	(-0.13)	(-0.25)
Observations	9503	4488	5011
R^2	0.008	0.014	0.002
Adjusted R^2	0.008	0.013	0.001

Table IAVII. Bitcoin Return Reversals and 1LSg Flow. This table shows OLS estimates for autocorrelation of Bitcoin returns:

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

where R_t is the hourly return of an equally-weighted price index aggregating Bitcoin prices on Tether exchanges, $Flow_t$ is a dummy variable that takes the value of one for hours with top 1%, 5%, and 10% of hours with high lagged flows for 1LSg, other Poloniex and Bittrex accounts, and other Tether exchanges, and the control variables include lagged returns, top 1%, 5%, and 10% high-volatility hours, and the interaction of lagged returns and high-volatility dummies. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

	Top 1%	Top 5%	Top 10%
Lag Ret	-0.0550	-0.0258	-0.0256
	(-1.76)	(-0.75)	(-0.64)
Lag High 1LSg Flow	0.0056	-0.0002	-0.0004
	(1.04)	(-0.08)	(-0.32)
Lag High 1LSg Flow=1 × Lag Ret	-0.5155**	-0.3077**	-0.1196
	(-2.59)	(-2.64)	(-1.31)
Lag High Vol	0.0166*	-0.0017	0.0009
	(2.53)	(-0.68)	(0.60)
Lag High Vol=1 × Lag Ret	0.2079	-0.1145	-0.0141
	(1.12)	(-1.33)	(-0.20)
Lag High PLX/BTX Flow=1 × Lag Ret	-0.0637	-0.0253	-0.0928
	(-0.37)	(-0.31)	(-1.35)
Lag High Other Flow=1 × Lag Ret	0.2575	0.0975	0.0356
	(1.15)	(1.15)	(0.52)
Constant	0.0000	0.0003	0.0002
	(0.07)	(0.99)	(0.58)
Observations	4488	4488	4488
R^2	0.026	0.016	0.009
Adjusted R^2	0.025	0.014	0.008

Table IAVIII. 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:

$$R_t^{EOM} = \beta_0 + \beta_1 Issuance_t + \epsilon_t$$

where the EOM return is defined as in Figure 9 and $Issuance_t$ is total monthly Bitcoin-denominated flow of Tether from the Tether treasury to Bitfinex, scaled by its standard deviation. Columns (1) and (3) show the results for raw EOM returns and Columns (2) and (4) for returns relative to the average return in the prior four days and subsequent four days. The value-weighted return shows the results for the returns on a value-weighted portfolio of top five cryptocurrencies. Each day in the sample, the top five cryptocurrencies are selected based on the average market cap in the previous week reported on *CoinMarketCap*. The sample is from March 2016 to March 2018. Panel B reports the results excluding the two months with extreme issuance, December 2017 and January 2018. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

A. All Months

	BTC Returns		Value-Weighted Index	
	Raw Returns	Relative to Days Around	Raw Returns	Relative to Days Around
Issuance	-0.0210**	-0.0222**	-0.0251***	-0.0269***
	(-2.85)	(-3.08)	(-4.85)	(-4.58)
Constant	0.00344	-0.00669	0.00696*	-0.00188
	(0.88)	(-1.72)	(2.27)	(-0.59)
Observations	25	25	25	25
Adjusted R^2	0.380	0.374	0.626	0.567

B. Excluding December 2017 and January 2018

	BTC Returns		Value-Weighted Index	
	Raw Returns	Relative to Days Around	Raw Returns	Relative to Days Around
Issuance	-0.00528	-0.0107	-0.0140**	-0.0186**
	(-1.26)	(-1.54)	(-2.97)	(-2.94)
Constant	-0.000449	-0.00869	0.00419	-0.00301
	(-0.11)	(-1.97)	(1.48)	(-0.86)
Observations	23	23	23	23
Adjusted R^2	0.021	0.130	0.403	0.453

Table IAIX. The Relationship between Monthly Tether Issuance and Outflow of Bitcoin from Exchange Reserve Wallets in days before EOM. This figure estimates OLS regressions of total net outflow of Bitcoin from exchanges reserve wallets on monthly Tether issuance. Exchange reserve wallets have a high balance of coins and a large number of transactions that are received from the same exchange. The wallets are captured through a multi-step procedure. As a first pass, each month, the wallets that receive at least 100 different deposits from different addresses and have transaction volumes of at least 100 Bitcoins are selected as potential reserve wallets. Second, the daily holding balances of all the candidate wallets are calculated using all their transactions on the blockchain. Finally, wallets that have an average daily balance of at least 1,000 Bitcoin during their active period and received at least 90% of their deposit incidences from wallets of the same exchange are labeled as deposit addresses for those exchanges. The top-five wallets with the highest average reserves that are identified with this procedure are 3Nxwenay9Z8Lc9JBiywExpnEFiLp6Afp8v (Bitstamp cold wallet), 3D2oetdNuZUqQHPJmcMDDHYoqkyNVsFk9r (Bitfinex cold wallet), 1MuYkciQTfRsU94ReAe5MiAfUpCrbLBcFR, 16rCmCmbuWDhPjWTrpQGaU3EPdZF7MTdUk (Bittrex cold wallet), and 18rnfoQgGo1HqvVQaAN4QnxjYE7Sez9eca. The sample period is from March 1, 2016 to March 1, 2018. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses. *p<.05, **p<.01, ***p<.001.

	Issuance	t_Issuance	Constant	t_Constant	N
Bitfinex	0.185**	3.14	-2516.0	-1.74	25
Bitflyer	-0.003	-0.12	-650.6	-1.33	25
Bitstamp	0.129	0.70	337.4	0.25	25
Bittrex	-0.114	-1.05	513.3	0.71	25
BTCtrade	-0.004	-0.85	162.8	0.80	25
Gemini	0.011	0.36	-361.7	-0.72	25
Huobi	-0.088	-1.01	1873.6	0.87	25
OKCoin	-0.228	-1.39	1085.0	1.47	12
Poloniex	0.002	0.04	-522.2	-0.54	25
Coinbase	0.007	1.28	-220.8	-1.84	20
All Oth. Comb.	-0.301	-1.30	594.4	0.17	25

Table IAX. p-values for Granger Causality Tests Between Bitcoin Returns on Bitfinex and Other Exchanges. This table examines the lead-lag relationship between price of Bitcoin on Bitfinex and other exchanges at the EOM. Using hourly Bitcoin returns on each exchange, this table estimates a Vector AutoRegression (VAR) model with five lags between Bitfinex returns and all the exchanges in *CoinAPI* data separately. Exchanges are labeled with the first four characters of their name. The first column shows the p-values of a Granger causality Wald test that the coefficients on the lags of Bitfinex returns in explaining the other exchange returns are jointly zero, which tests whether Bitfinex leads the other exchange. The second column shows the p-values for the test that the other exchange leads Bitfinex. The sample includes returns in the five days prior to the end-of-the-month from March 1, 2017 to March 1, 2018.

	Bitfinex p-value	Other Ex p-value
ABUC	0.001***	0.136
BINA	0.003**	0.018*
BITS	0.001***	0.002**
BITT	0.000***	0.296
BTCE	0.000***	0.012*
BTCX	0.057	0.091
CCEX	0.000***	0.002**
CEXI	0.882	0.893
COIN	0.101	0.002**
CRYP	0.000***	0.911
DSX	0.000***	0.226
EXMO	0.000***	0.130
GATE	0.000***	0.245
GEMI	0.304	0.126
HITB	0.000***	0.820
HUOB	0.008**	0.063
ITBI	0.032*	0.626
KRAK	0.000***	0.266
KUCO	0.000***	0.293
LAKE	0.028*	0.063
LIQU	0.000***	0.006**
LIVE	0.000***	0.452
MIXC	0.607	0.790
OKCO	0.000***	0.164
OKEX	0.002**	0.189
POLO	0.001***	0.000***
QUAD	0.000***	0.356
QUOI	0.630	0.068
SOUT	0.000***	0.247
THER	0.000***	0.431
TIDE	0.000***	0.247
YOBI	0.000***	0.623

Table IAXI. The Relationship between Tether and Bitcoin Flows and Synthetic Tether-USD versus BTC-USD Rates. This table shows OLS estimates for which the dependent variables are the net flow of Tether from Bitfinex (Panel A) and the net flow of Bitcoin to Bitfinex (Panel B), and the independent variables are multiple lags of BTC-USD and synthetic Tether-USD returns. The synthetic Tether-USD rate is calculated by dividing the average Bitcoin price on Dollar exchanges by Bitcoin price on Bitfinex.

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

where $R_t^{BTC-USD}$ is the hourly return of Bitcoin prices in U.S. dollars and $SynthR_t^{Tether-USD}$ is the hourly return of the synthetic Tether-USD rate. The sample period is from March 1, 2017 to March 1, 2018. 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.Tether_USD_SynthRet	-0.0186	-0.0212	-0.0233	-0.0244	-0.0244
	(-1.37)	(-1.52)	(-1.63)	(-1.69)	(-1.68)
L2.Tether_USD_SynthRet		-0.0172	-0.0200	-0.0230	-0.0233
		(-1.30)	(-1.36)	(-1.52)	(-1.51)
L3.Tether_USD_SynthRet			-0.0097	-0.0129	-0.0140
			(-0.72)	(-0.89)	(-0.94)
L4.Tether_USD_SynthRet				-0.0114	-0.0119
				(-0.88)	(-0.83)
L5.Tether_USD_SynthRet					-0.0032
					(-0.25)
L.BTC_USD_Ret	-0.0451***	-0.0495***	-0.0503***	-0.0516***	-0.0521***
	(-3.31)	(-3.62)	(-3.69)	(-3.78)	(-3.80)
L2.BTC_USD_Ret		-0.0673***	-0.0694***	-0.0706***	-0.0713***
		(-4.90)	(-4.95)	(-5.02)	(-5.06)
L3.BTC_USD_Ret			-0.0287*	-0.0314**	-0.0320**
			(-2.56)	(-2.79)	(-2.79)
L4.BTC_USD_Ret				-0.0396**	-0.0409**
				(-3.04)	(-3.11)
L5.BTC_USD_Ret					-0.0248
					(-1.82)
Constant	0.0000	0.0000	-0.0002	-0.0006	-0.0007
	(0.00)	(0.00)	(-0.02)	(-0.06)	(-0.07)
Observations	9476	9469	9462	9455	9448
Adjusted R^2	0.002	0.007	0.007	0.009	0.009

B. Bitcoin Flow

	BTC Flow	BTC Flow	BTC Flow	BTC Flow	BTC Flow
L.Tether_USD_SynthRet	0.0159	0.0198	0.0191	0.0176	0.0177
	(1.07)	(1.28)	(1.22)	(1.12)	(1.13)
L2.Tether_USD_SynthRet		0.0046	0.0042	0.0003	-0.0014
		(0.31)	(0.27)	(0.02)	(-0.09)
L3.Tether_USD_SynthRet			-0.0079	-0.0133	-0.0168
			(-0.53)	(-0.83)	(-1.04)
L4.Tether_USD_SynthRet				-0.0172	-0.0205
				(-1.16)	(-1.33)
L5.Tether_USD_SynthRet					-0.0076
					(-0.55)
L.BTC_USD_Ret	-0.0942***	-0.0966***	-0.0997***	-0.1012***	-0.1022***
	(-5.78)	(-5.94)	(-6.10)	(-6.21)	(-6.28)
L2.BTC_USD_Ret		-0.0749***	-0.0783***	-0.0803***	-0.0814***
		(-5.00)	(-5.22)	(-5.34)	(-5.41)
L3.BTC_USD_Ret			-0.0666***	-0.0702***	-0.0692***
			(-4.46)	(-4.68)	(-4.62)
L4.BTC_USD_Ret				-0.0438**	-0.0455**
				(-3.14)	(-3.22)
L5.BTC_USD_Ret					-0.0210
					(-1.49)
Constant	-0.0007	-0.0010	-0.0007	-0.0007	-0.0010
	(-0.07)	(-0.10)	(-0.07)	(-0.07)	(-0.10)
Observations	9476	9469	9462	9455	9448
Adjusted R^2	0.009	0.015	0.019	0.021	0.021

Table IAXII. The Relationship between Tether and Bitcoin Flows and Value-Weighted Tether-USD Rate Across Exchanges versus BTC-USD Rates. This table shows OLS estimates for which the dependent variables are the net flow of Tether from Bitfinex (Panel A) and the net flow of Bitcoin to Bitfinex (Panel B), and the independent variables are multiple lags of BTC-USD and value-weighted Tether-USD returns. The value-weighted Tether-USD returns are calculated using hourly returns of Tether-USD rates across all exchanges that list the Tether-USD pair, weighted by trading volume.

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

where $R_t^{BTC-USD}$ is the hourly return of Bitcoin prices in U.S. dollars and $VWRet_t^{Tether-USD}$ is the value-weighted average of hourly returns of Tether-USD pairs. The sample period is from March 1, 2017 to March 1, 2018. 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.Tether_USD_VWRet	-0.0028	0.0017	0.0046	0.0045	0.0061
	(-0.29)	(0.16)	(0.42)	(0.40)	(0.53)
L2.Tether_USD_VWRet		0.0110	0.0164	0.0164	0.0191
		(0.83)	(1.17)	(1.16)	(1.27)
L3.Tether_USD_VWRet			0.0162	0.0173	0.0208
			(1.54)	(1.42)	(1.55)
L4.Tether_USD_VWRet				0.0029	0.0117
				(0.25)	(0.76)
L5.Tether_USD_VWRet					0.0206
					(1.19)
L.BTC_USD_Ret	-0.0459***	-0.0489***	-0.0508***	-0.0508***	-0.0505***
	(-3.38)	(-3.60)	(-3.77)	(-3.76)	(-3.74)
L2.BTC_USD_Ret		-0.0689***	-0.0709***	-0.0733***	-0.0727***
		(-5.03)	(-5.16)	(-5.31)	(-5.24)
L3.BTC_USD_Ret			-0.0308**	-0.0329**	-0.0342**
			(-2.78)	(-2.96)	(-3.04)
L4.BTC_USD_Ret				-0.0392**	-0.0395**
				(-3.01)	(-3.06)
L5.BTC_USD_Ret					-0.0262
					(-1.92)
Constant	-0.0002	-0.0014	-0.0025	-0.0028	-0.0036
	(-0.02)	(-0.14)	(-0.24)	(-0.28)	(-0.35)
Observations	9453	9440	9427	9414	9401
Adjusted R^2	0.002	0.007	0.008	0.009	0.010

B. Bitcoin Flow

	BTC Flow	BTC Flow	BTC Flow	BTC Flow	BTC Flow
L.Tether_USD_VWRet	0.0026	0.0086	0.0082	0.0089	0.0107
	(0.20)	(0.65)	(0.61)	(0.66)	(0.79)
L2.Tether_USD_VWRet		0.0095	0.0075	0.0091	0.0108
		(0.77)	(0.56)	(0.67)	(0.78)
L3.Tether_USD_VWRet			-0.0095	-0.0051	-0.0042
			(-0.74)	(-0.37)	(-0.30)
L4.Tether_USD_VWRet				0.0100	0.0084
				(0.80)	(0.64)
L5.Tether_USD_VWRet					0.0051
					(0.44)
L.BTC_USD_Ret	-0.0964***	-0.1003***	-0.1037***	-0.1038***	-0.1044***
	(-5.91)	(-6.17)	(-6.42)	(-6.44)	(-6.51)
L2.BTC_USD_Ret		-0.0769***	-0.0813***	-0.0837***	-0.0832***
		(-5.17)	(-5.48)	(-5.63)	(-5.59)
L3.BTC_USD_Ret			-0.0672***	-0.0698***	-0.0710***
			(-4.57)	(-4.74)	(-4.82)
L4.BTC_USD_Ret				-0.0418**	-0.0439**
				(-3.01)	(-3.17)
L5.BTC_USD_Ret					-0.0254
					(-1.82)
Constant	0.0005	0.0006	0.0007	0.0004	-0.0006
	(0.05)	(0.06)	(0.07)	(0.04)	(-0.06)
Observations	9453	9440	9427	9414	9401
Adjusted R^2	0.009	0.015	0.020	0.022	0.022

Table IAXIII. The Relationship between Tether and Bitcoin Flows and Equally-Weighted Tether-USD Rate Across Exchanges versus BTC-USD Rates. This table shows OLS estimates for which the dependent variables are the net flow of Tether from Bitfinex (Panel A) and the net flow of Bitcoin to Bitfinex (Panel B), and the independent variables are multiple lags of BTC-USD and equally-weighted Tether-USD returns. The equally-weighted Tether-USD returns are calculated using hourly returns of Tether-USD rates across all exchanges that list the Tether-USD pair.

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

where $R_t^{BTC-USD}$ is the hourly return of Bitcoin prices in U.S. dollars and $EWRet_t^{Tether-USD}$ is the equally-weighted average of hourly returns of Tether-USD pairs. The sample period is from March 1, 2017 to March 1, 2018. 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.Tether_USD_EWRet	0.0049	0.0033	0.0044	0.0032	0.0028
	(0.49)	(0.30)	(0.40)	(0.29)	(0.24)
L2.Tether_USD_EWRet		0.0028	0.0025	-0.0002	-0.0002
		(0.20)	(0.17)	(-0.01)	(-0.01)
L3.Tether_USD_EWRet			0.0033	-0.0028	-0.0037
			(0.29)	(-0.22)	(-0.27)
L4.Tether_USD_EWRet				-0.0136	-0.0144
				(-1.09)	(-0.97)
L5.Tether_USD_EWRet					-0.0010
					(-0.06)
L.BTC_USD_Ret	-0.0458***	-0.0491***	-0.0511***	-0.0512***	-0.0509***
	(-3.38)	(-3.62)	(-3.80)	(-3.80)	(-3.78)
L2.BTC_USD_Ret		-0.0690***	-0.0713***	-0.0738***	-0.0733***
		(-5.04)	(-5.18)	(-5.34)	(-5.28)
L3.BTC_USD_Ret			-0.0304**	-0.0328**	-0.0343**
			(-2.73)	(-2.95)	(-3.04)
L4.BTC_USD_Ret				-0.0386**	-0.0395**
				(-2.98)	(-3.07)
L5.BTC_USD_Ret					-0.0266
					(-1.95)
Constant	-0.0002	-0.0014	-0.0025	-0.0029	-0.0037
	(-0.02)	(-0.14)	(-0.24)	(-0.28)	(-0.36)
Observations	9453	9440	9427	9414	9401
Adjusted R^2	0.002	0.007	0.007	0.009	0.009

B. Bitcoin Flow

	BTC Flow	BTC Flow	BTC Flow	BTC Flow	BTC Flow
L.Tether_USD_EWRet	0.0078	0.0083	0.0066	0.0062	0.0060
	(0.63)	(0.65)	(0.51)	(0.49)	(0.47)
L2.Tether_USD_EWRet		0.0030	-0.0029	-0.0040	-0.0048
		(0.24)	(-0.22)	(-0.29)	(-0.35)
L3.Tether_USD_EWRet			-0.0141	-0.0165	-0.0188
			(-1.04)	(-1.13)	(-1.28)
L4.Tether_USD_EWRet				-0.0044	-0.0131
				(-0.31)	(-0.87)
L5.Tether_USD_EWRet					-0.0153
					(-1.18)
L.BTC_USD_Ret	-0.0965***	-0.1006***	-0.1040***	-0.1042***	-0.1047***
	(-5.92)	(-6.19)	(-6.44)	(-6.47)	(-6.53)
L2.BTC_USD_Ret		-0.0767***	-0.0810***	-0.0835***	-0.0831***
		(-5.14)	(-5.45)	(-5.60)	(-5.58)
L3.BTC_USD_Ret			-0.0667***	-0.0697***	-0.0709***
			(-4.52)	(-4.72)	(-4.79)
L4.BTC_USD_Ret				-0.0425**	-0.0449**
				(-3.04)	(-3.23)
L5.BTC_USD_Ret					-0.0254
					(-1.82)
Constant	0.0005	0.0007	0.0007	0.0004	-0.0007
	(0.05)	(0.06)	(0.07)	(0.04)	(-0.07)
Observations	9453	9440	9427	9414	9401
Adjusted R^2	0.009	0.015	0.020	0.022	0.022

Table IAXIV. The Relationship between Tether and Bitcoin Flows for 1LSg and other accounts and Tether-USD versus BTC-USD Rates. This table shows OLS estimates similar to the Column (5) of Table VIII, where the dependent variables are the average net flows of Tether and Bitcoin between Bitfinex and 1LSg accounts, other Poloniex and Bittrex accounts, and other Tether exchanges, Binance, Huobi, HitBTC, OKEx, and Kraken. Panel A shows the results for Tether-USD rate on Kraken, and Panel B for the synthetic Tether-USD rate calculated as in Table IAXI. The sample period is from April 1, 2017 (when Kraken prices are available) to March 1, 2018 in Panel A and from March 1, 2017 to March 1, 2018 in Panel B. Panel C estimates the same regression as Panel C of Table VIII for 1LSg and other flows. 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. Kraken Rates

	1LSg	Other PLX/BTX	Binance	Huobi	HitBTC	OKEx	Kraken
L.Tether_USD_Ret	0.004	0.011	0.002	0.001	0.003	-0.010	0.029**
	(0.32)	(0.78)	(0.07)	(0.23)	(0.37)	(-0.69)	(2.91)
L2.Tether_USD_Ret	0.022	0.021	0.013	-0.002	0.003	0.020	0.023*
	(1.32)	(1.45)	(0.47)	(-0.24)	(0.35)	(1.05)	(2.02)
L3.Tether_USD_Ret	0.019	0.012	0.003	0.001	0.002	-0.004	0.017
	(1.26)	(0.86)	(0.12)	(0.17)	(0.21)	(-0.25)	(1.62)
L4.Tether_USD_Ret	0.033*	-0.009	0.033	0.009	-0.002	0.000	0.013
	(2.05)	(-0.56)	(1.25)	(0.97)	(-0.24)	(0.01)	(1.20)
L5.Tether_USD_Ret	0.028	0.003	0.042	0.009	-0.010	0.013	0.006
	(1.58)	(0.23)	(1.82)	(1.55)	(-1.10)	(1.02)	(0.50)
L.BTC_USD_Ret	-0.083***	-0.061***	-0.069***	0.048***	-0.017	0.016	-0.013
	(-5.40)	(-4.97)	(-3.84)	(3.63)	(-1.19)	(1.27)	(-1.46)
L2.BTC_USD_Ret	-0.085***	-0.065***	-0.035*	0.022	-0.034	0.022	-0.026**
	(-5.81)	(-4.73)	(-2.19)	(1.67)	(-1.56)	(1.78)	(-2.88)
L3.BTC_USD_Ret	-0.049***	-0.057***	-0.019	0.044*	0.003	0.023*	-0.018*
	(-3.65)	(-4.80)	(-1.34)	(2.56)	(0.17)	(2.03)	(-2.04)
L4.BTC_USD_Ret	-0.047***	-0.043**	-0.016	0.035**	0.002	0.025*	-0.013
	(-3.59)	(-3.17)	(-1.07)	(2.82)	(0.14)	(2.07)	(-1.57)
L5.BTC_USD_Ret	-0.025	-0.037**	0.001	0.031*	0.016	0.015	-0.022*
	(-1.66)	(-2.83)	(0.04)	(2.35)	(1.34)	(1.10)	(-2.07)
Constant	0.007	-0.002	0.000	0.007	0.000	0.001	-0.005
	(0.65)	(-0.21)	(0.00)	(0.63)	(0.01)	(0.04)	(-0.42)
Observations	8746	8746	6556	8746	8746	4096	8746
Adjusted R^2	0.017	0.012	0.007	0.005	0.001	0.001	0.001

B. Synthetic Rates

	1LSg	Other PLX/BTX	Binance	Huobi	HitBTC	OKEx	Kraken
L.Tether_USD_SynthRet	-0.012	0.001	0.022	0.003	-0.012	-0.018	0.011
	(-0.79)	(0.09)	(1.23)	(0.27)	(-0.96)	(-1.12)	(0.76)
L2.Tether_USD_SynthRet	-0.022	0.002	0.022	0.006	-0.001	-0.023	-0.004
	(-1.36)	(0.19)	(1.20)	(0.50)	(-0.05)	(-1.24)	(-0.35)
L3.Tether_USD_SynthRet	-0.019	-0.007	-0.002	0.005	-0.002	0.000	-0.009
	(-1.22)	(-0.52)	(-0.09)	(0.41)	(-0.15)	(0.02)	(-0.53)
L4.Tether_USD_SynthRet	-0.019	-0.008	-0.020	-0.000	-0.009	-0.003	-0.021
	(-1.31)	(-0.56)	(-1.21)	(-0.00)	(-0.64)	(-0.17)	(-1.87)
L5.Tether_USD_SynthRet	-0.008	0.003	0.000	0.004	0.010	-0.003	-0.010
	(-0.61)	(0.23)	(0.01)	(0.45)	(0.88)	(-0.25)	(-0.81)
L.BTC_USD_Ret	-0.082***	-0.054***	-0.065***	0.047***	-0.017	0.014	-0.011
	(-5.49)	(-4.09)	(-3.65)	(3.64)	(-1.21)	(1.12)	(-1.25)
L2.BTC_USD_Ret	-0.083***	-0.066***	-0.037*	0.021	-0.032	0.021	-0.028**
	(-5.89)	(-4.88)	(-2.28)	(1.67)	(-1.63)	(1.70)	(-2.99)
L3.BTC_USD_Ret	-0.047***	-0.054***	-0.022	0.042*	0.003	0.024*	-0.020*
	(-3.57)	(-4.58)	(-1.51)	(2.53)	(0.15)	(2.04)	(-2.33)
L4.BTC_USD_Ret	-0.046***	-0.040**	-0.019	0.033**	0.003	0.025*	-0.013
	(-3.68)	(-3.01)	(-1.22)	(2.75)	(0.21)	(2.07)	(-1.65)
L5.BTC_USD_Ret	-0.021	-0.034**	0.002	0.030*	0.016	0.014	-0.020
	(-1.47)	(-2.63)	(0.11)	(2.43)	(1.44)	(1.07)	(-1.89)
Constant	-0.001	-0.001	-0.001	-0.001	-0.000	0.001	-0.000
	(-0.08)	(-0.10)	(-0.08)	(-0.09)	(-0.02)	(0.07)	(-0.02)
Observations	9448	9448	6544	9448	9448	4084	9448
Adjusted R^2	0.015	0.010	0.007	0.005	0.001	0.001	0.001

C. Price Differences Between USD and Tether Exchanges

	1LSg	Other PLX/BTX	Binance	Huobi	HitBTC	OKEx	Kraken
Arbitrage Spread	0.00445	0.0201	0.0528*	0.0258**	-0.00615	0.0135	0.00556
	(0.29)	(1.68)	(2.42)	(2.63)	(-0.57)	(0.68)	(0.46)
Average Return	-0.114***	-0.0926***	-0.0626***	0.0598***	-0.0266	0.0333**	-0.0283**
	(-7.47)	(-6.76)	(-3.60)	(3.87)	(-1.55)	(2.68)	(-3.13)
Constant	0.0000272	0.0000307	-0.0000180	0.0000272	-0.000000127	0.000323	-0.00000198
	(0.00)	(0.00)	(-0.00)	(0.00)	(-0.00)	(0.02)	(-0.00)
Observations	9501	9501	6556	9501	9501	4096	9501
Adjusted R^2	0.013	0.010	0.008	0.003	0.000	0.001	0.001

Table IAXV. The Relationship between Flow, Bitcoin Returns, and Cross-Exchange Spread. Columns (1) and (2) estimate OLS regressions of net Tether and Bitcoin flows on the difference three-hour Bitcoin lagged returns between Bitfinex and Poloniex ($Cross\text{-}ExchSpread$) and the average of three-hour Bitcoin lagged returns on Bitfinex and Poloniex ($AverageReturn$):

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

where $AverageReturn_t = \frac{(R_t^{BFX} + R_t^{PLX})}{2}$ and $Cross\text{-}ExchSpread_t = R_t^{BFX} - R_t^{PLX}$, 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 net flows between Bitfinex and Bittrex exchanges. Panels B and C estimate a similar regression where the dependent variables are the net flows of Tether and Bitcoin between Bitfinex and 1LSg accounts, other Poloniex and Bittrex accounts, and other Tether exchanges, Binance, Huobi, HitBTC, OKEx, and Kraken. The cross-exchange spread and average returns are calculated as in Panel A but between Bitfinex returns and the returns on the exchange under study in each column. For 1LSg flows, the average of Poloniex and Bittrex returns are used. 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.

A. Aggregate Net Flows

	(1) Poloniex_Tether	(2) Poloniex_BTC	(3) Bittrex_Tether	(4) Bittrex_BTC
Cross_Exch Spread	0.0419**	0.0370*	0.0336**	0.0400*
	(3.13)	(2.39)	(2.72)	(2.39)
Average Return	-0.0430***	-0.0912***	-0.0626**	-0.120***
	(-3.76)	(-6.30)	(-3.15)	(-6.68)
Constant	-0.0174	-0.0205	0.00867	0.0301**
	(-1.80)	(-1.93)	(0.73)	(2.61)
Observations	7986	7986	8193	8193
Adjusted R^2	0.005	0.011	0.005	0.017

B. Decomposed Net Tether Flows

	1LSg	Other PLX	Other BTX	Binance	Huobi	HitBTC	OKEx	Kraken
Cross_Exch Spread	0.039**	0.008	0.017*	0.122***	0.034	-0.002	0.040*	0.010
	(2.72)	(0.41)	(2.14)	(3.32)	(0.53)	(-0.71)	(1.96)	(0.50)
Average Return	-0.059***	-0.043***	-0.013	-0.067	0.196**	-0.014	0.032	-0.022
	(-4.36)	(-3.73)	(-0.91)	(-1.76)	(2.85)	(-0.88)	(1.37)	(-1.50)
Constant	-0.003	-0.014	0.007	0.075*	0.129*	-0.004	0.021	-0.000
	(-0.33)	(-1.28)	(0.62)	(2.21)	(2.07)	(-0.35)	(0.80)	(-0.02)
Observations	8979	7986	8193	2349	1255	7990	2447	9155
Adjusted R^2	0.006	0.002	0.000	0.008	0.007	-0.000	0.001	0.000

C. Decomposed Net Bitcoin Flows

	1LSg	Other PLX	Other BTX	Binance	Huobi	HitBTC	OKEx	Kraken
Cross_Exch Spread	-0.000	0.020	0.035**	0.136***	0.109	-0.002	0.033	-0.031**
	(-0.01)	(1.46)	(2.61)	(3.39)	(1.94)	(-0.21)	(0.62)	(-2.99)
Average Return	-0.112***	-0.058***	-0.078***	-0.140***	0.311***	-0.025	0.074**	-0.016*
	(-6.88)	(-5.18)	(-4.78)	(-3.89)	(5.86)	(-1.41)	(2.89)	(-1.98)
Constant	-0.006	-0.018	0.031**	0.323***	0.125**	-0.000	0.024	-0.001
	(-0.62)	(-1.69)	(2.71)	(10.95)	(2.97)	(-0.03)	(0.94)	(-0.13)
Observations	8979	7986	8193	2349	1255	7990	2447	9155
Adjusted R^2	0.013	0.004	0.008	0.022	0.049	0.000	0.003	0.001