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Flight to Safety: Evaluating Stablecoin's Role as a Safe-Haven Asset in DeFi Markets

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Abstract

This study examines the impact of the stablecoin Tether (USDT) on systemic liquidity across the Ethereum and Bitcoin markets, utilizing an event study approach that integrates on-chain wallet data, pricing, and financial metrics. By analyzing cryptocurrency market responses to key protocol and market-moving events, augmented by nonlinear volatility models, we identify distinct, chain-specific flight-to-safety behaviors. Our results show that USDT acts as a primary liquidity lifeline for Ethereum holders during stress, particularly among retail investors, whereas its role for Bitcoin holders is more muted and stabilizing. Notably, we find stronger flight-to-safety evidence in Wrapped Bitcoin (Ethereum-based) than in native Bitcoin, highlighting that USDT's function is network-dependent. These findings imply that effective regulatory frameworks must be differentiated, accounting for chain-specific liquidity, investor composition, and risk dynamics, as a uniform approach would likely be systematically miscalibrated.

Keywords: Cryptocurrency; Stablecoins; Bitcoin; Ethereum; Tether; Flight to safety; BTC, ETH, USDT
JEL Classifications: G14, G23, G28, G41

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I. Introduction

Sharp price fluctuations and limited investor protections have become a hallmark of cryptocurrency markets. During periods of heightened volatility in traditional financial markets, investors with greater risk exposure often reallocate their capital in search of safer assets. While the broader financial literature has examined "flight-to-safety" behavior among traditional investors in response to adverse economic shocks (Baele et al., 2020; Kekre and Lenel, 2024), there remains a gap in the literature regarding how such reallocation unfolds within the cryptocurrency ecosystem. Specifically, it is unclear whether crypto holders tend to shift into stablecoins, exit into fiat currencies, rotate into other blockchain-native assets, or simply hold through periods of turbulence.

Stablecoins have become central to this dynamic, as they offer a blockchain-native means of value preservation without fully exiting the digital asset ecosystem. However, this leads to additional questions, especially regarding their perceived safety, regulatory risk, and ability to maintain pegs under stress. These concerns were highlighted during the collapse of TerraUSD (UST) and remain salient in debates about the role of stablecoins as a digital cash substitute. More broadly, the interactions between crypto-native assets and traditional safe havens like gold and government bonds remain an open empirical question, particularly when observed from the perspective of capital flows originating from within the crypto sector.

One possibility is that this behavior varies across investor types. Large institutional players, crypto "whales," may be better positioned to act strategically during periods of stress, rotating into dollar-pegged stablecoins or moving capital off-chain entirely. In contrast, smaller retail investors may lack the infrastructure or foresight to navigate volatility efficiently, resulting in greater exposure to drawdowns. This divide reflects a broader set of structural asymmetries that exist in cryptocurrency markets, as noted in Cornelli et al. (2023) and Chernoff and Jagtiani (2025), where informational advantages and platform access may allow crypto whales to respond more nimbly to shocks.

Our goal in this paper is to investigate how cryptocurrency holders, particularly Bitcoin (BTC) and Ethereum (ETH) investors, reallocate capital during periods of elevated volatility and adverse market-moving events. Given the structural limitations (weak integration between the banking and crypto sectors) in on-ramping and off-ramping between traditional finance and the crypto ecosystem, we also examine in this paper whether crypto investors utilize stablecoins as a temporary safe haven for crypto-native capital to mitigate risk during moments of uncertainty We aim to determine if crypto investors treat stablecoins as a flight-to-safety asset in decentralized financial markets rather than moving back to traditional fiat during key episodes of stress (such as during high cryptocurrency volatility indices or indicators of cryptocurrency shocks).

II. Related Literature and Our Contribution

Previous studies have investigated the integration of Bitcoin (BTC) and Ethereum (ETH) into investment portfolios, specifically focusing on their utility for asset allocation and risk mitigation. Literature regarding their role in the broader, decentralized ecosystem remains sparse. Most studies analyze crypto holdings on centralized exchanges, overlooking the unique risk management strategies required for decentralized finance (DeFi) environments. Because BTC and ETH are the top two cryptocurrencies by market cap, understanding their role in new digital landscapes is vital. In this study, we address this gap by exploring asset reallocation and flight-to-safety behavior within the decentralized ecosystem, focusing on the two leading cryptocurrencies.

II.1 Literature Related to Crypto Asset Allocation and Flight to Safety

Katsiampa (2019) investigates volatility interdependency among crypto assets, using daily closing prices for BTC and ETH during the period August 2015 to January 2018. The paper examines how holders of BTC may shift to ETH in times of BTC instability, suggesting that there are strong positive correlations and interdependencies across cryptocurrencies, namely BTC and ETH. Despite their strong positive correlation, holding a diversified portfolio (with both BTC and ETH) can help investors optimize risk, and ETH could potentially be an effective hedge against BTC volatility.

Kajtazi and Moro (2019) take a more global but still similar approach to examine the role of BTC in portfolios of US, European, and Chinese assets. They compare portfolio performance under various scenarios for those with BTC and those without BTC in the portfolio. Using data over 60 months from February 2012 to January 2017, they find superior portfolio performance among those with BTC, though the improved performance from adding BTC to the portfolio seems to be related to increased returns rather than reduced volatility.

Yousaf and Ali (2020) examine returns and volatility spillover for a broader set of cryptocurrencies, including BTC, ETH, and Litecoin, using intraday data during the pre-Covid and Covid periods. They find that the return spillovers vary across the two periods for the BTC-ETH, BTC-Litecoin, and ETH–Litecoin pairs. The volatility transmissions are different during the two sample periods for the BTC-ETH and BTC–Litecoin pairs. The overall finding from their exercise seems to be that crypto returns and volatility could behave quite differently across currency pairs, time periods, and economic environments, implying that previous findings on crypto roles in portfolio risk management may be specific to currencies and time periods that may not be applicable in other economic and regulatory environments.

A few previous studies have explored asset reallocation within the crypto asset space from exchanges that are riskier or are being noncompliant towards larger, safer, and more regulated domestic US crypto exchanges. For example, Fang, Chen, and Jiang (2025) examine crypto investors' flight-to-safety behavior in 39 countries, focusing on cyberattacks on crypto exchanges that led to assets leaving the cryptocurrency ecosystem, specifically from BTC to traditional stock markets. The flight-to-safety behavior was triggered by hacking attacks on cryptocurrency exchanges, which resulted in loss of trust in the crypto exchanges and a flight to safer, more regulated stock markets and US mutual funds following these attacks.

Given the lack of structural integration between the crypto ecosystem and the traditional financial/payment systems, there might be a superior pathway for flight-to-safety allocation of assets from risky crypto assets to safer assets without going off-ramp into traditional stock markets. Stablecoins could potentially play an important role in allowing a smooth flight to safety without having to leave the crypto ecosystem. Crypto investors could reallocate from their risky crypto assets into stablecoins within the crypto ecosystem, without exposing themselves to any potential crypto off-ramp regulatory scrutiny.

A few studies have explored the potential roles of stablecoins in facilitating more efficient ways to move across blockchain networks to access safer assets within the crypto ecosystem. Liao and Caramichael (2022) find that dollar-pegged stablecoins backed by adequate high-quality collateral demonstrate safe haven characteristics during crypto market distress, with prices in the secondary market temporarily rising above their $1 peg as investors liquidate speculative positions into stablecoins. The paper stresses being US dollar pegged and having adequate high-quality collateral as key features needed for stablecoins to serve as a safe haven and store-of-value investment.

Lyons and Viswanath-Natraj (2023), using data of signed trades and order books on multiple exchanges, find that the migration of the stablecoin USDT from the Bitcoin Omni Layer to the Ethereum blockchain in 2019 was a pivotal event that improved efficiency and its peg stability. The expansion of the USDT network of investors through increasing access helped to reduce transaction costs and democratize arbitrage opportunities. Specifically, the expanded access to USDT, following USDT's introduction to the Ethereum blockchain in 2019, increased investor access to arbitrage trades and reduced arbitrage spreads significantly (from 70 to 30 basis points). The spreads represent insurance premiums due to stablecoins' role as a safe haven asset, with premiums greater than 100 basis points during the COVID-19 crisis that started in March 2020. Lyons and Viswanath-Natraj (2023) demonstrate that a specific stablecoin, Tether USDT, could serve as a safe haven tool during a period of crypto market volatility.

There is further evidence from the literature that supports findings that USDT can potentially serve as a safe haven in the crypto ecosystem. Baur and Hoang (2021) examine whether stablecoins can serve as a safe haven for BTC investors during periods of extreme volatility. They explore how stablecoin prices respond to extreme negative returns in BTC, using high-frequency data on price changes of the six largest stablecoins, including Tether (USDT), Circle (USDC), TrueUSD (TUSD), Paxos (PAX), Dai (DAI) and Gemini (GUSD) during the period June 2018 to July 2019. They find that stablecoins may act as a safe haven during periods of BTC volatility, allowing investors to use stablecoins to de-risk their portfolios without exiting the cryptocurrency market entirely. They also find that among all large stablecoins, USDT had the strongest effect as a safe haven and store of value.

Consistent with Baur and Hoang (2021), other papers have confirmed USDT being a safe haven asset. Barucci, Giuffra Moncayo, and Marazzina (2022) find evidence that USDT functions as a crucial store of value and safe haven within the crypto ecosystem, facilitating high-frequency trading without transitioning through traditional currencies. The paper highlights that USDT serves this function by offering lower fees and higher liquidity than US dollar-based trading pairs.

Our Contribution: In this paper, we fill the literature gap by exploring the role of the stablecoin USDT as a safe haven asset in the crypto ecosystem, focusing on asset reallocation and flight-to-safety behavior within the DeFi world (on-chain transactions) without leaving the crypto ecosystem. We focus on migration towards USDT from the two largest cryptocurrencies, BTC and ETH. In addition, we explore investors' asset reallocation during various specific stress periods driven by off-chain shocks, such as FTX and SVB failures, crypto ban in China, approval of spot Bitcoin ETF, and other recent market shocks/stress events leading to "crypto winter" periods. In addition, we add to the existing literature by exploring how different classes of investors (crypto whales vs. small retail investors) may react differently in response to the same market shocks and stress events.

II.2 Literature Related to Measures of Crypto Risk and Volatility

In analyzing flight-to-safety behavior from BTC and ETH into USDT, we utilize a comprehensive set of measures of risk and volatility that have been widely accepted in both academic and industry communities. We discuss literature related to the various measures of crypto volatility in this section.

The most well-known volatility measure has been the Chicago Board Options Exchange (CBOE) Volatility Index, or VIX, which has emerged as a widely accepted measure of market expectations of near-term volatility. Originally introduced by Whaley (1993), the VIX initially captured implied volatility derived from S&P 100 index options and later evolved to its current methodology based on S&P 500 index options. The conceptual underpinnings and practical implications of the VIX are discussed comprehensively in Whaley (2009), which goes into detail on the index's role as a fear gauge for US equity markets.

The VIX has become increasingly prominent as both a hedge and a speculative tool due to its inverse correlation with the S&P 500, and its dynamics have been extensively analyzed in the literature. The VIX, which is often referred to as the "fear index," measures the market's expectation of volatility based on S&P 500 options. When the S&P 500 index experiences a downturn, the fear index rises, and when the S&P 500 index performs well and market confidence grows, the fear index decreases. Bollerslev, Tauchen, and Zhou (2009) argue that the VIX reflects not only expected future volatility but also a risk premium component, which they interpret as a measure of the aggregate economic uncertainty, reflecting an aggregate level of risk aversion in the economy.

Regarding the degree of risk aversion, market expectation, and the associated risk premium, Drechsler and Yaron (2011) demonstrate that the variance risk premium in the VIX (the difference between risk-neutral expected variance and actual realized variance) captures attitudes towards market uncertainty. The variance risk premium here may be viewed as an insurance premium, reflecting the increased amount investors are willing to pay for assets that pay higher returns during a turbulent period. Market participants expect higher returns if they hold on to assets in high-VIX environments. In addition, the development of the VIX as a market-determined forecast, rather than a model-based one, is explored in Becker, Clements, and McClelland (2009). They show that the VIX reflects not only the past jump activity but also incremental information for explaining future jump activity. Together, these two studies underscore the VIX's importance not only as a forward-looking volatility forecast but also as a measure of investor sentiment across financial markets.

Furthermore, there seems to be evidence of a connection between the VIX and flight-to-safety behavior in equity markets. Adrian, Crump, and Vogt (2019) uncover a significant time-varying relationship between market volatility (measured by VIX) and future stock and bond returns, using a novel nonparametric sieve reduced-rank regression to reveal mirror-image nonlinearities indicative of flight-to-safety behavior. They show that during a low volatility period (i.e., the VIX is low), the relationship between VIX and stock and bond returns is relatively flat, with tight spreads and a lower cost of moving between assets. As the VIX rises above a certain threshold, cross-asset returns become increasingly sensitive to the variance risk premium during periods of high volatility. When the VIX rises above its median of 18, there is a strong relationship such that the expected stock returns increase while Treasury returns decline, a pattern robust across forecasting horizons and pre-2008 crisis data, driven by a common volatility function.

Given the success and popularity of VIX in equity markets, the VIX index has been applied in other markets, including cryptocurrency markets. The novel cryptocurrency volatility index (CVIX), proposed by Bonaparte (2023), attempts to incorporate both systematic and idiosyncratic risk unique to the cryptocurrency markets into the original VIX, which was initially developed for traditional equity markets. Using asymptotic distribution theory, the CVIX has demonstrated superior performance –

offering a robust alternative to option-implied volatility, predicting 30-day forward crypto volatility with 89% accuracy.

Related to this, Han (2024) utilizes the traditional CBOE VIX as a "market fear index" to evaluate its relationship with a totally different market structure: cryptocurrency markets. While the VIX is meant to be a proxy for equity market sentiment, the author explores its predictive power and correlation with crypto assets' returns and volatility. In later research, Han (2025) proposes a specialized multidimensional Crypto Fear and Greed Index, which captures cryptocurrency investor sentiment across multiple dimensions, rather than focusing on price volatility only. This specialized Crypto Fear and Greed Index recognizes the inadequacies of traditional volatility-based metrics, and it is designed to better capture the complex emotional drivers and unique structural risks of cryptocurrency markets.

In this paper, we explore flight-to-safety behavior in the cryptocurrency market and explore the potential role of USDT as a safe haven asset in the crypto ecosystem.[1] To conduct a robust analysis and to achieve reliable results, we utilize several measures of crypto market volatility – with several variations in model specifications. We report results for the most common standard approach and the most complex approach (with the most flexibility in the model). The results from other intermediate model specifications are reported in the Appendix.[2]

We take two approaches to our crypto volatility measures: using the CVI and the CVIX. The simpler version of crypto volatility is the more well-known Crypto Volatility Index (CVI), calculated based on the Black-Scholes options pricing model, with the index value ranging between 0 and 200. This index is designed as a decentralized "VIX for crypto," tracking the 30-day implied volatility of BTC and ETH. It is currently widely used by traders, hedge funds, and institutional investors. The CVI data has been readily available from data vendors.

The other volatility measure considered is the CVIX, which is a crypto VIX designed to track 30-day future volatility of cryptocurrency, with the index value ranging between 0 and 300. We follow Bonaparte (2023) and Bonaparte, Chatrath, and Christie-David (2023) in the process of calculating CVIX in our analysis of flight to safety in highly volatile crypto market environments. We seek to utilize investor sentiment in cryptocurrency markets as a predictor in our analysis of flight to safety in addition to shocks that come from traditional market-moving events.

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[1] While the opacity of USDT's reserves means it does not satisfy all criteria for an idealized safe haven, notably failing the 'no questions asked' (NQA) principle of Holmström (2015), its superior liquidity and dominant role as the primary medium of exchange across blockchains enable it to function effectively as the cryptocurrency market's internal cash equivalent.

[2] Figures 4, 5, and 6 in the Appendix show plots corresponding to Figures 1, 2, and 3, respectively, based on additional model specifications.

III. The Data and Empirical Methodology

III.1 The Data

Our analysis requires data from several different sources. The cryptocurrencies we examine in this paper are: 1) native Bitcoin; 2) Wrapped Bitcoin, which is a tokenized version of Bitcoin that operates primarily on the Ethereum blockchain (maintaining a 1:1 peg with Bitcoin); 3) Ethereum, which is a native currency on the Ethereum blockchain; and 4) USDT stablecoin issued by Tether, which is traded on both the Ethereum network and the Omni layer of the Bitcoin blockchain. Summary of the data sources is presented in Table 1 Panel A.

Throughout the paper, we consider USDT traded on the Omni protocol and USDT traded on the Ethereum blockchain separately. That is, we use USDT traded on the Omni protocol when exploring flight from Bitcoin (BTC) to USDT; and we use USDT traded on the Ethereum network when exploring flight from Wrapped Bitcoin (WBTC) to USDT and flight from Ethereum (ETH) to USDT. The data on WBTC in our analysis include all WBTC traded on the Ethereum network, which is where most WBTC is traded.

As mentioned in the previous section, our analysis of flight to safety from volatile cryptocurrencies to Tether USDT during periods of high market stress requires robust measures of crypto volatility. We employ two distinct metrics: CVI and CVIX. Although CVI and CVIX are both intended to capture market-wide stress in cryptocurrency markets, they differ fundamentally in construction and economic interpretation.

Crypto Volatility Index (CVI) is designed to measure expected volatility in the cryptocurrency market, particularly for major assets like BTC and ETH. It functions as a "decentralized VIX" for the crypto market, using the Black-Scholes options pricing model to calculate implied volatility indices for BTC and ETH from options prices. It then combines them into a single final index using a weighted average according to their market capitalizations.[3] It is a decentralized index tracking 30-day forward-looking expectations of volatility for BTC and ETH, to capture market "fear" (like the VIX for traditional stocks in the S&P 500). The value of CVI is between 0 and 200 but generally fluctuates between 75 and 150, reflecting market sentiment and volatility. A rising CVI implies increased market uncertainty and potential for price swings. We collect closing values of CVI from investing.com[4] between January 1, 2020, and November 28, 2024.

Forward-based Crypto Volatility Index (CVIX) is not readily available like the CVI. We conduct our own estimation of CVIX, following the methodology used in Bonaparte (2023) as described in the

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[3] For more details on the calculations behind the CVI, see the CVI white paper: https://cvi.finance/files/cvi-white-paper.pdf

[4] https://www.investing.com/indices/crypto-volatility-index-historical-data

literature review Section II.2. The raw CVIX estimates are scaled by a factor of 100,000 to improve interpretability (more comparable with the CVI), resulting in values ranging approximately from 50 to 300. The CVIX index is used in our analysis to provide a comprehensive view of crypto market sentiment. In calculating our own CVIX index, we use individual forward-based volatility calculations for BTC and ETH separately and then use a weighted average according to their market capitalizations.

As previously noted, CVI is derived from option-implied volatility to reflect forward-looking, near-term risk expectations, while CVIX is constructed from return dynamics via a model-based forward variance approach. Because these measures capture distinct dimensions of perceived risk and need not move in tandem, differences in results across CVI and CVIX specifications should be interpreted as heterogeneous investor responses to varying market stress signals, rather than as inconsistencies in investor behavior.

Data on *daily closing prices* of cryptocurrencies were collected from *CoinMetrics*[5] for Bitcoin (BTC), Ethereum (ETH), Wrapped Bitcoin (WBTC), and the stablecoin Tether (USDT) for the period January 1, 2020, to December 31, 2024.

We determined specific event dates for our study using *CryptoCompare* data provided by *Inca Digital*. Relevant news stories were pulled from outlets such as *CoinDesk*[6], *Blockworks*, *Decrypt*, and *Bitcoin.com* using the CryptoCompare News API.

We collected data on daily USDT holdings at the end of each day for each segment of investors (large vs. small investors based on their wallet size) from *CoinMetrics* for the period January 1, 2020, to December 31, 2024. Our calculation of USDT velocity, based on USDT holdings and current active supply of USDT data from *CoinMetrics*, is described in the next section.

We collected daily USDT holdings from *CoinMetrics* between January 1, 2020, and December 31, 2024, tracking segments of large and small investors by wallet size. Section III describes our calculation of USDT velocity based on these holdings and the active supply of USDT.

III.2 Empirical Methodology: Flight-to-Safety Analysis

This section examines how crypto investors react to market stress, utilizing the Crypto Volatility Index (CVI) and the associated volatility index (CVIX). We hypothesize that during periods of high market stress, as characterized by elevated CVI/CVIX levels, investors liquidate cryptocurrency holdings (specifically BTC and ETH) in favor of the Tether stablecoin (USDT) as a safe haven. Because USDT is pegged to the US dollar, our analysis focuses on observing an increase in USDT holdings rather than

[5] *CoinMetrics* has since been acquired by Talos (acquisition date July 16, 2025), https://www.talos.com/our-solutions/data/community-resources
[6] http://developers.coindesk.com/documentation/data-api/news

changes in its price. We expect to see rising USDT holdings during the stress periods rather than price fluctuations.

Our analysis is divided into two parts: 1) estimation of CVIX as a measure of crypto stress levels; and 2) estimation of changes in USDT holdings during the stress periods.

Estimation of CVIX:

While the CVI data is readily available from investing.com, the CVIX is not readily available. We estimate the CVIX for each individual cryptocurrency by following the methodology used in Bonaparte (2023) and Bonaparte, Chatrath, and Christie-David (2023).

First, we compute coefficients by estimating a model for return variance using a 30-day rolling window, given in Equation (1):

$$Var(ret_t) = Constant_{jt} + \emptyset_{1j} \times \tau_{jt,1} + \emptyset_{2j} \times \tau_{jt,2} + \emptyset_{3j} \times \rho_{jt} + \emptyset_{4j} \times \sigma^2_{jt,\epsilon}. \qquad (1)$$

Independent variables are defined as in Bonaparte (2023). Using a rolling AR(1) model for returns, given by $ret_t = \alpha + \rho ret_{t-1} + \varepsilon_t$, which is estimated on a rolling 30-day window, σ^2_ε is the residual variance and ρ_{jt} the coefficient of lagged returns.

Second, we follow this by taking R_{jt} as the sequence from $-4\sigma_y$ to $4\sigma_y$ of length T with equidistant spacing, emulating the discretization technique of Bonaparte (2023). We define ω as the step size of the R_{jt} sequence. We further define τ_1 and τ_2 using the following:

$$\tau_1 = \Phi\left(\frac{R_{1t} - \rho R_{jt} + {}^{\omega}/_{2}}{\sigma_\varepsilon}\right)$$

$$\tau_2 = \sqrt{\sigma^2_\varepsilon / 1 - \rho^2}.$$

Third, the coefficients are used to estimate CVIX for each cryptocurrency in Equation (2):

$$CVIX_{coin_t} = Constant_{jt} + \emptyset_{1j} \times \tau_{jt,1} + \emptyset_{2j} \times \tau_{jt,2} + \emptyset_{3j} \times \rho_{jt} + \emptyset_{4j} \times \sigma^2_{jt,\epsilon}. \qquad (2)$$

We then compute a CVIX estimate for BTC and ETH, giving us our CVIX market estimate at time t as in Equation (3):

$$CVIX_t = \left(w_{BTC} \times CVIX_{BTC_t} + w_{ETH} \times CVIX_{ETH_t}\right). \qquad (3)$$

Here w_{BTC} and w_{ETH} are the weighted market caps of the associated cryptocurrencies, which are calculated using the market caps of BTC and ETH in USD according to Equation (4):

$$w_{coin} = \frac{market\_cap_{\ coin}}{market\_cap_{BTC} + market\_cap_{ETH}}. \qquad (4)$$

Estimation of Changes in Daily USDT Holdings and Expected Crypto Returns:

To estimate the change in the amount of USDT holdings in response to crypto stress, we model cryptocurrency returns and stablecoin USDT holdings according to polynomial regressions. All USDT variables are modeled as *daily percentage changes* in USDT holdings. This transformation mitigates scaling issues, reduces non-stationarity, and aligns the stablecoin variables more closely with the return-based framework used in the analysis of risky assets. These models take the form shown in Equations (5.1) and (5.2) when returns and holdings are calculated based on the estimated CVIX stress index. The models take the form shown in Equations (6.1) and (6.2) when returns and holdings are calculated based on the CVI index.

$$Ret_{t+1} = \beta_0 + \beta_1 CVIX_t + \beta_2 CVIX_t^2 + \beta_3 CVIX_t^3 + u_t \tag{5.1}$$

$$holdings_{t+1} = \beta_0 + \beta_1 CVIX_t + \beta_2 CVIX_t^2 + \beta_3 CVIX_t^3 + u_t \tag{5.2}$$

$$Ret_{t+1} = \beta_0 + \beta_1 CVI_t + \beta_2 CVI_t^2 + \beta_3 CVI_t^3 + u_t \tag{6.1}$$

$$holdings_{t+1} = \beta_0 + \beta_1 CVI_t + \beta_2 CVI_t^2 + \beta_3 CVI_t^3 + u_t \tag{6.2}$$

During periods of high crypto stress—indicated by high CVI and CVIX—investors demand a higher risk premium to continue holding volatile cryptocurrencies. Risk-averse investors would likely shift their holdings toward safer assets, using USDT as a safe haven within the ecosystem to avoid leaving the crypto market entirely. Consequently, this narrative suggests that USDT holdings would move in tandem with crypto (BTC, WBTC, ETH) returns during high stress periods, as increased risk premiums are correlated with higher USDT demand. Figures 1 and 2 illustrate these results.

Alternative Estimation of USDT Holdings and Expected Crypto Returns:

We estimate in this section the returns and holdings using alternative modeling assumptions that allow for more flexibility and potential nonlinear relationships between market stress and investor behavior. We use the nonparametric sieve framework developed by Adrian, Crump, and Vogt (2019). In this framework, expected crypto returns and stablecoin holdings are modeled as functions of a common latent risk factor, calculated using cubic and quartic spline bases. Our implementation closely follows the original identification strategy of Adrian, Crump, and Vogt (2019), with minor modifications appropriate for cryptocurrency markets. This model allows us to trace how expected crypto returns and USDT holdings may co-move as functions of market stress without imposing parametric restrictions on the shape of this relationship. The model developed by Adrian, Crump, and Vogt (2019) takes the form shown in Equation (7) when individual assets are considered. When we stack the n assets, this model can equivalently be expressed as in Equation (8), where Z_t are other control variables.

$$Rx_{t+h}^i = a_h^i + b_h^i \phi_h(v_t) + \varepsilon_{t+h}^i \tag{7}$$

$$Rx_{t+h} = a_h + A_h X_{m,t} + F_h Z_t + \tilde{\varepsilon}_{t+h} \quad (8)$$

In our implementation, we do not consider other control variables, and we set a fixed horizon of $h = 1$ or 1 day ahead. The function $\phi_h(v_t)$ is assumed to be an arbitrary, smooth (potentially nonlinear) function of risk. We approximate the function over the set of cubic and quartic base splines, following the original estimation method of Adrian, Crump, and Vogt (2019). This model resembles the standard linear factor model, and to be able to separately identify a_h and b_h we impose the same two identifying assumptions as the original authors. Namely, we impose that $\phi_h(0) = 0$, allowing for the identification of the intercept, and $b_h^1 = b_h^{MKT} = 1$, allowing for the identification of the individual slope coefficients. We make a minor alteration to the second identifying assumption. Instead of imposing $b_h^1 = b_h^{MKT} = 1$, we impose $b_h^1 = b_h^{coin} = 1$, where b_h^{coin} is the loading on BTC, WBTC, or ETH depending on the model being considered.

Adrian, Crump, and Vogt (2019) develop four hypothesis tests, of which we adopt the first. The first test is one of joint significance analogous to an F-test or other similar joint test in the more familiar context of linear regression. In the simpler linear regression context, such a test is usually formulated as $\beta_1 = \beta_2 = \ldots = \beta_n = 0$ versus the two-sided alternative, where $\beta_1, \ldots, \beta_n$ are the slope parameters excluding the intercept. Such a test is one of the overall explanatory power of the independent variables. Due to the nonparametric estimation, the test is instead formulated as in Equations (9) and (10). The corresponding test statistic is defined as in Equation (11), where n denotes the size of the cross section and m is the number of sieve expansion terms.[7]

$$H_0: \forall v \in V, \phi_h(v) = 0 \quad (9)$$

$$H_1: \exists v \in V s.t. \phi_h(v) \neq 0 \quad (10)$$

$$\widehat{\tau_1} = \frac{vec(\hat{A})^T \widehat{V_1}^{-1} vec(\hat{A}) - mn}{\sqrt{2mn}} \sim N(0,1) \quad (11)$$

III.3 Empirical Methodology: Crypto Events

We examine how various market shocks trigger flight-to-safety behavior among crypto investors. Our analysis investigates how USDT velocity on the Bitcoin and Ethereum blockchains responds to market-moving events. Given Tether's (USDT's) position as the dominant stablecoin by market capitalization, we follow the established literature in treating USDT as a safe haven asset: see Lyons and Viswanath-Natraj (2023); Baur and Hoang (2021); Barucci, Giuffra Moncayo, and Marazzina (2022); and Liao and

[7] See the work by Adrian, Crump, and Vogt (2019) for the definitions of the various component matrices and other technical details. They interpret rejection of the null hypothesis as evidence of loading on a common (nonlinear) function of risk. We adopt this interpretation.

Caramichael (2022). Consequently, we hypothesize that USDT velocity increases following shocks to BTC and ETH.

For events that are expected to drive flight-to-safety behavior, we anticipate an increase in USDT velocity on the *relevant* blockchain, specifically the Omni protocol for Bitcoin-related events and the Ethereum blockchain network for Ethereum-related events.

To capture short-term market reactions to key crypto events, we employ an event study methodology focused on BTC and ETH, using ±30-day event windows around major protocol updates, policy announcements, and market shocks. Within these windows, we incorporate dummy variables for the event day, as well as three days before and after, to measure dynamic responses. All analyses also benchmark cryptocurrency performance against traditional market factors by including S&P 500 and gold returns.

We analyze the impact of major cryptocurrency events on BTC and ETH markets, using the date of the first relevant news story as the event date. To identify this date, we sourced, through the *CryptoCompare News API*, articles from reputable outlets, including CoinDesk, Blockworks, and Bitcoin.com. Based on these dates, we formulate specific hypotheses for each event, as summarized in **Table 1 Panel B.**

- May 18, 2021
  The announcement of China's cryptocurrency mining ban is expected to exert temporary downward pressure on BTC prices, reflecting China's dominant share of the global BTC hash rate (approximately 75% prior to the ban).
- September 15, 2022
  The transition of ETH from a Proof-of-Work (PoW) to a Proof-of-Stake (PoS) consensus mechanism is expected to positively influence ETH prices through improved scalability, reduced energy consumption, and lower new token issuance. The impact on BTC prices would be limited, given the ETH-specific nature of the upgrade.
- November 6, 2022
  The collapse of FTX is expected to generate a negative price shock for both BTC and ETH, with a larger adverse effect on BTC due to FTX's connection with the Grayscale Bitcoin Trust and the failure of the proposed Binance rescue plan.
- March 10, 2023
  The failure of SVB is expected to exert downward pressure on both BTC and ETH prices, driven by its role in the collateral network supporting Circle's USDC in addition to broader contagion fears within the crypto ecosystem.
- April 23, 2023

Prior to the Ethereum Shanghai upgrade, anticipation of large-scale withdrawals of staked ETH is expected to lead to downward pressure on ETH prices, while BTC prices would remain largely unaffected given the ETH-specific scope of the event.

- January 11, 2024
  The launch of a Bitcoin-based ETF is expected to increase demand and create upward price pressure for BTC. Price effects on ETH would likely be neutral or slightly negative, as ETH investors may move capital to BTC.
- May 24, 2024
  The SEC approval of an Ethereum-based ETF is expected to increase demand and put upward price pressure on ETH, potentially accompanied by neutral or slightly negative price effects on BTC as investors reallocated capital toward ETH.
- July 23, 2024
  The launch of an Ethereum-based ETF is expected to increase demand and put upward price pressure on ETH, potentially accompanied by neutral or slightly negative price effects on BTC as investors reallocated capital toward ETH.

We employ a standard event study methodology with a [-3, +3] day window to analyze the impact of each event on USDT velocity, defined as the ratio of adjusted transfer value to USDT market capitalization. Our model controls for market effects by including the log returns of the S&P 500 and gold. This analysis is conducted separately for USDT velocity on the BTC and ETH networks, as specified in Equation (12).

$$USDT\ velocity = \beta_0 + \beta_1(t-3) + \beta_2(t-2) + \beta_3 t + \beta_4(t+1) + \beta_5(t+2) + \beta_6(t+3) + \beta_7 Gold\ Returns + \beta_8\ S\&P500\ Returns + u. \tag{12}$$

To analyze how different crypto wallet-size segments responded to the events, additional models were tested based on USDT wallet size. These models used the amount of USDT held in small wallets ($10–$100K, in Equation 13), medium wallets ($100K–$10M, in Equation 14), and large wallets (>$10M, in Equation 15) as the dependent variables. [8]

$$\$(10-100K) USDT = \beta_0 + \beta_1(t-3) + \beta_2(t-2) + \beta_3(t-1) + \beta_4 t + \beta_5(t+1) + \beta_6(t+2) + \beta_7(t+3) + \beta_8 gold\ returns + +\beta_9\ S\&P500\ returns + u \tag{13}$$

$$\$(100K-10M)\ USDT = \beta_0 + \beta_1(t-3) + \beta_2(t-2) + \beta_3 t + \beta_4(t+1) + \beta_5(t+2) + \beta_6(t+3) + \beta_7 gold\ returns + \beta_8\ S\&P500\ returns + u \tag{14}$$

$$\$10M\ USDT = \beta_0 + \beta_1(t-3) + \beta_2(t-2) + \beta_3 t + \beta_4(t+1) + \beta_5(t+2) + \beta_6(t+3) + \beta_7 gold\ returns + \beta_8\ S\&P500\ returns + u \tag{15}$$

[8] As before, our data on USDT holdings are collected from transactions that occurred on the two largest blockchain networks, Bitcoin blockchain (on the Omni protocol) and Ethereum blockchain networks.

The variable *$(10-100K) USDT* represents the total USDT holdings across all small wallets (holding between $10 and $100K of USDT). Similarly, the variable *$(100K–10M) USDT* represents the total USDT holdings across all medium wallets (holding between $100K and $10M of USDT), and the variable *$10M USDT* represents the total USDT holdings across all large wallets (holding at least $10M of USDT).

IV. The Empirical Results

IV.1 Crypto Flight to Safety (During High Stress Periods)

Following the methodology in Section III.2, we estimate the stress levels (CVI and CVIX); expected returns for BTC, WBTC, and ETH; and changes in USDT holdings. Using the framework developed by Adrian et al., we analyze the flight to safety, with the main results presented in Figures 1–3: flight from BTC to USDT (Figure 1), ETH to USDT (Figure 2), and WBTC to USDT (Figure 3).

Figures 1–3 present plots based on stress measured by CVI on the left and CVIX on the right. The top row of each figure shows results from the simplest model (a cubic polynomial regression of risk), while the bottom row shows results from the most complex model (a reduced-rank sieve model using quartic base splines).[9]

Across all reduced-rank sieve model implementations, we strongly reject the null hypothesis (P-values < 1%), suggesting a strong loading on a common risk function. While we find limited evidence of flight-to-safety behavior, these dynamics are highly dependent on model specification, the risk measure used (CVI vs. CVIX), and investor size (USDT wallet size).[10]

While CVI measures option-implied risk, CVIX offers a broader gauge of cryptocurrency market volatility. Evidence of a flight to safety is consistently stronger when using CVI. This suggests that market participants likely base allocation decisions on CVI, or that the more complex CVIX measure has not yet gained widespread adoption among USDT holders.

Flight from BTC to USDT:

Figure 1(a) illustrates Bitcoin (BTC) network dynamics, highlighting a flight to safety from BTC to Tether (USDT) using a polynomial regression and CVI-based risk measurements. Focusing on high-risk scenarios (CVI values above the median), the results strongly suggest a flight to safety. Notably,

[9] The cubic polynomial regression is generally considered the simplest model for incorporating non-linearity into volatility measurement. We also report the plots from several other models considered (between the simplest and the most flexible and complex model): individual sieve models over the set of cubic and quartic base splines and a reduced-rank sieve model over the set of cubic base splines, in Figures 4, 5, and 6 in the Appendix.

[10] This is not surprising and roughly coincides with the findings of Adrian, Crump, and Vogt (2019), who find that when they limit their sample to pre-2008 data, they only reject the null of no predictability for equities at longer horizons. They further note that money market funds are not found to be a safe asset. This then suggests limited short horizon flight to stablecoins in the digital asset space. We consider 1-day ahead changes in Tether holdings and cryptocurrency returns.

BTC returns and expected USDT holdings move in the same direction, validating our model's expectations.

Expected USDT holdings become positive for the largest wallet category, those holding more than $10 million of USDT, when CVI exceeds 125. Expected Tether holdings become positive for the smallest category, wallets holding $10 to $100,000 of USDT, when CVI exceeds 150. Expected USDT holdings for the middle category of wallets, those holding $100,000 to $10 million of USDT, never become positive. We interpret this as flight to safety only occurring at the most extreme values of CVI and only among the smallest and largest wallet categories.

When the CVI is below approximately 125, all wallet categories show negative expected stablecoin holdings, indicating reduced USDT positions during calm market conditions. A flight to safety is observed only at extreme CVI values and only among specific groups: largest wallets (>$10M) turn positive when CVI exceeds 125, while smallest wallets ($10–$100k) turn positive when CVI exceeds 150. Notably, middle-category wallets ($100k–$10M) maintain negative expected holdings throughout all CVI ranges.

Substituting CVIX as the risk measure, **Figure 1(b)** reveals no evidence of flight-to-safety behavior. However, adopting a reduced-rank sieve model with CVI, shown in **Figure 1(c)**, yields strong evidence of a common risk function, yet only limited evidence of overall flight behavior. While no flight is observed for moderate-sized wallets, we find evidence of such behavior among small and large wallets, but only during the most stressful periods characterized by extreme CVI values. Similarly, **Figure 1(d)** confirms a common factor loading, yet visual evidence of a flight to safety remains limited. Such behavior is only observed among the largest wallets.

Flight from ETH to USDT:

We next analyze asset reallocation dynamics on the Ethereum network, focusing on the flight from ETH to USDT as illustrated in Figure 2. Findings indicate a stronger case for asset reallocation among ETH investors. Using a simple polynomial regression of the CVI, shown in **Figure 2(a)**, we identify evidence of capital flight across all wallet categories; this behavior is most pronounced in the largest wallets and weakest among moderate-sized wallets. Measuring risk via CVIX, shown in **Figure 2(b),** confirms this trend across all categories, although the reallocation is somewhat limited, with USDT positions not growing as rapidly as the rise in expected returns on ETH.

When using the flexible model and CVI, the reduced-rank sieve specification again indicates evidence of asset reallocation. From **Figure 2(c)**, we observe a common loading effect and strong visual evidence of "flight" among small wallets when CVI exceeds its median value. While the USDT holdings of moderate USDT holders closely match expected ETH returns, their USDT positions remain negative below a CVI of 150, suggesting limited flight except during extreme risk scenarios. Conversely, the largest USDT holders display positions that mirror expected ETH returns, indicating profit-seeking behavior rather than a flight to safety. When substituting CVIX as the measure of risk in **Figure 2(d)**, there is evidence of a common loading but no compelling evidence of flight among any category of investor.

Flight from WBTC to USDT:

Evidence of flight to safety is more pronounced among WBTC investors than BTC investors, likely due to the relative ease of asset reallocation within the Ethereum ecosystem compared to the Bitcoin network. As illustrated in **Figure 3(a)**, polynomial regressions using CVI indicate flight behavior among both small and large wallets, though this is not clear for medium-sized investors. Conversely, substituting CVIX in **Figure 3(b)** reveals flight behavior among moderate and large wallets, alongside limited risk-seeking behavior among small wallets.

Using CVI with the reduced-rank sieve specification in **Figure 3(c)** reveals evidence of a common risk function and strong visual evidence of flight among the smallest wallets. Conversely, expected USDT holdings for moderately sized wallets are nearly flat, while those for the largest wallets mirror expected WBTC returns. Substituting CVIX as the risk measure in **Figure 3(d)** changes this trend: expected WBTC returns and USDT holdings across all wallet categories become relatively flat, with returns trending upward and holdings trending downward, suggesting no clear evidence of flight.

IV.2 Event Study Results

We conducted several event studies to analyze how different investor cohort sizes respond to major shocks and structural developments within the cryptocurrency ecosystem. Each event window is evaluated using regressions on Tether (USDT) activity measures, specifically velocity and holdings, to trace liquidity reallocations and shifts in investor positioning. USDT velocity is calculated using Equation (12), while changes in Tether holdings resulting from reallocations out of BTC or ETH are derived from Equations (13), (14), and (15) for small, medium, and large wallets, respectively. **Table 2** presents the results regarding asset reallocation to USDT on the Bitcoin blockchain, with corresponding results for the Ethereum network reported in **Table 3**.

China Cryptocurrency Ban (Column 1 of Tables 2 and 3): The Chinese regulatory *announcement* triggered a surge in Tether velocity on the Ethereum network, with significant spikes occurring one and two days post-announcement. Conversely, the market response to the *implementation* of the crypto ban was more muted for BTC, showing no statistically significant changes in velocity.

ETH Proof of Stake Transition (Column 2 of Tables 2 and 3): As expected, Ethereum's transition to Proof of Stake (PoS) did not significantly impact USDT velocity on the Bitcoin network. Conversely, USDT velocity on the Ethereum network saw a statistically significant decrease on Day 2 and Day 3 following the announcement, suggesting a decline immediately post-transition. This drop in USDT velocity may reflect a reduced need for stablecoins as safe haven assets following the successful upgrade.

FTX Collapse (Column 3 of Tables 2 and 3): Following the FTX collapse, USDT velocity on the Ethereum network spiked significantly two to three days later, suggesting flight-to-safety behavior. Conversely, the Bitcoin network saw a muted response, with no statistically significant changes observed.

SVB Collapse (Column 4 of Tables 2 and 3): Following the collapse of Silicon Valley Bank (SVB), crypto asset positioning shifted significantly, marked by a statistically significant increase in USDT velocity on the Bitcoin network over the subsequent three days. This spike is consistent with flight-to-safety behavior in response to a major market disruption of this magnitude.[11]

ETH Shanghai Upgrade (Column 5 of Tables 2 and 3): While the Ethereum Shanghai upgrade enabled staked ETH withdrawals, it had minimal impact on USDT velocity across both the Ethereum and Bitcoin networks. However, analysis of USDT holdings revealed coordinated yet divergent behavior among investor categories, as shown in **Tables 4A and 4B**.[12] Following the upgrade, retail investors on the Bitcoin network significantly reduced their holdings, suggesting profit-taking behavior following the successful implementation of withdrawal functionality. Conversely, large holders of USDT on the same Bitcoin network increased their positions, indicating strategic accumulation during periods of retail selloffs. Furthermore, our analysis of USDT balances suggests notable capital movement into and out of USDT by both small and large investors across both chains immediately preceding the event.

Spot Bitcoin ETF Approval (Column 6 of Tables 2 and 3): USDT velocity remained largely unchanged following the spot BTC ETF approval. This stability was expected, as the anticipated positive market shock did not trigger a flight-to-safety behavior, with investors viewing the approval as a significant long-term growth catalyst rather than a high-volatility event.

Spot ETH ETF Announcement and Implementation (Columns 7 and 8 of Tables 2 and 3): Spot Ethereum ETF announcements and implementation failed to produce statistically significant shifts in USDT velocity on either the Bitcoin network or the Ethereum network. As with the BTC ETF, the market had already priced in this event, and the launch did not trigger expected flight-to-safety behavior.

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[11] Following the SVB failure, USDT also became a preferred choice for some stablecoin holders relative to USDC (second largest stablecoin by market cap) due to some of USDC's reserves being held in the form of deposits remaining at SVB when the bank failed.

[12] Tables 4A and 4B present separate regressions for large, medium, and small investor groups—categorized by wallet size—to analyze potential flight-to-safety behavior.

V. Overall Findings and Implications

Our findings delineate complex and heterogeneous patterns of investor behavior during cryptocurrency market stress, highlighting that evidence for flight to safety is highly contingent upon the network, investor type, and model specification examined. Furthermore, the relationship between volatility and asset reallocation exhibits significant non-linearity, whereby the strength of observed flight-to-safety dynamics is heavily dependent on how risk is measured, which blockchain network is being examined, and which investor cohort is analyzed.

While certain patterns emerge, particularly among small retail ETH investors, the evidence for systematic flight-to-safety behavior is more nuanced than a simple narrative would suggest. The results provide evidence of differential responses across investor categories, though the nature of these differences varies by network and event. While statistical significance for wallet-level responses was limited across most events -- with the ETH Shanghai upgrade being a notable exception -- nonparametric analysis reveals consistent heterogeneity. Specifically, whale behavior during moderate-risk periods on Ethereum often exhibits a mirror-image relationship with expected returns, suggesting profit maximization rather than risk aversion. Conversely, retail investors display holding patterns more consistent with flight-to-safety dynamics when risk thresholds are exceeded.

For BTC and WBTC, whale responses are often muted or move in directions inconsistent with safety-seeking, though retail investors show some evidence of flight behavior in certain specifications. Important differences emerge between BTC and ETH markets in both event responses and volatility-driven reallocation patterns. While Ethereum-specific technical upgrades generated minimal velocity responses on the Bitcoin network, broader shocks, such as the SVB collapse and China ban, produce measurable USDT velocity increases on Ethereum, with more muted responses on Bitcoin. Expected ETH returns and USDT holdings among retail investors frequently track each other across model specifications, providing consistent evidence of flight dynamics on Ethereum. Notably, WBTC shows stronger flight evidence than native BTC, suggesting that Ethereum's multi-asset ecosystem facilitates smoother transitions to stablecoins, whereas Bitcoin's isolation creates barriers to rapid reallocation.

Analyzing USDT velocity and holdings reveals distinct, network-dependent roles for the stablecoin. On the Ethereum blockchain, evidence points toward USDT serving as a retail-driven liquidity channel, with retail investors showing consistent reallocation patterns and velocity increases following major market disruptions. Conversely, on the Bitcoin blockchain, dynamics are more muted and transaction-oriented, with USDT velocity shifts correlating with market events rather than sustained portfolio reallocations. The stronger flight-to-safety patterns observed in Wrapped BTC (WBTC) on Ethereum than in native BTC, reinforce this network-specific distinction. However, differentiating genuine safety-seeking behavior from high-frequency trading (HFT) at lower volatility levels remains an empirical challenge.

Our analysis reveals that USDT's role as a safe haven asset is not absolute, but highly dependent on the chosen volatility measure, model specification, and investor type. While CVI-based models often produce extreme outliers, CVIX-based models yield clearer, albeit sometimes divergent, patterns. Flight-to-safety behavior is most robust for retail ETH investors during high-volatility periods, yet this evidence remains sensitive to model specifications. For Bitcoin and whale investors, the evidence is considerably weaker and less consistent. These findings are consistent with Anadu et al. (2024), who find that stablecoin flight-to-safety dynamics are similarly network-specific. Taken together, the heterogeneous behavior across blockchain contexts is a robust empirical regularity, rather than incidental noise. This suggests that regulatory frameworks must be differentiated, recognizing that behavioral patterns are highly context-dependent, varying significantly by market conditions and participant types. That is, regulatory frameworks should not treat stablecoins as a monolith; rather, oversight must be tailored to the specific, context-dependent behavioral patterns.

VI. Concluding Remarks

This study establishes Tether (USDT) as a heterogeneous systemic liquidity channel whose functional role varies substantially across blockchain networks. Our analysis reveals a bifurcated landscape: on Ethereum, USDT operates as a retail-driven flight-to-safety mechanism, with small holders exhibiting clear defensive rebalancing behavior; on Bitcoin, it functions primarily as a transactional, flow-oriented tool, with wallet-level flight-to-safety responses that are weak and inconsistent. These findings extend across assets: retail ETH investors behave differently from BTC whales, and both differ meaningfully from WBTC holders. This exemplifies the heterogeneity observed across blockchains and market segments.

Our mixed results highlight critical regulatory implications. USDT's flight-to-safety role is not uniform; it is strongest among retail ETH investors and more pronounced for WBTC than native BTC, with added sensitivity to volatility metrics. Because investor behavior varies significantly across contexts, regulatory oversight must be equally context-sensitive. While USDT is issued by a single entity, our results show that treating USDT as a single, uniform stablecoin for oversight would overlook crucial, chain-specific variations. Because investor behavior varies so substantially across platforms, uniform reporting requirements would fail to capture critical risks, allowing stress events on specific networks to be diluted or hidden in aggregate data.

Existing regulatory frameworks have yet to fully grapple with the complexities of stablecoin ecosystems. In the United States, comprehensive stablecoin legislation remains absent, with the

GENIUS Act not expected to take effect until 2027. In Europe, the EU's Markets in Crypto-Assets (MiCA) regulation represents the most advanced effort at oversight, yet its application to USDT as a single issuer creates challenges. Consider MiCA's redemption-at-par requirement: this provision is well-suited to the retail-dominated Ethereum environment our results describe, where investors demonstrably seek liquidity and stability during stress. However, it would be a poor fit for the Bitcoin network, where activity is more concentrated among larger participants and flight-to-safety dynamics are largely absent. Ultimately, a regulatory calibration designed around one of these contexts would likely be systematically miscalibrated for the others.

A key practical implication of our findings is that effective regulatory oversight must account for the heterogeneous behaviors observed across blockchains, wallets, and investor types. Oversight frameworks should be tailored to the specific blockchain architecture, the composition of the investor base, and the liquidity or risk characteristics of the network. Retail-focused safeguards are paramount where retail activity is dominant, whereas market integrity tools for institutional or whale-dominated networks must address distinct, large-scale behavioral patterns. As stablecoins become foundational to the digital asset ecosystem, future research should explore the interaction between network-specific behavioral responses, regulatory interventions, technical shocks, and broader macro-financial conditions.

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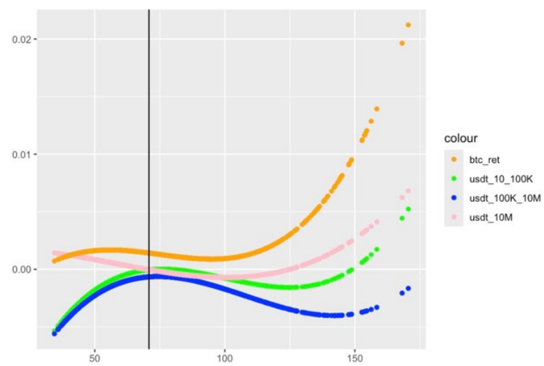
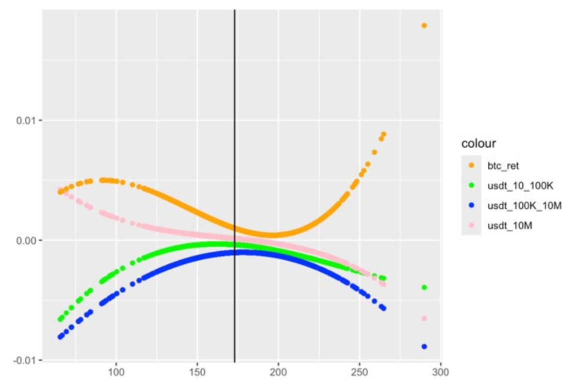
Figure 1: Evidence of Flight to Safety from Bitcoin (BTC) to USDT January 2020 to December 2024

Figures 1(a) to 1(d) display the BTC returns (1-day ahead predicted returns for BTC) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Bitcoin network) as functions of risk. Figures 1(a) and 1(c) proxy risk with CVI, while Figures 1(b) and 1(d) proxy risk with 30-day CVIX.

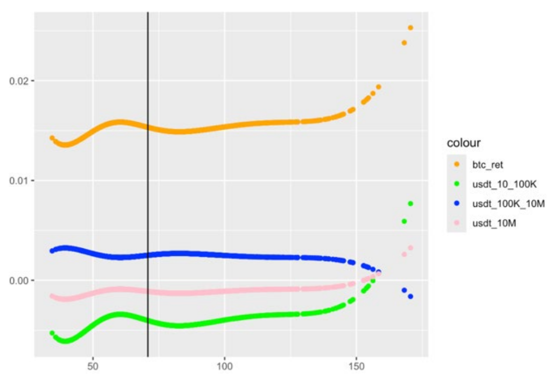
1(a) CVI Polynomial



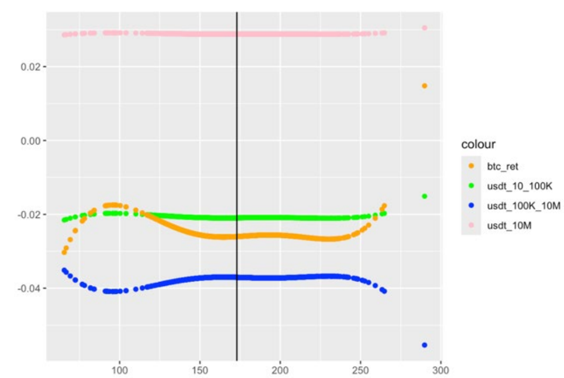
1(b) CVIX Polynomial



1(c) CVI ACV Quartic



1(d) CVIX ACV Quartic

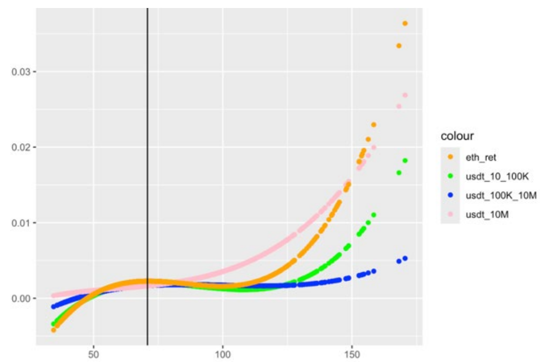


Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in Section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com.

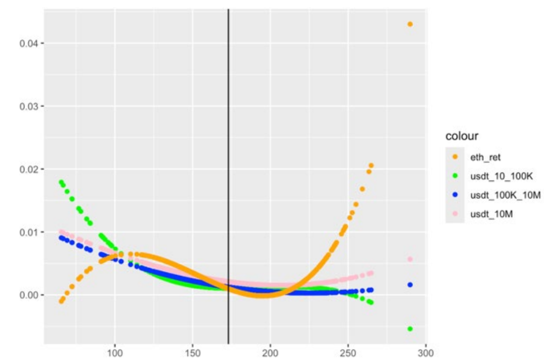
Figure 2: Evidence of Flight to Safety from Ethereum (ETH) to USDT
January 2020 to December 2024

Figures 2(a) to 2(d) display the ETH returns (1-day ahead predicted returns for ETH) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Ethereum network) as functions of risk. Figures 2(a) and 2(c) proxy risk with CVI, Figures 2(b) and 2(d) proxy risk with 30-day CVIX.

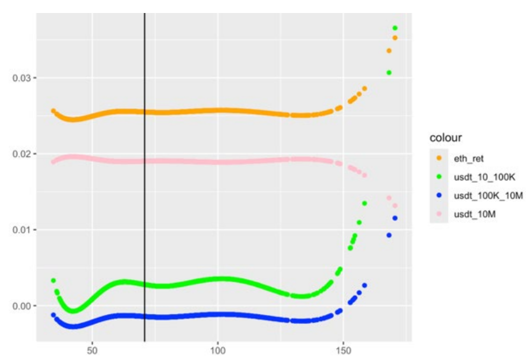
2(a) CVI Polynomial



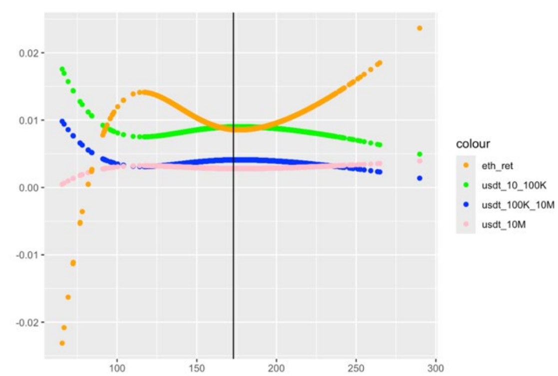
2(b) CVIX Polynomial



2(c) CVI ACV Quartic



2(d) CVIX ACV Quartic

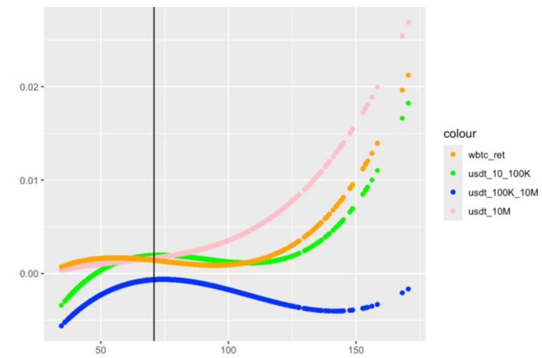


Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in Section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com.

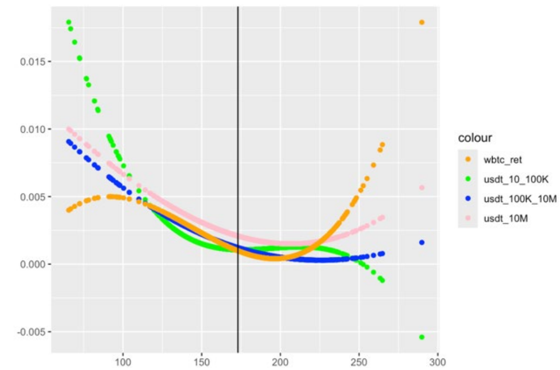
Figure 3: Evidence of Flight to Safety from Wrapped Bitcoin (WBTC) to USDT January 2020 to December 2024

Figures 3(a) to 3(d) display the WBTC returns (1-day ahead predicted returns for WBTC) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Ethereum network) as functions of risk. Figures 3(a) and 3(c), proxy risk with CVI, Figures 3(b) and 3(d) proxy risk with 30-day CVIX.

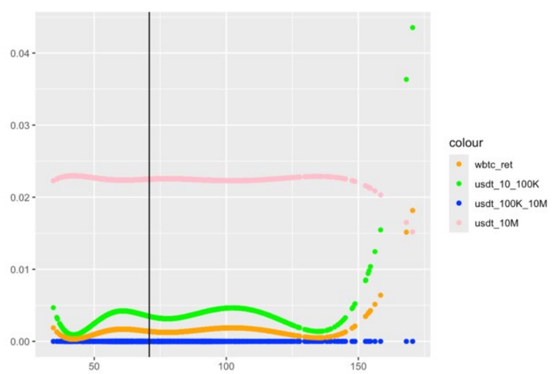
3(a) CVI Polynomial



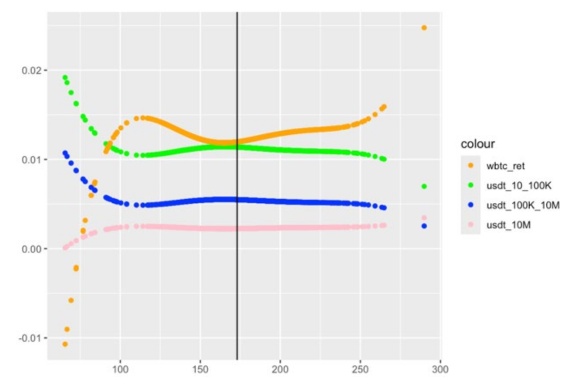
3(b) CVIX Polynomial



3(c) CVI ACV Quartic



3(d) CVIX ACV Quartic



Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in Section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com.

Table 1: Summary of Data Sources and Key Events

Panel A: Summary of the Data Sources

Data Sources	Variables Collected	Links
Coinmetrics	All Bitcoin (BTC) transaction data All Ethereum (ETH) transaction data All Wrapped BTC transaction data All USDT transactions on the Ethereum All USDT transactions on the Omni	https://coinmetrics.io/community-network-data/
FRED	S&P500 DJIA	https://fred.stlouisfed.org/graph/?g=zR9T https://fred.stlouisfed.org/series/DJIA
macrotrends.net	Gold price	https://www.macrotrends.net/1333/historical-gold-prices-100-year-chart#google_vignette
investing.com	CVI	https://www.investing.com/indices/crypto-volatility-index-historical-data

Panel B: This table summarizes the major BTC and ETH market events included in our regression analysis. Main regression results are presented in Tables 2 and 3, with investor-type breakdowns available in Tables 4A and 4B.

Date	Event Name	Description
5/18/2021	China Cryptocurrency Ban Announcement	Comprehensive prohibition of cryptocurrency activities in China
9/15/2022	ETH Proof of Stake Transition	Ethereum's shift from Proof of Work to Proof of Stake consensus
11/6/2022	FTX Collapse	Bankruptcy of major cryptocurrency exchange FTX
3/10/2023	SVB Collapse	Bankruptcy of Silicon Valley Bank
4/23/2023	ETH Shanghai Upgrade	Ethereum upgrade enabling staking withdrawals
1/11/2024	Spot BTC ETF Approval and Implementation	Approval and implementation of Bitcoin exchange-traded funds (ETFs)
5/24/2024	Spot ETH ETF Announcement	SEC approval of spot Ethereum exchange-traded funds (ETFs)
7/23/2024	Spot ETH ETF Trade	ETH ETF launches and begins trading

Data Sources: We identified these dates using *CryptoCompare News API*, which contains articles from reputable outlets, including CoinDesk, Blockworks, and Bitcoin.com.

Table 2: Flight to Safety Event Studies (Bitcoin Blockchain)
Investigation of Flight from BTC to USDT

This table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	China Announcement (1)	PoS Implementation (2)	FTX Failure (3)	SVB Failure (4)
(Intercept)	0.029***	0.002***	0.011***	0.000***
	(0.005)	(0.001)	(0.004)	(0.000)
d_m3	-0.005	0.001	0.009	-0.000
	(0.037)	(0.004)	(0.032)	(0.001)
d_m2	-0.007	0.001	-0.006	-0.000
	(0.037)	(0.004)	(0.032)	(0.001)
d_0	-0.019	0.000	-0.011	-0.000
	(0.037)	(0.004)	(0.031)	(0.001)
d_1	-0.005	-0.003	0.016	0.003***
	(0.038)	(0.005)	(0.031)	(0.001)
d_2	-0.016	-0.002	-0.024	-0.000
	(0.037)	(0.004)	(0.032)	(0.001)
d_3	-0.009	-0.002	0.030	-0.000
	(0.038)	(0.004)	(0.037)	(0.001)
Gold return	-0.002	0.000	-0.003	-0.000
	(0.006)	(0.001)	(0.005)	(0.000)
S&P 500 return	0.002	0.001	-0.007*	-0.000
	(0.008)	(0.000)	(0.004)	(0.000)
Num. Obs.	61	61	61	61
R^2	0.014	0.061	0.094	0.391
R^2 Adj.	-0.138	-0.083	-0.045	0.298
AIC	-219.6	-488.5	-241.4	-729.6
BIC	-198.5	-467.4	-220.3	-708.4
Log. Lik.	119.793	254.245	130.722	374.777

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Table 2: Flight to Safety Event Studies (Bitcoin Blockchain) -- Continued
Investigation of Flight from BTC to USDT

This table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	Shanghai Implement (5)	BTC ETF Approval (6)	ETH ETF Announce (7)	ETH ETF Trade (8)
(Intercept)	0.001***	0.000*	0.000***	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
d_m3	-0.000	-0.000	-0.000	-0.002
	(0.002)	(0.001)	(0.000)	(0.007)
d_m2	-0.001	-0.000	0.000	-0.002
	(0.002)	(0.001)	(0.000)	(0.007)
d_0	-0.000	-0.000		-0.007
	(0.002)	(0.001)		(0.007)
d_1	0.002	-0.000	0.000	-0.004
	(0.002)	(0.001)	(0.000)	(0.007)
d_2	0.001	-0.000		0.001
	(0.002)	(0.001)		(0.007)
d_3	-0.001	-0.000	0.000	-0.002
	(0.002)	(0.001)	(0.000)	(0.007)
Gold return	0.000	0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
S&P 500 return	0.000	-0.000	0.000	-0.003**
	(0.000)	(0.000)	(0.000)	(0.001)
Num. Obs.	61	61	57	55
R^2	0.042	0.015	0.024	0.154
R^2 Adj.	-0.106	-0.137	-0.093	0.007
AIC	-585.4	-671.3	-783.8	-386.9
BIC	-564.3	-650.2	-767.5	-366.8
Log. Lik.	302.702	345.653	399.900	203.425

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Table 3: Flight to Safety Event Studies (Ethereum Blockchain)
Investigation of Flight from ETH to USDT

This table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	China Announcement (1)	PoS Implementation (2)	FTX Failure (3)	SVB Failure (4)
(Intercept)	0.230***	0.067***	0.098***	0.111***
	(0.012)	(0.003)	(0.009)	(0.008)
d_m3	-0.028	-0.018	-0.017	0.006
	(0.090)	(0.022)	(0.071)	(0.057)
d_m2	-0.034	0.036+	-0.006	-0.015
	(0.090)	(0.021)	(0.070)	(0.061)
d_0	0.029	0.029	-0.054	0.110+
	(0.090)	(0.020)	(0.069)	(0.057)
d_1	0.433***	0.009	0.035	0.510***
	(0.092)	(0.022)	(0.069)	(0.056)
d_2	0.188**	-0.042**	0.147**	0.159**
	(0.090)	(0.020)	(0.072)	(0.056)
d_3	0.117	-0.036+	0.262***	0.175***
	(0.092)	(0.020)	(0.082)	(0.058)
Gold return	0.000	-0.002	-0.005	0.004
	(0.014)	(0.004)	(0.010)	(0.009)
S&P 500 return	-0.001	-0.004+	0.004	0.003
	(0.020)	(0.002)	(0.008)	(0.011)
Num. Obs.	61	61	61	61
R^2	0.359	0.241	0.293	0.666
R^2 Adj.	0.260	0.124	0.184	0.615
AIC	-111.8	-294.0	-143.9	-170.2
BIC	-90.7	-272.9	-122.8	-149.1
Log. Lik.	65.880	156.995	81.937	95.084

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Table 3: Flight to Safety Event Studies (Ethereum Blockchain) -- Continued
Investigation of Flight from ETH to USDT

This table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	Shanghai Implement (5)	BTC ETF Approval (6)	ETH ETF Announce (7)	ETH ETF Trade (8)
(Intercept)	0.080***	0.087***	0.086***	0.099***
	(0.004)	(0.004)	(0.004)	(0.006)
d_m3	0.048	0.046	0.118***	-0.052
	(0.032)	(0.032)	(0.032)	(0.045)
d_m2	0.019	0.072*	0.024	-0.053
	(0.031)	(0.033)	(0.033)	(0.045)
d_0	-0.016	0.052	0.051	0.049
	(0.031)	(0.032)	(0.032)	(0.050)
d_1	0.016	0.036	-0.036	0.013
	(0.034)	(0.033)	(0.032)	(0.045)
d_2	0.006	-0.035	-0.039	0.015
	(0.031)	(0.032)	(0.032)	(0.046)
d_3	0.010	-0.048	0.008	0.001
	(0.034)	(0.032)	(0.032)	(0.045)
Gold return	-0.003	-0.008	-0.000	0.000
	(0.006)	(0.009)	(0.005)	(0.008)
S&P 500 return	0.007	0.007	0.015	0.008
	(0.007)	(0.008)	(0.009)	(0.007)
Num. Obs.	61	61	61	61
R^2	0.090	0.221	0.287	0.086
R^2 Adj.	-0.050	0.101	0.177	-0.054
AIC	-241.2	-236.7	-238.1	-197.2
BIC	-220.1	-215.6	-217.0	-176.1
Log. Lik.	130.608	128.362	129.046	108.604

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Table 4A: Flight to Safety During ETH Shanghai Implementation
Flight from BTC to USDT – by Investor Type

The analysis in this table repeats what was presented earlier in Column (5) of Table 2 but we also segment investors into size-brackets (based on their USDT holdings) in this table. Like in Table 2, this table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	USDT $10-$100K (Small Investors)	USDT $100K - $10M (Medium-Size)	USDT $10M (Large Investors)
(Intercept)	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.000)
d_m3	-0.000	0.001	0.000
	(0.004)	(0.009)	(0.002)
d_m2	0.017***	-0.008	0.000
	(0.004)	(0.008)	(0.002)
d_0	0.001	0.000	0.000
	(0.004)	(0.008)	(0.002)
d_1	-0.012**	0.007	0.000
	(0.005)	(0.009)	(0.002)
d_2	-0.009**	0.006	0.000
	(0.004)	(0.009)	(0.002)
d_3	-0.001	0.001	0.000
	(0.005)	(0.009)	(0.002)
Gold return	-0.002**	0.001	0.000
	(0.001)	(0.002)	(0.000)
S&P 500 return	0.000	0.000	0.000
	(0.001)	(0.002)	(0.000)
Num. Obs.	61	61	61
R^2	0.409	0.046	0.002
R^2 Adj.	0.318	-0.101	-0.151
AIC	-483.4	-399.8	-581.7
BIC	-462.3	-378.7	-560.6
Log. Lik.	251.693	209.897	300.848

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Table 4B: Flight to Safety During ETH Shanghai Implementation
Flight from ETH to USDT – by Investor Type

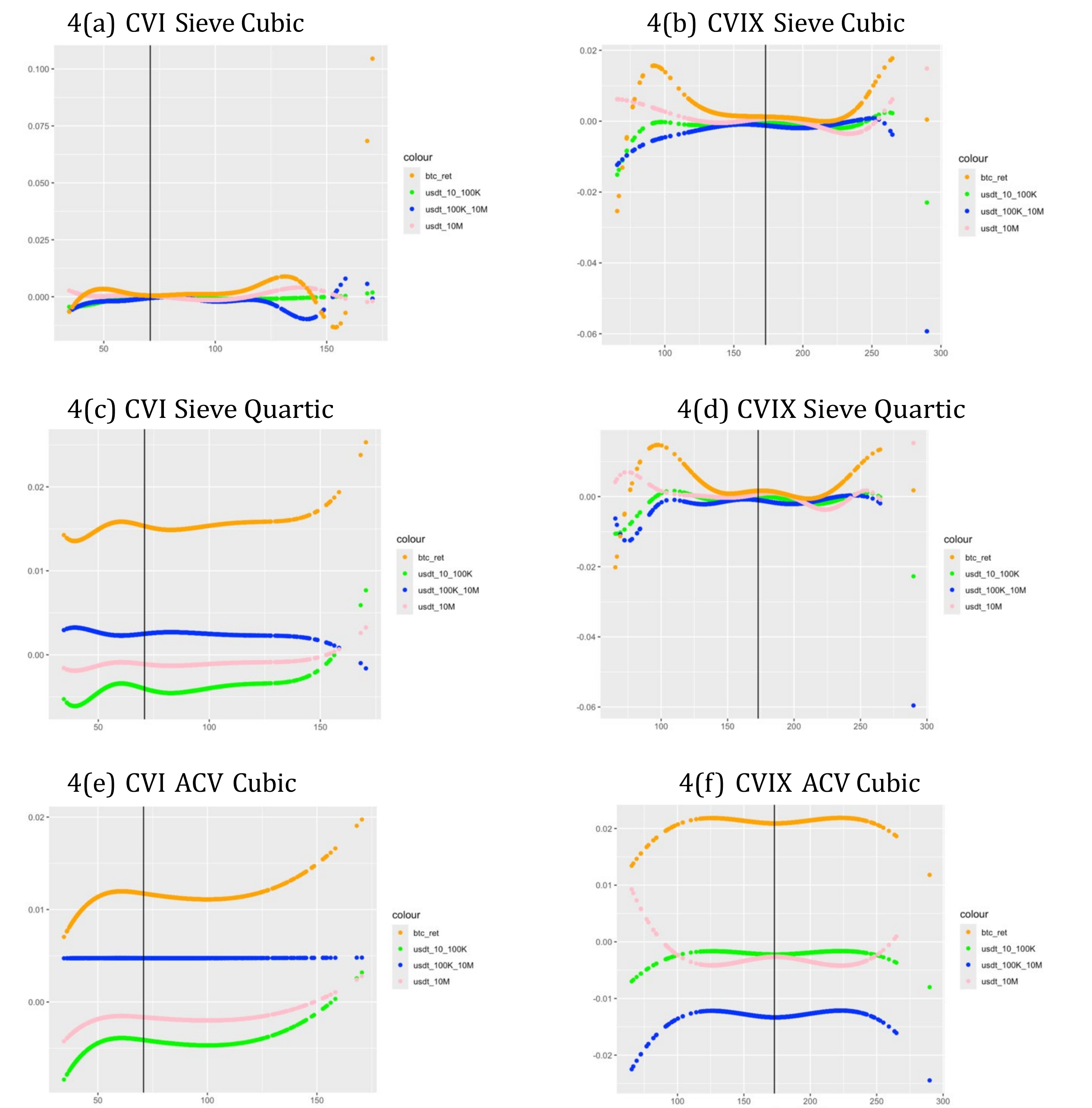
The analysis in this table repeats what was presented earlier in Column (5) of Table 3 but we also segment investors into size-brackets (based on their USDT holdings) in this table. Like in Table 3, this table examines flight to safety behavior from native bitcoin (on Bitcoin blockchain) to USDT, where USDT velocity is calculated using Equation (12) and asset reallocations out of BTC to USDT are derived using Equations (13), (14), and (15) for small, medium, and large wallets, respectively. Each data set is centered such that we consider a [t−30, t+30] day window around the reported date of the event summarized in Table 1.

	USDT $10 - $100K (Small Investors)	USDT $100K - $10M (Medium Size)	USDT $10M (Large Investors)
(Intercept)	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
d_m3	-0.001	0.001	0.054***
	(0.006)	(0.004)	(0.008)
d_m2	0.015**	0.006	-0.008
	(0.006)	(0.004)	(0.008)
d_0	-0.001	0.001	-0.002
	(0.006)	(0.004)	(0.008)
d_1	-0.000	0.003	-0.001
	(0.007)	(0.004)	(0.009)
d_2	-0.004	-0.000	-0.000
	(0.006)	(0.004)	(0.008)
d_3	-0.000	0.001	-0.005
	(0.007)	(0.004)	(0.009)
Gold return	-0.001	0.001	-0.002
	(0.001)	(0.001)	(0.002)
S&P 500_return	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.002)
Num. Obs.	61	61	61
R^2	0.132	0.099	0.523
R^2 Adj.	-0.001	-0.039	0.450
AIC	-439.9	-499.1	-407.3
BIC	-418.8	-478.0	-386.2
Log. Lik.	229.960	259.552	213.657

Note: Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01
Data Source: We use daily closing values reported on CoinMetrics.

Appendix
Figure 4: Evidence of Flight to Safety from Bitcoin (BTC) to USDT
January 2020 to December 2024

Figures 4(a) to 4(f) display the BTC returns (1-day ahead predicted returns for BTC) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Bitcoin network) as functions of risk. Figures 4(a), 4(c), and 4(e) proxy risk with CVI, while Figures 4(b), 4(d), and 4(f) proxy risk with 30-day CVIX.

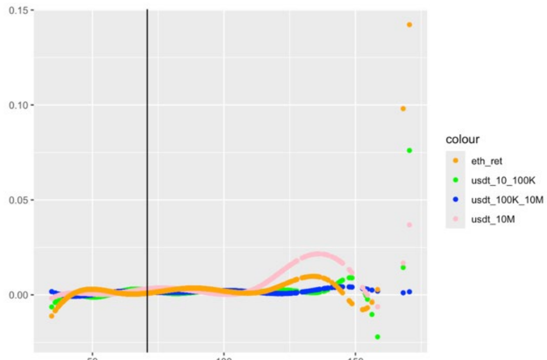


Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com

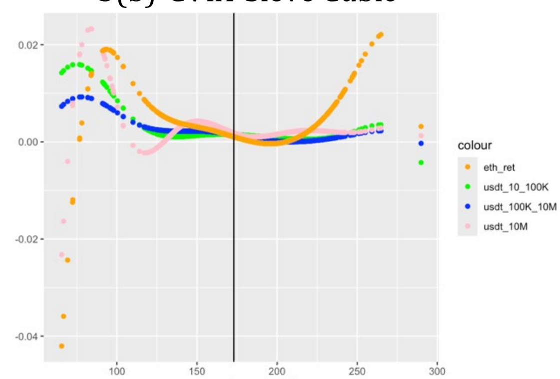
Figure 5: Evidence of Flight to Safety from Ethereum (ETH) to USDT
January 2020 to December 2024

Figures 5(a) to 5(f) display the ETH returns (1-day ahead predicted returns for ETH) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Ethereum network) as functions of risk. Figures 5(a), 5(c), and 5(e) proxy risk with CVI, Figures 5(b), 5(d), and 5(f) proxy risk with 30-day CVIX.

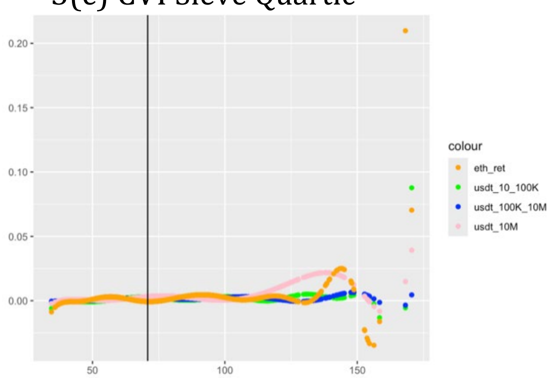
5(a) CVI Sieve Cubic



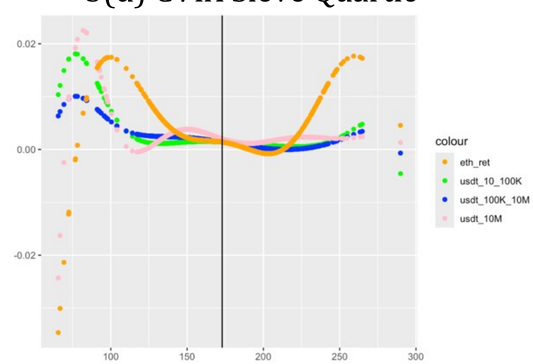
5(b) CVIX Sieve Cubic



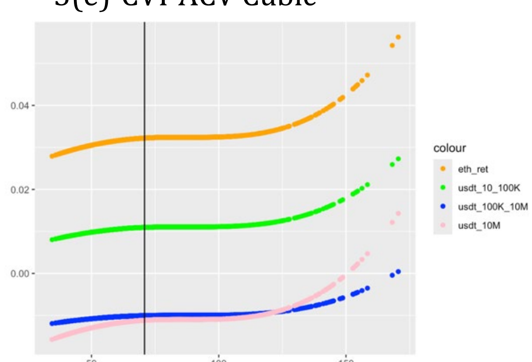
5(c) CVI Sieve Quartic



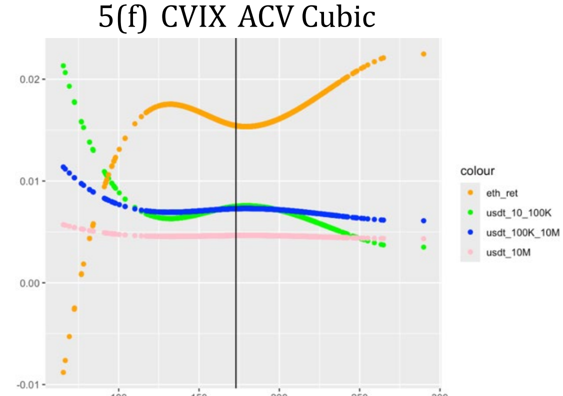
5(d) CVIX Sieve Quartic



5(e) CVI ACV Cubic



5(f) CVIX ACV Cubic

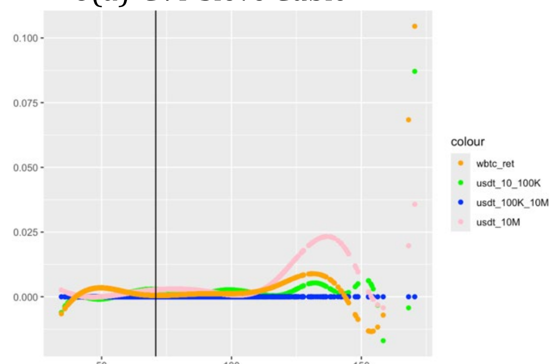


Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com

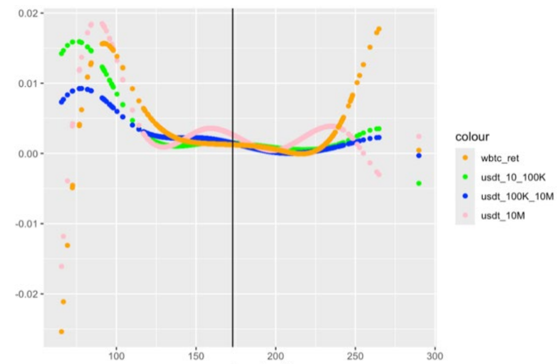
Figure 6: Evidence of Flight to Safety from Wrapped Bitcoin (WBTC) to USDT (January 2020 to December 2024)

Figures 6(a) to 6(f) display the WBTC returns (1-day ahead predicted returns for WBTC) and the USDT holdings (1-day ahead predicted USDT holdings of USDT traded on the Ethereum network) as functions of risk. Figures 6(a), 6(c), and 6(e) proxy risk with CVI, Figures 6(b), 6(d), and 6(f) proxy risk with 30-day CVIX.

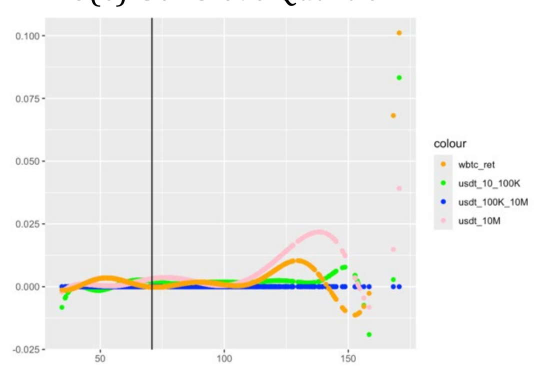
6(a) CVI Sieve Cubic



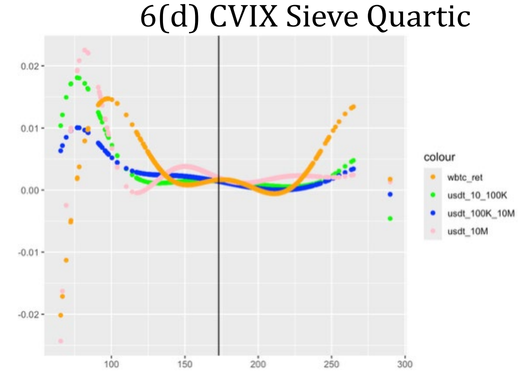
6(b) CVIX Sieve Cubic



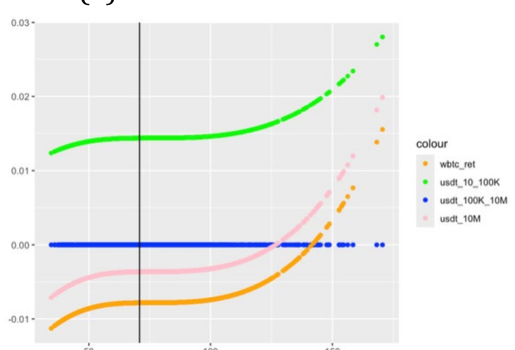
6(c) CVI Sieve Quartic



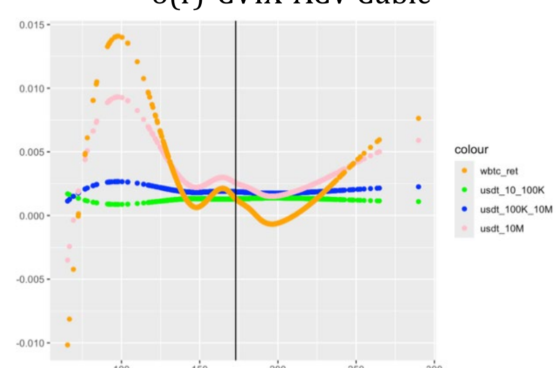
6(d) CVIX Sieve Quartic



6(e) CVI ACV Cubic



6(f) CVIX ACV Cubic



Data Sources: Daily closing prices from CoinMetrics and daily closing values of CVI from investing.com. CVIX calculations follow the methodology set forth in section III.1.
Data Period: January 1, 2020, to December 31, 2024, for daily closing prices from CoinMetrics; and January 1, 2020, to November 28, 2024, for daily closing values of CVI from investing.com.