Journal of Corporate Finance 96 (2026) 102904

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

The crypto multiplier[☆,☆☆]

Rodney J. Garratt [a], Maarten R.C. van Oordt [b,c,*]

[a] University of California at Santa Barbara, United States of America
[b] Vrije Universiteit Amsterdam, Netherlands
[c] Tinbergen Institute, Netherlands

ARTICLE INFO

Editor: E Lyandres

Keywords:
Cryptocurrencies
Bitcoin
Exchange rate
Risk management
Valuation

ABSTRACT

This paper develops the concept of a "crypto multiplier," which measures the equilibrium response of a cryptocurrency's market capitalization to aggregate inflows and outflows of investors' funds. The crypto multiplier takes high values when a large share of a cryptocurrency's coins is held as an investment rather than being used as a means of payment. Blockchain data show that the share of coins held for the purpose of making payments is rather small for major cryptocurrencies suggesting large crypto multipliers. Our results highlight the need for market participants to be vigilant when accepting block holdings of a cryptocurrency as collateral or as compensation for seed funding. The crypto multiplier indicates that the liquidation value of block holdings of cryptocurrencies can be substantially below their prevailing market values.

1. Introduction

The prevalence of large fluctuations in cryptocurrency prices has been well-documented (e.g., Yermack, 2015; Dwyer, 2015; Shen et al., 2020; Catania and Grassi, 2022; Pessa et al., 2023). The situation is more pronounced for smaller cryptocurrencies, but even the larger, more established ones exhibit levels of volatility that far exceed that of sovereign currencies. Fig. 1 shows the standard deviation of the daily percentage changes in the exchange rates of various currencies vis-à-vis the US dollar. The daily standard deviations for the exchange rates of cryptocurrencies occasionally exceed a level of 10 percent (Fig. 1a). Those for major fiat currencies (i.e., official currencies) stay below a level of 1 percent most of the time (Fig. 1b). Regulators across the world have introduced standards that require banks to apply the highest possible risk weights to cryptocurrencies, for the purpose of capital requirements (BCBS, 2022).[1]

Many factors contribute to the high levels of volatility in the exchange rates of cryptocurrencies, including the inelastic supply (Claeys et al., 2018) and the relative ease with which one can switch between them (Garratt and Wallace, 2018). While these papers identify circumstances that are conducive to high volatility, they are not useful for understanding structural relationships between volatility and coin holder motives.

☆ This article is part of a Special issue entitled: 'Blockchain-based finance' published in Journal of Corporate Finance.

☆☆ We are thankful to Evgeny Lyandres (Editor), two anonymous referees, Jonathan Chiu, Charles M. Kahn, Francesco Pierangeli, Russell (Tsz-Nga) Wong, Peter Zimmerman, and participants in the 9th International Workshop on P2P Financial Systems (Rome), the Economics of Payments XII conference (Washington), the 4th Crypto Asset Lab conference (Milan), and seminar series at the Bank of Canada, Vrije Universiteit Amsterdam and University of California at Santa Barbara for helpful comments and suggestions. This research was conducted partly while Rodney Garratt was a Senior Adviser at the Bank for International Settlements and Maarten van Oordt visited under their research fellowship program. We thank Jose Maria Vidal for statistical assistance. Views expressed do not necessarily represent those of the Bank for International Settlements.

* Corresponding author at: Vrije Universiteit Amsterdam, Netherlands.
E-mail addresses: garratt@ucsb.edu (R.J. Garratt), m.van.oordt@vu.nl (M.R.C. van Oordt).

[1] The standards use the term "unbacked cryptoassets" to refer to cryptocurrencies such as Bitcoin.

https://doi.org/10.1016/j.jcorpfin.2025.102904
Received 14 December 2023; Received in revised form 30 September 2025; Accepted 1 October 2025

Available online 9 October 2025
0929-1199/

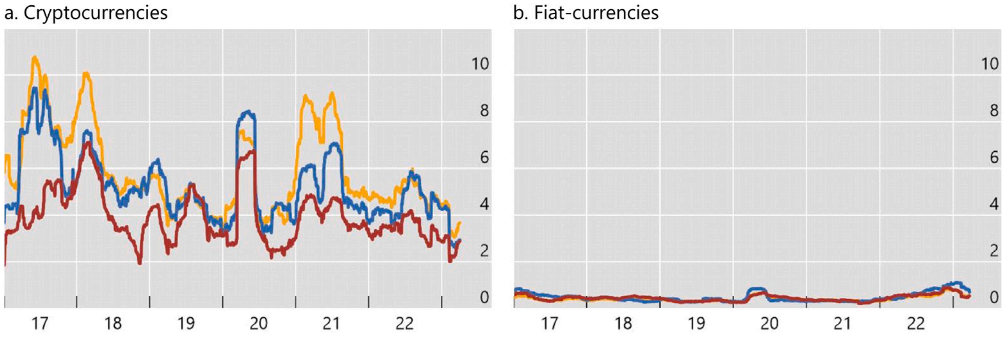

Fig. 1. The exchange rate volatility of cryptocurrencies and fiat currencies.
Note: In percents. Exchange rate volatility is measured as the 90-day rolling standard deviation of daily returns in USD. Panel (a): Top-10 native cryptocurrencies by market capitalization for which the share of inactive coins was available on coinmetrics.io as of end-2016: BTC, ETH, XRP, XLM, LTC, ETC, DASH, DOGE, ZEC and DCR. Panel (b): Top-10 fiat currencies by FX turnover based on BIS Triennial Survey 2016: EUR, JPY, GBP, CNY, AUD, CAD, CHF, HKD SGD and SEK.
Source: Sources: coinmetrics.io; BIS.

This paper studies the value of cryptocurrencies such as Bitcoin and Ethereum that are used as a means of payment but not as a unit of account. We show how the high exchange rate volatility can be understood through the lens of a *crypto multiplier* which measures the equilibrium change in a cryptocurrency's market capitalization in response to a one-dollar aggregate inflow or outflow of investors' funds. Building on the quantity equation (Fisher, 1911; Bolt and Van Oordt, 2020), we derive the theoretical formula for the crypto multiplier as a simple ratio that takes high values with no upper limit when a large share of a cryptocurrency's coins is held as an investment rather than being used as a means of payment. Blockchain data demonstrate that the number of coins held for the purpose of making payments is rather small for major cryptocurrencies, suggesting large crypto multipliers. Such large crypto multipliers help to explain the high price elasticities of investors' demand for cryptocurrencies found in empirical work (Divakaruni and Zimmerman, 2024).

Empirically, we explore whether various blockchain-based proxies for the share of a cryptocurrency held as an investment have predictive power for the exchange rate volatility of that cryptocurrency. Our estimation results suggest that the proxies are indeed positively related to future volatility, in line with the theory of the crypto multiplier. The baseline regression results suggest that an increase in the most significant proxy for the investment share, from its 10th percentile to its 90th percentile, is associated with an expected increase in the standard deviation of daily returns during the next two quarters of approximately 3 percentage points. Sensitivity analysis confirms the robustness of the positive empirical relationship between proxies for the investment share and future exchange rate variation for various alternative measures of exchange rate risk, alternative timing of the predictive regressions and data frequencies, and mathematical transformations of the proxies for the investment share into proxy-based multipliers.

The crypto multiplier indicates a need for significant caution when evaluating the value of block holdings in cryptocurrency. This is particularly important for investors who accept large amounts of a cryptocurrency with high speculative holdings as collateral, because of the potential inability of the holder to liquidate large quantities anywhere near the prevailing market price. Likewise, investors should be cautious about accepting large blocks of cryptocurrency as whole or partial compensation for seed funding. The crypto multiplier predicts that winding down a large speculative position is likely to have a significant price impact unless the position is absorbed by other speculators. Put succinctly, the current market value of a cryptocurrency block may be a poor indicator of its liquidation value.

1.1. Related literature

Cryptocurrencies have been the subject of a rapidly expanding economic literature (Hałaburda et al., 2022). The levels of cryptocurrency exchange rates have been studied through the lens of various theoretical models (e.g., Athey et al., 2016; Biais et al., 2023; Bolt and Van Oordt, 2020; Garratt and Wallace, 2018; Karau and Mönch, 2023; Lee et al., 2021; Pagnotta, 2022; Prat et al., 2025; Schilling and Uhlig, 2019). A variety of theoretical studies analyze how firms or platforms could rely on the economics of cryptocurrencies or tokens to raise funding and sell products (Bakos and Hałaburda, 2022; Chod and Lyandres, 2023; Cong et al., 2021, 2022; Garratt and Van Oordt, 2022, 2024; Gryglewicz et al., 2021; Lee and Parlour, 2022; Li and Mann, 2025; Malinova and Park, 2023; Rogoff and You, 2023; Sockin and Xiong, 2023b,a). Others have looked at the monetary implications of competition between cryptocurrencies and fiat currencies (Benigno et al., 2022; Zhu and Hendry, 2019). The design of economic incentives in the consensus protocols that secure the transaction records of cryptocurrencies in blockchains has been another fascinating research topic (e.g., Abadi and Brunnermeier, 2018; Biais et al.; 2019, Budish, 2018; Chiu and Koeppl, 2019, 2022; Garratt and Van Oordt, 2023; Hałaburda et al., 2021; Prat and Walter, 2021).

Many of the aforementioned papers that develop theoretical models for cryptocurrency prices rely either implicitly or explicitly on the observation that cryptocurrencies are not used as a unit of account (Athey et al., 2016; Biais et al., 2023; Bolt and Van Oordt, 2020; Cong et al., 2021, 2022; Garratt and Van Oordt, 2022; Gryglewicz et al., 2021; Karau and Mönch, 2023; Lee et al., 2021; Pagnotta, 2022; Prat et al., 2025; Schilling and Uhlig, 2019). Using this observation as an assumption is an important stepping stone in the derivation of the crypto multiplier, as we will show under a very general setup.

Finally, there is an interesting parallel between our framework and the broader asset pricing literature on the sensitivity of security prices to demand shocks (Petajisto, 2009; Koijen and Yogo, 2019). Recent papers have estimated multipliers for the market capitalization of aggregated stock and bond portfolios if investors reallocate one more dollar to them. Empirical estimates suggest that such multipliers may have an order of magnitude of 3 to 8 (e.g., Gabaix and Koijen, 2021; Chaudhary et al., 2023).[2] Although there is an interesting parallel between this concept and the crypto multiplier, there are also important differences. The multipliers for stock and bond portfolios measure the price impacts of investors reallocating their portfolios toward funds holding stocks or bonds, without affecting the aggregate number of stocks or bonds held by investors. For every investor who buys, there is also an investor who sells. In contrast, cryptocurrency may also be used for payment purposes. If individuals start accumulating coins of a cryptocurrency solely for investment purposes, then those purchases can reduce the number of coins that are available as a means of payment. The crypto multiplier measures the price impact of investment flows that increase the aggregate number of coins held solely for investment purposes (implying a reduction in the aggregate number of coins available as a means of payment). In the most stylized version of our model, the crypto multiplier turns out to be theoretically equal to the inverse of the share of coins used for payments. Hence, a crypto multiplier in a similar range of 3 to 8, as observed for broadly aggregated stock portfolios, would require that approximately 12 to 33 percent of the coins of a cryptocurrency are used to make payments. The crypto multiplier would be substantially higher than this if a cryptocurrency is mostly held as an investment and hardly used to make any payments.

2. Derivation of the crypto multiplier

2.1. Cryptocurrencies do not serve as a unit of account

We start our theoretical analysis from the observation that cryptocurrencies typically do not serve as a unit of account. The number of coins one must pay when making a purchase with cryptocurrency usually depends on a price that is posted in fiat currency (e.g., dollars or euros) and the latest available exchange rate of the cryptocurrency.

Prices of products and services in cryptocurrency tend to be perfectly flexible with respect to changes in the cryptocurrency's exchange rate.[3] Consider a car dealership that, given an exchange rate of $30,000 per bitcoin, would be willing to accept a payment of two bitcoin for a car with a price tag of $60,000. If the exchange rate of bitcoin were to drop to $20,000 per bitcoin, then the dealership would generally increase the number of bitcoins one has to pay from two to three, while leaving the price tag of $60,000 unchanged. The number of coins one must pay when paying with cryptocurrency tends to fully adjust to changes in the cryptocurrency's exchange rate, while the prices of goods and services in terms of fiat currency tend to be unaffected. Fiat currency acts as the unit of account, even though cryptocurrency can serve as the means of payment.

Telecommunication technology allows any store to update the number of coins the customer must pay in near real-time when the customer arrives at the checkout to pay. When accepting a cryptocurrency payment, a store simply calculates the number of cryptocurrency units the customer must pay, P, by dividing the value of the purchase in fiat currency, $P^{\$}$, by the latest available exchange rate of the cryptocurrency, $S^{\$/\text{coin}}$, so that

$$P = P^{\$}/S^{\$/\text{coin}}. \tag{1}$$

It is common for stores to rely on third-party payment service providers to accept cryptocurrency payments for them, so that store owners themselves do not need to do these calculations nor handle cryptocurrency directly.[4] Instead, the store owners receive fiat currency from the payment service provider in their bank accounts.

2.2. The exchange rate equation

The observation that cryptocurrencies are not used as a unit of account has implications for the exchange rate of cryptocurrencies. These can be demonstrated using the classical transaction version of the quantity equation (Fisher, 1911):

$$PT = MV. \tag{2}$$

The quantity equation states that the total value of all payments made with a certain currency within a period (the left-hand side) must equal the amount of the currency that changed hands for payments (the right-hand side). In the context of a cryptocurrency,

[2] Stolborg (2023) provides an interesting application of the methodology of Gabaix and Koijen (2021) to Bitcoin based on what is interpreted as a blockchain-based classification of investors.

[3] This generally does not hold true for all the prices expressed in a fiat currency. For a fiat currency, there are generally some prices expressed in that currency that do not respond immediately to changes in the exchange rate of that currency. The price of a car at a dealership located in the euro area is unlikely to respond minute-by-minute to changes in the euro-dollar exchange rate. Even fiat currency prices for online subscription services may be inflexible with respect to exchange rate shocks (Ambros, 2022). That said, there are several historical inflationary episodes where fiat currencies completely lost their function as a unit of account even though they continued to function as a means of payment (e.g., Sgard, 2003). Finally, it is worth noting that the derivations below can be generalized to accommodate scenarios where a given amount of products and services paid for with cryptocurrency have prices quoted in cryptocurrencies that are unresponsive to changes in the exchange rate. Such a change increases the level of the crypto multiplier in Eq. (5).

[4] Examples of providers of such payment services include Bitpay.com, Coinbase Commerce, Coinpayments.net, Coingate.com and Paypal US.

the symbols on the left-hand side are interpreted as the average number of coins paid per payment, P (for "Price"), multiplied by the number of payments made with that cryptocurrency, T (for "Transactions"). The symbols on the right-hand side represent the total number of coins in existence, M (for "Money"), multiplied by how often the coins were used on average to make a payment for purchases within the period, V (for "Velocity"). The quantity equation follows immediately from the definition of velocity — divide both sides by M to see why — and holds true for any object that acts as a means of payment.

The velocity in the quantity equation, V, measures how often all existing coins are used on average to make payments for goods and services within a period. It can be considered as a weighted average of the group-specific velocities of different groups of coins, with each group-specific velocity measuring how often the coins within that group are used on average to make a payment within the period. This is in a similar spirit to Fisher (1911) who considered different velocities for different types of money balances. For the purpose of deriving the crypto multiplier, we distinguish between two groups: coins that are used to make payments within a period and the coins that are not. Following the notation of Bolt and Van Oordt (2020), let Z denote the number of coins that are *not* used to make any payments within a period. The velocity of those coins is zero by definition. Let V^* denote the velocity of any coins that are used to make payments. Then, we can write MV as

$$MV = (M - Z)V^* + Z \cdot 0 = (M - Z)V^*. \tag{3}$$

We can loosely think of Z as reflecting coins that were held only as a store of value (that is, not to make payments for purchases). These coins could include investment or speculative holdings, as well as staked coins for cryptocurrencies such as Ethereum.

If cryptocurrencies are used as a means of payment but not as a unit of account, then it is possible to use the quantity equation to obtain an equation for the exchange rate of cryptocurrencies (Bolt and Van Oordt, 2020). In the quantity equation, we replace P with the expression in (1) and MV with the expression in (3). This yields the exchange rate equation for a cryptocurrency as

$$S^{\$/\mathrm{coin}} = \frac{T^{\$}/V^*}{M - Z}, \tag{4}$$

where $TP^{\$}$ is conveniently rewritten as $T^{\$}$ to reflect the dollar value of cryptocurrency payments (the number of purchases paid for with the cryptocurrency multiplied with the average value of those purchases in dollars). Appendix A.1 provides a formal derivation.

The exchange rate equation reveals how the exchange rate increases with the transactional demand, decreases with the total number of coins, and increases with the number of coins that are held exclusively as a store of value. The equation has a straightforward interpretation as the ratio between the transactional demand – that is, the value of coins needed to process payments measured in terms of dollars, $T^{\$}/V^*$ – and the number of coins that is available to process payments, $M - Z$.

The assumptions underlying the exchange rate equation in (4) are relatively general. The exchange rate equation is the immediate implication of the definition of velocity, the assumption in (1) that the number of coins one must transfer when making a payment with cryptocurrency is determined by the price in fiat currency and the latest available exchange rate ("Assumption 1"), and the assumption that the cryptocurrency is used as a means of payment in *at least some* transactions, so that $MV \neq 0$ ("Assumption 2"). Hence, the exchange rate equation must hold true for any cryptocurrency (as well as any other means of payment) that satisfies Assumptions 1 and 2.

2.3. The crypto multiplier

We can use the exchange rate equation to derive the quantitative impact of aggregate inflows and outflows of investors' funds on the equilibrium exchange rate by adding two further assumptions. The first additional assumption is that the number of existing coins is non-responsive to market conditions ("Assumption 3"). This assumption holds, by and large, for cryptocurrencies where a protocol predetermines the issuance of new coins such as Bitcoin. The second additional assumption is that a change in the number of coins that are held only as a store of value will not permanently affect the transactional demand for a cryptocurrency in terms of fiat currency ("Assumption 4").[5] Assumptions 3 and 4 imply mathematically that a change in Z does not affect the equilibrium values of, respectively, M and $T^{\$}/V^*$. Hence, the only change in the exchange rate in Eq. (4) from investors buying up coins comes from the direct impact of Z on $S^{\$/\mathrm{coin}}$. The exchange rate equation informs us that the exchange rate must increase when investors buy up coins so that fewer coins are available for payments.

Consider the crypto multiplier, which is defined as *the dollar change in the equilibrium market capitalization of a cryptocurrency in response to a single dollar of aggregate inflows or outflows of investors' funds*.[6] The crypto multiplier can be derived from the exchange rate equation as

$$\frac{\partial S^{\$/\mathrm{coin}}}{\partial Z}\frac{M}{S^{\$/\mathrm{coin}}} = \frac{M}{M - Z}. \tag{5}$$

Appendix A.2 provides the formal derivation. Intuitively, the partial derivative $\partial S^{\$/\mathrm{coin}}/\partial Z$ approximates the impact on the exchange rate of investors buying one more *coin*. To calculate the equilibrium impact on the exchange rate if investors invest one more *dollar*,

[5] Assumption 4 is the most contested in the context of cryptocurrencies, and will be relaxed in Section 3. This assumption holds true if decisions to pay with cryptocurrency are ultimately determined by technology and preferences and not by the exchange rate or the number of coins that are held solely as a store of value. This would ensure that how often you pay (the number of transactions T), how much you pay (the dollar-price per transaction, $P^{\$}$), and the velocity of coins used to make payments V^* would be unresponsive in equilibrium to a change in the number of coins held as a store of value.

[6] The concept of a multiplier is applied in a sense similar to that used by Keynes (1936, Chapter 8) in that it refers to how much an incremental change in one economic quantity results in a multiplicative change in another related economic quantity.

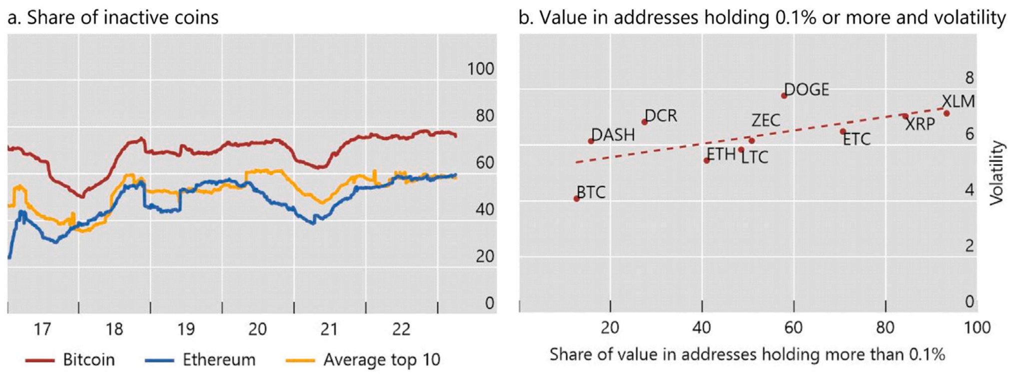

Fig. 2. Cryptocurrency investment and volatility.
Note: In percents. Panel (a). The share is calculated as 100 - 100 * (180 Day Active Supply/Current Supply (native units)). Top-10 native cryptocurrencies by market capitalization for which the share of inactive coins was available on coinmetrics.io as of end-2016: BTC, ETH, XRP, XLM, LTC, ETC, DASH, DOGE, ZEC and DCR. Panel (b). Volatility measured as the standard deviation of daily returns in USD and the average share of coins in addresses holding 0.1% or more, calculated over the period 2017Q1-2023Q1.
Source: coinmetrics.io.

one has to divide the partial derivative by the exchange rate, $S^{\$/\text{coin}}$. Finally, to obtain the equilibrium impact on the market capitalization, one must multiply the change in the exchange rate by the total number of coins, M.[7]

The crypto multiplier reveals that the market capitalization of a cryptocurrency responds more strongly to net investment flows when a smaller share of its coins are used to make payments. Intuitively, the expression in (5) can be understood as follows. For a one-dollar net investment inflow to occur, investors have to buy one dollar of coins from individuals who use them for payments. Since the transactional demand in dollars is given in equilibrium, users would be happy to sell one dollar of coins to investors if the exchange rate appreciates sufficiently to increase to total value of their remaining coins by one dollar. If the rise in the exchange rate is sufficient to increase the total value of the coins that are used to make payments (i.e., $M - Z$ coins) by one dollar, then the total value of all existing coins (i.e., M coins) must increase by $M/(M - Z)$ dollars. This increase corresponds precisely to the equilibrium increase predicted by the formula for the crypto multiplier.

The crypto multiplier takes values of at least one so that the market capitalization must change by a larger amount in equilibrium than the aggregate inflow or outflow of investors' funds. The level of the crypto multiplier can be calculated as the ratio between the total number of existing coins and the number of coins that are used to make payments. If all coins were used to make payments, so that $Z = 0$, then the crypto multiplier would equal $M/M = 1$. In this situation, the inflow of a single dollar of aggregate investors' funds would be expected to increase the market capitalization of the cryptocurrency by approximately a single dollar in equilibrium. By contrast, if the number of coins used for payments were only 5 percent of the existing coins, then the crypto multiplier would equal $1/0.05 = 20$. In this situation, the equilibrium change in the market capitalization of the cryptocurrency would be approximately as much as 20 times the aggregate inflow or outflow of investors' funds.

Blockchain data suggests that the theoretical multiplier must be large for popular cryptocurrencies. Over 75 percent of the bitcoins are held in addresses that were not used over the past 6 months (Fig. 2a). For Ethereum, the equivalent number is around 60 percent. One can consider these numbers as lower bounds for the fraction of coins that were held only as a store of value.[8] For the remaining coins that were active over the past 6 months, it is not clear whether they were really used to make any real payments because investment activities can also trigger activity on the blockchain.[9] In other words, most coins for cryptocurrencies such as Bitcoin and Ethereum are held only as a store of value.

The relationship between the volatility of cryptocurrency exchange rates and the number of coins held for store-of-value motives is illustrated in Fig. 2b. The share of coins held as a store of value is proxied by the share of coins held in addresses that contain at least 0.1 percent of the total market capitalization of the coin. Although this measure is imperfect, the argument for using it as a proxy for the store-of-value motive is that balances in such large addresses are less likely to be maintained for the purpose of making payments. There are weak signs (i.e., statistically insignificant signs) of a positive correlation between the proxy and

[7] It is also possible to derive an elasticity by multiplying $\partial S^{\$/\text{coin}}/\partial Z$ with $Z/S^{\$/\text{coin}}$ rather than $M/S^{\$/\text{coin}}$. This elasticity approximates the percentage change in the equilibrium exchange rate if investors were to increase the number of coins they hold by one percent. The levels of both the crypto multiplier and the elasticity increase in the level of Z, but the increase in the elasticity is in part because a *one-percent* increase in Z requires investors to purchase more coins for higher values of Z.

[8] A qualification is that coins in some addresses may be allocated to protocols that facilitate cheaper off-chain payments such as the lightning network (Poon and Dryja, 2016; Divakaruni and Zimmerman, 2024). Coins in such addresses could appear as inactive. The quantitative impact is reasonably small. Less than 0.3 percent of all bitcoins were allocated to the lightning network at the end-of −2022 (source: txstats.com).

[9] Short-term investment was the most popular option as the primary reason for acquiring cryptocurrency in the survey by Akana and Li (2022). Moreover, the number of inactive coins in Fig. 2a decreases during periods of strong appreciations such as the end-of −2017 and early-2021 when the exchange rate of bitcoin hit 20,000 USD and 60,000 USD, respectively.

volatility, which is consistent with the observation that the crypto multiplier takes higher values if the share of coins held as a store of value increases. Section 5 presents a formal statistical analysis of the empirical relationship between speculative holdings and exchange rate volatility based on a variety of proxies for the store-of-value motive.

3. The crypto multiplier with endogenous transactional demand

The crypto multiplier in Eq. (5) was derived under Assumption 4 which states that, in equilibrium, the transactional demand for a cryptocurrency does not depend on the number of coins that are held only as a store of value. This assumption is difficult to test empirically because the transactional demand and speculative holdings are not directly observable. It seems plausible that big shifts by speculators in or out of a cryptocurrency would generate publicity and affect the adoption of that cryptocurrency for payments through network effects (Bakos and Hałaburda, 2022; Gryglewicz et al., 2021; Cong et al., 2021; Chiu and Wong, 2022). Alternatively, speculators flocking into a cryptocurrency could be associated with an increase in transaction fees and, hence, an increase in the cost of paying with that cryptocurrency (Zimmerman, 2020). As mentioned above, these impacts will be inconsequential for the transactional demand *in equilibrium* if they are temporary. To the extent that they have permanent effects, we can quantify their impact on the crypto multiplier. The following equation computes the crypto multiplier while allowing for an endogenous response of the transactional demand:

$$\frac{\partial S^{\$/\mathrm{coin}}}{\partial Z}\frac{M}{S^{\$/\mathrm{coin}}} = \frac{M}{M-Z} + \frac{\partial (T^{\$}/V^{*})}{\partial Z}\frac{M}{T^{\$}/V^{*}}. \tag{6}$$

The derivation of Eq. (6) relies solely on Assumptions 1-3: (1) the number of coins one must pay when making a purchase with cryptocurrency is determined by the price in fiat currency and the latest available exchange rate, (2) the cryptocurrency is used as a means of payment, and (3) the total number of coins that exists is not affected by market conditions.

The crypto multiplier with endogenous transactional demand has an additional term. The sign of this term will depend on whether the relationship between speculative holdings and the transactional demand is positive or negative in equilibrium. If it is positive, then the crypto multiplier will be larger than before, meaning that the impact of changes in speculative holdings on the exchange rate would be even bigger. If speculative holdings result in a permanent negative shift in transactional demand, then the crypto multiplier would be smaller than before.

An interesting aspect is to identify the condition under which the crypto multiplier is larger than one. In this case, an inflow or outflow of one dollar of investors' funds would change the market capitalization by more than one dollar. From Eq. (6), we can derive that the crypto multiplier is larger than one whenever

$$\frac{\partial (T^{\$}/V^{*})}{\partial Z}\frac{1}{S^{\$/\mathrm{coin}}} \geq -\frac{Z}{M}. \tag{7}$$

This seems like a weak condition. The condition holds always if the permanent impact of speculative holdings on transactional demand is positive. Even if the permanent impact were negative, it must be sufficiently strong for the crypto multiplier to be smaller than one. More precisely, for the crypto multiplier to be smaller than one, it would require a one-dollar *inflow* of investors' funds to permanently *reduce* the transactional demand measured in terms of dollars by more than the fraction of coins held as a store of value, which is substantial for the major cryptocurrencies (Fig. 2).

4. Applicability

Whether the expression for the exchange rate equation in (4) and the expressions for the crypto multiplier in (5) and (6) apply depends on the extent to which Assumptions 1-3 are satisfied. These assumptions are not universally applicable to all crypto assets and scenarios.

The expressions for the exchange rate and the crypto multiplier do not apply to crypto assets that are not used as a means of payment in any transactions. Such crypto assets fail to satisfy Assumption 2. Cryptocurrencies such as Bitcoin and Ethereum that are native tokens of a blockchain generally satisfy Assumption 2. The role of native tokens as a means of payment for transaction fees and/or the execution of smart contracts on their respective blockchains ensures that they are used as a means of payment in at least some transactions. The empirical analysis in the next section will concentrate on native tokens for this reason.

Stablecoins do not satisfy the assumption that the number of existing coins is non-responsive to market conditions (Assumption 3), because their supply fluctuates with demand in order to maintain a stable exchange rate. The expressions for the crypto multiplier do not apply to stablecoins for this reason. The exchange rate equation in (4), which only requires that Assumptions 1–2 are satisfied, still applies. However, for stablecoins, the exchange rate equation implies little more than that to maintain a stable exchange rate, the issuer must increase the supply M by one unit if the amount of stablecoin held as a store of value Z were to increase by one unit.

A potential concern is that the number of cryptocurrency units one has to transfer when paying with cryptocurrency may not be exactly equal to the amount specified in (1). This would constitute a violation of Assumption 1. Market frictions such as trading fees and illiquidity may result in payment service providers offering unfavorable exchange rates to users when they pay with cryptocurrency. In contrast, costs of traditional payment methods, such as interchange fees for card payments, could be a reason to offer discounts when users pay with cryptocurrency. Assumption 1 can be modified to account for these scenarios by specifying that the number of cryptocurrency units to be paid when making a purchase costing $P^{\$}$ dollars is given by $P = (1+f)P^{\$}/S^{\$/\mathrm{coin}}$, where

Table 1
Descriptive statistics.

	Mean	Standard deviation	10th percentile	90th percentile	Observations (cryptocurrencies)
Daily exchange rate volatility (180 days), %	6.191	2.226	3.976	8.988	544 (24)
Mean absolute deviation of daily returns (180 days), %	4.218	1.460	2.714	6.154	544 (24)
Empirical 1-day Value-at-Risk with 95% confidence level, %	9.004	2.759	5.837	12.814	544 (24)
Daily exchange rate volatility (90 days), %	5.990	2.574	3.499	9.207	544 (24)
Weekly exchange rate volatility (26 weeks), %	16.011	6.811	9.182	23.779	544 (24)
Share of coins in addresses with at least 0.1%	0.539	0.251	0.168	0.909	544 (24)
Share of coins in the top-100 addresses	0.525	0.239	0.195	0.923	544 (24)
Share of coins in addresses ≥1,000,000 USD	0.521	0.294	0.130	0.935	544 (24)
Number of addresses with less than 100 USD	5,050,220	10,158,625	47,753	18,468,768	544 (24)
Principal component for speculative share	0.000	1.611	−2.146	2.505	544 (24)
Transactions per second	3.196	9.690	0.006	8.469	544 (24)
Estimated market capitalization in billion USD	23.154	97.325	0.033	34.759	544 (24)
Mean amount per transaction in USD	11,651.97	99,660.56	57.75	17,982.85	544 (24)
Google Trend for cryptocurrency	18.2	18.0	1.0	37.0	544 (24)

Note: All variables are measured on the last day of each quarter, except for the Google Trends variable, which is measured over the last month of each quarter. Sources: coinmetrics.io; trends.google.com; authors' calculations.

f reflects an average additional transaction fee. This modification would change the numerator of the exchange rate equation in (4) to $(1+f)T^{\$}/V^{*}$.[10] Interestingly, the expressions for the crypto multiplier in (5) and (6) are invariant to the fee, as long as the level of f remains constant. If net investment flows would be associated with a persistent change in the fee f, then the relationship between net investment flows and the equilibrium market capitalization could deviate from the theoretical expressions for the crypto multiplier in (5) and (6).

5. Statistical analysis of speculation and future volatility

Testing whether the crypto multiplier is empirically relevant for the returns of cryptocurrencies is not straightforward. External factors can simultaneously drive both the exchange rate of a cryptocurrency and the amount of cryptocurrency held by investors. This can bias the coefficients in a regression where changes in the exchange rate are explained by changes in proxies for the speculative position. Moreover, using the lagged change in the speculative position to predict a future change in the exchange rate is unlikely to be successful because exchange rates behave largely as martingales with low predictability (e.g., Hu et al., 2019; Makarov and Schoar, 2019).[11]

To circumvent these issues, we opt for predicting the volatility of the exchange rate rather than the change in the exchange rate. Appendix C shows mathematically how the future exchange rate volatility increases in the current level of the crypto multiplier. The requirement for this relationship to be positive is that changes in transactional demand and changes in the speculative position are not too negatively correlated, which seems reasonable based on correlations in the data.[12] The regression coefficients for the speculative position in our predictive regression for exchange rate volatility may also be considered as a joint hypothesis test for both the crypto multiplier effect and a correlation between changes in transactional demand and speculation that is not too negative.

To analyze the empirical relationship between the size of the speculative position and exchange rate volatility, we obtain cryptocurrency price data and blockchain analytics from *coinmetrics.io*. The analysis considers cryptocurrencies that are the "native tokens" of a blockchain (see Section 4). To select those cryptocurrencies, we select all cryptocurrencies that are classified by our data provider as being based on any consensus mechanism ("POS", "POW", "dPOS" or "other"). We collect data measured on the last day of each quarter over a period from 2014Q4 until 2023Q1. For each cryptocurrency, we exclude the first quarter with available data. Moreover, we include an observation only if there are no missing values for all variables. This yields a dataset of 544 quarterly observations for 24 cryptocurrencies. The cryptocurrencies in the sample have a combined market capitalization that exceeds 60 percent of the global market capitalization of all cryptocurrencies during the entire sample period.[13] Table 1 reports the descriptive statistics. Definitions of all variables and data sources are provided in Appendix D.

The dependent variable in our baseline regressions is the volatility of the exchange rate, calculated as the standard deviation of the daily returns over a period of 180 days. The independent variables of interest are various proxies that are believed to be positively correlated with the speculative position. The statistical power of the analysis depends on the extent to which a proxy is

[10] If the fee is positive, then the direct effect is that customers need a fraction f more cryptocurrency units for any given payment. A higher fee would likely steer customers away from paying with cryptocurrency, reducing the dollar value of cryptocurrency payments, $T^{\$}$.

[11] Appendix B shows that the empirical proxies for the speculative position are almost uncorrelated with future returns, which is consistent with the low predictability observed in these earlier studies.

[12] See the discussion of Table C.1 in Appendix C for more details.

[13] The share of the combined market capitalization of the cryptocurrencies in the sample reached its highest point in 2015Q2, accounting for 98 per cent of the global market capitalization of all cryptocurrencies, and its lowest point in 2022Q3, at 62 percent (based on data for the global market capitalization of all cryptocurrencies from coingecko.com).

Table 2
Speculation and future exchange rate volatility.

Variables	(I) Standard deviation of returns (180 days)	(II) Standard deviation of returns (180 days)	(III) Standard deviation of returns (180 days)	(IV) Standard deviation of returns (180 days)	(V) Standard deviation of returns (180 days)	(VI) Standard deviation of returns (180 days)
Share of coins in addresses with at least 0.1%	1.536***			4.362***		
	(0.406)			(1.501)		
Share of coins in the top-100 addresses		1.456***			2.918**	
		(0.428)			(1.287)	
Principal component for speculative share			0.238***			0.683***
			(0.067)			(0.186)
Transactions per second (log)	0.067	0.085	0.080	−0.039	−0.022	0.029
	(0.112)	(0.112)	(0.108)	(0.138)	(0.144)	(0.132)
Market capitalization in billions of USD (log)	−0.397***	−0.411***	−0.414***	−0.378**	−0.431**	−0.439***
	(0.140)	(0.143)	(0.138)	(0.159)	(0.168)	(0.150)
Mean amount per transaction in USD (log)	−0.024	−0.020	−0.031	0.092	0.112	0.107
	(0.082)	(0.082)	(0.083)	(0.099)	(0.094)	(0.096)
Google Trends for cryptocurrency	0.025***	0.025***	0.025***	0.023***	0.024***	0.021***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
Constant	5.201***	5.262***	6.102***	2.718***	3.410***	5.115***
	(0.452)	(0.477)	(0.461)	(0.743)	(0.743)	(0.593)
Observations (cryptos)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)
R-squared	0.231	0.226	0.232	0.183	0.195	0.175
Fixed effects	No	No	No	Yes	Yes	Yes

Note: The dependent variable is the future standard deviation of daily returns measured over a period of 180 days. All independent variables are measured on the last day of the preceding quarter, except for the Google Trends variable, which is measured over the last month of the preceding quarter. Variable definitions and data sources are in Appendix D. Models are estimated with least squares. Standard errors clustered at the cryptocurrency level are reported in parentheses. The regression with fixed effects reports the overall R-squared. Statistical significance at the 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

truly correlated with the speculative position. Any noise in our proxy for the speculative position is expected to bias the estimated coefficient in our regression toward zero and reduce its statistical significance (Hausman, 2001).

We use three different proxies for the speculative position. The first proxy is the share of coins held in addresses with at least 0.1 percent of the total supply (as in Fig. 2b). The second proxy is the total share of coins held in the top-100 addresses.[14] Our third proxy combines various variables. It is calculated as the first principal component extracted from the previous two proxies as well as the share of coins held in addresses with at least 1 million USD and the logarithm of the number of addresses with positive balances with less than 100 USD (the latter is expected to be negatively correlated to the speculative position).[15] The principal component is expected to be the least noisy proxy for the speculative position since combining various proxies may cancel out the noise of individual proxies.

As control variables, we include the number of transactions per second, the market capitalization in billions of USD, the average amount per transaction in USD, and the global trend in Google web searches for "cryptocurrency" (obtained from *trends.google.com*).[16] These control variables, which tend to be positively skewed, are included in the regression analysis in logs, except for the Google Trends data, which is statistically more significant without taking logs. The independent variables are measured on the last day of the quarter preceding the 180-day estimation window for the standard deviation of daily returns.

The results of the regression analysis are reported in Table 2. The results generally confirm a positive relationship between the speculative position and future exchange rate volatility. We report results for both a simple pooled regression (columns I-III) and a regression that includes fixed effects (columns IV-VI).[17] All standard errors are clustered at the cryptocurrency level to adjust for serial correlation. We observe positive and statistically significant relationships between the future exchange rate volatility and the individual variables that are used as proxies for the speculative position (columns I and II and columns IV and V). The strongest results are observed for the proxy obtained as the principal component from various speculation-related variables (columns III and

[14] Some of the owners of the top-100 addresses for Bitcoin are publicly known. They include among others cold wallets of the largest crypto exchanges and government-held addresses with confiscated balances; see, e.g., https://bitinfocharts.com/top-100-richest-bitcoin-addresses.html.

[15] The first principle component explains 64.9 percent of the total variance of the four proxies. The loadings on the different proxies are 0.6063 for the share of coins held in addresses with at least 0.1 percent of the total supply, 0.6056 for the share of coins held in the top-100 addresses, 0.4250 for the share of coins held in addresses with at least 1 million USD, and −0.2916 for the logarithm of the number of addresses with positive balances with less than 100 USD.

[16] Unreported results show that the statistically significant coefficients on the proxies for the speculative position in Table 2 increase somewhat in magnitude when the control variables are excluded. We obtain similar results in terms of magnitude and statistical significance if we include on-chain transaction fees as an additional control variable. This series reflects payments for processing transactions or the execution of smart contracts, but is available for fewer observations in our dataset. We also obtain qualitatively similar, though statistically less significant, results when replacing the proxy variable based on the share of coins in addresses with balances exceeding USD 1 million with a proxy variable based on the share of coins held by the top-1% of addresses.

[17] Fixed effects refer to cryptocurrency-specific constants in the regressions. These constants may capture unchanging differences between cryptocurrencies that are not captured by the other independent variables (e.g., launch date, consensus protocol, etc.).

Table 3
Speculation and future exchange rate risk (alternative risk measures).

Variables	(I) Mean absolute deviation of returns	(II) Mean absolute deviation of returns	(III) Mean absolute deviation of returns	(IV) Value-at-Risk with 95% confidence level	(V) Value-at-Risk with 95% confidence level	(VI) Value-at-Risk with 95% confidence level
Share of coins in addresses with at least 0.1%	3.142***			4.931**		
	(0.978)			(1.902)		
Share of coins in the top-100 addresses		2.066***			3.418**	
		(0.729)			(1.265)	
Principal component for speculative share			0.500***			0.878***
			(0.119)			(0.221)
Transactions per second (log)	0.020	0.032	0.070	0.029	0.050	0.118
	(0.098)	(0.102)	(0.095)	(0.208)	(0.215)	(0.205)
Market capitalization in billions of USD (log)	−0.249**	−0.288**	−0.292***	−0.286	−0.344	−0.348*
	(0.103)	(0.110)	(0.101)	(0.205)	(0.205)	(0.195)
Mean amount per transaction in USD (log)	0.093	0.108	0.104	0.158	0.181	0.173
	(0.070)	(0.068)	(0.069)	(0.124)	(0.123)	(0.121)
Google Trends for cryptocurrency	0.022***	0.023***	0.021***	0.055***	0.056***	0.052***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.007)
Constant	1.514**	2.030***	3.244***	4.291***	5.015***	7.042***
	(0.549)	(0.466)	(0.424)	(1.143)	(0.901)	(0.657)
Observations (cryptos)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)
Overall R-squared	0.180	0.205	0.169	0.199	0.231	0.169
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable in models (I)-(III) is the future mean absolute return measured over a period of 180 days. The dependent variable in models (IV)-(VI) is the future 95% Value-at-Risk measured as the 5th percentile of the empirical loss distribution over a period of 180 days. All independent variables are measured on the last day of the preceding quarter, except for the Google Trends variable, which is measured over the last month of the preceding quarter. Variable definitions and data sources are in Appendix D. Models are estimated with least squares. Standard errors clustered at the cryptocurrency level are reported in parentheses. Statistical significance at the 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

VI). The estimated coefficient for the principal component in the fixed effects regression implies that an increase in the proxy for the speculative position from its 10th percentile to its 90th percentile is associated with an expected increase in the daily volatility during the next two quarters of approximately 3 percentage points.[18]

The most statistically significant control variables are global web search intensity and the size of cryptocurrencies, as measured by their market capitalization. Global web search intensity for cryptocurrency is associated with higher return volatility, which is consistent with the findings of, e.g., Liu and Tsyvinski (2021). Larger cryptocurrencies are associated with lower return volatility, which is consistent with the findings of, e.g., Pessa et al. (2023).

5.1. *Sensitivity for alternative methodological choices*

Sensitivity analysis shows that the empirical relationship is qualitatively robust to the selection of alternative measures of exchange rate risk (Section 5.1.1), to alternative choices regarding the timing and frequency of exchange rate risk (Section 5.1.2), and to transformations of the speculative share proxies into proxy-based multipliers (Section 5.1.3). For brevity, we only report the regressions with fixed effects when considering alternative risk measures and alternative timing. The parallel results from our baseline regressions can be found in Table 2, columns (IV)-(VI), which we will refer to as the baseline results.

5.1.1. *Alternative exchange rate risk measures*

Table 3 reports the results for two alternative measures for future exchange rate risk. Columns (I)-(III) report results based on using the *mean absolute deviation* of daily returns as a measure of exchange rate risk, rather than the standard deviation. The mean absolute deviation is less commonly used to measure return variation, but it is known to be more persistent than the standard deviation (e.g., Forsberg and Ghysels, 2007). The regression results confirm a positive relationship between the speculative position and future exchange rate risk, measured as the mean absolute deviation. The statistical significance of the coefficients for the speculative position is comparable or stronger when compared to the baseline results. The coefficient estimates are approximately one-quarter lower than in the baseline results, which is line with the average value of the mean absolute deviation being approximately one-quarter lower than the average standard deviation of daily returns (see Table 1).

Table 3, columns (IV)–(VI) report regression results using the *1-day Value-at-Risk with a 95% confidence level* as a measure of future downside risk. The Value-at-Risk is defined as the percentage loss that is not exceeded on 95% of the days. We estimate

[18] This is calculated as $[2.505 - (-2.146)] \times 0.683$, where -2.146 and 2.505 correspond to the 10th and 90th percentiles of the proxy variable in Table 1 and where 0.683 corresponds to the relevant coefficient in column (VI) of Table 2.

Table 4
Speculation and future exchange rate volatility (alternative timing).

Variables	(I) Standard deviation of returns (90 days)	(II) Standard deviation of returns (90 days)	(III) Standard deviation of returns (90 days)	(IV) Standard deviation of returns (26 weeks)	(V) Standard deviation of returns (26 weeks)	(VI) Standard deviation of returns (26 weeks)
Share of coins in addresses with at least 0.1%	4.797***			12.365**		
	(1.593)			(5.644)		
Share of coins in the top-100 addresses		3.497***			8.640**	
		(1.134)			(4.041)	
Principal component for speculative share			0.854***			1.987***
			(0.176)			(0.634)
Transactions per second (log)	0.068	0.088	0.154	−0.159	−0.107	0.041
	(0.161)	(0.171)	(0.155)	(0.332)	(0.331)	(0.311)
Market capitalization in billions of USD (log)	−0.488***	−0.536***	−0.550***	−0.840	−0.984*	−1.009**
	(0.151)	(0.170)	(0.148)	(0.503)	(0.513)	(0.463)
Mean amount per transaction in USD (log)	0.296***	0.319***	0.316***	0.079	0.138	0.122
	(0.084)	(0.085)	(0.085)	(0.297)	(0.277)	(0.279)
Google Trends for cryptocurrency	0.036***	0.036***	0.033***	0.067***	0.069***	0.061***
	(0.006)	(0.006)	(0.006)	(0.015)	(0.016)	(0.015)
Constant	0.856	1.477*	3.510***	7.332***	9.111***	14.146***
	(0.981)	(0.790)	(0.495)	(2.154)	(1.759)	(1.645)
Observations (cryptos)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)
Overall R-squared	0.119	0.128	0.105	0.111	0.119	0.103
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable in models (I)-(III) is the future standard deviation of daily returns measured over a period of 90 days. The dependent variable in models (IV)-(VI) is the future standard deviation of weekly returns measured over a period of 26 weeks. All variables are measured on the last day of the preceding quarter, except for the Google Trends variable, which is measured over the last month of each quarter. Variable definitions and data sources are in Appendix D. Models are estimated with least squares. Standard errors clustered at the cryptocurrency level are reported in parentheses. Statistical significance at the 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

the measure by the 5th percentile of the empirical distribution of daily returns (e.g., Van Oordt and Zhou, 2019).[19] The regression results based on the Value-at-Risk confirm a positive relationship between the speculative position and future exchange rate risk. The results are again somewhat comparable in terms of statistical significance to the baseline results.

5.1.2. Alternative timing and frequency

Table 4 considers alternative choices regarding the timing and frequency when measuring exchange rate volatility. Columns (I)–(III) report the results based on the standard deviation of daily return during the next quarter rather than the next two quarters. The shorter prediction horizon increases the statistical significance and the size of the reported coefficients for the speculative position compared to the baseline results. This is consistent with the general principle that forecast uncertainty tends to increase in the length of the forecasting horizon. The estimated coefficient for the principal component in the regression implies that an increase in the proxy for the speculative position from its 10th percentile to its 90th percentile is associated with an expected increase in the standard deviation of daily returns during the next quarter of almost 4 percentage points.[20]

Table 4, columns (IV)-(VI) report the results when using the standard deviation of weekly returns rather than the standard deviation of daily returns as a measure of return volatility. Weekly returns may be less affected by short-term liquidity pressures, but the standard deviations have to be estimated from relatively few observations (i.e., 26 weekly returns). The statistical significance of the regression estimates based on weekly returns is somewhat comparable to the baseline results. The coefficients are almost three times larger in magnitude, consistent with the approximately 2.6 times larger estimates for the standard deviation based on weekly returns (see Table 1).

5.1.3. Proxy-based multipliers

The baseline specification regresses the future exchange rate risk on the proxies for the speculative share of coins. Table 5 reports the results after using Eq. (5) to transform the proxies for the speculative share, $\hat{Z}_{it}/M_{it}$, into proxy-based multipliers that are calculated as $1/(1-\hat{Z}_{it}/M_{it})$.[21] An advantage of the transformation is that the explanatory variable becomes closer to the theoretical expression for the multiplier; a disadvantage is that the proxy-based multipliers exhibit extreme positive outliers due to observations

[19] The loss represented by the Value-at-Risk is generally expressed as a positive number. Therefore, we multiply the 5th percentile of the daily return distribution — a low negative return — by minus one.

[20] This is calculated as $[2.505-(-2.146)]\times 0.854$ where -2.146 and 2.505 correspond to the 10th and 90th percentiles of the proxy variable in Table 1 and where 0.854 corresponds to the relevant coefficient in column (III) of Table 4.

[21] Note that $1/(1-\hat{Z}_{it}/M_{it}) = M_{it}/(M_{it}-\hat{Z}_{it})$, which corresponds to the expression in Eq. (5) except that the actual number of coins that is not used for making payments, Z, is replaced by its empirical proxy, $\hat{Z}$.

Table 5
Speculation and future exchange rate volatility (proxy-based multipliers).

Variables	(I) Standard deviation of returns (180 days)	(II) Standard deviation of returns (180 days)	(III) Standard deviation of returns (180 days)	(IV) Standard deviation of returns (180 days)	(V) Standard deviation of returns (180 days)	(VI) Standard deviation of returns (180 days)
Multiplier based on addresses with at least 0.1% (log)	0.440***			1.247**		
	(0.138)			(0.553)		
Multiplier based on coins in the top-100 addresses (log)		0.345***			0.625**	
		(0.118)			(0.294)	
Principal component based on log proxy-based multipliers			0.219***			0.575**
			(0.066)			(0.229)
Transactions per second (log)	0.099	0.118	0.106	0.019	0.003	0.056
	(0.106)	(0.105)	(0.103)	(0.131)	(0.133)	(0.132)
Market capitalization in billions of USD (log)	−0.452***	−0.465***	−0.463***	−0.440***	−0.466**	−0.477***
	(0.130)	(0.133)	(0.129)	(0.155)	(0.169)	(0.155)
Mean amount per transaction in USD (log)	0.000	0.004	−0.002	0.121	0.128	0.129
	(0.076)	(0.077)	(0.077)	(0.094)	(0.093)	(0.094)
Google Trends for cryptocurrency	0.027***	0.027***	0.026***	0.024***	0.025***	0.023***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)
Constant	5.438***	5.539***	5.915***	3.689***	4.239***	4.988***
	(0.472)	(0.471)	(0.442)	(0.683)	(0.616)	(0.568)
Observations (cryptos)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)
R-squared	0.229	0.223	0.230	0.173	0.191	0.176
Fixed effects	No	No	No	Yes	Yes	Yes

Note: The dependent variable is the future standard deviation of daily returns measured over a period of 180 days. All independent variables are measured on the last day of the preceding quarter, except for the Google Trends variable, which is measured over the last month of the preceding quarter. Variable definitions and data sources are in Appendix D. Proxy-based multipliers are calculated as $1/(1-\hat{Z}_{it}/M_{it})$, where $\hat{Z}_{it}/M_{it}$ is the indicated proxy for the speculative share used in Table 2. The right tails of the proxy-based multipliers are winsorized at the 5th percentile. Models are estimated with least squares. Standard errors clustered at the cryptocurrency level are reported in parentheses. The regression with fixed effects reports the overall R-squared. Statistical significance at the 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

in which the proxy for the speculative share is close to one.[22] We winsorize the right tail of the proxy-based multipliers at the 5th percentile and use a log transformation to address the extreme skewness. We also reconstruct the proxy variable based on principle component analysis using the logs of the winsorized proxy-based multipliers as input variables rather than the shares of coins.

The results in Table 5 show that the proxy-based multipliers have a statistically significant positive relationship with future exchange rate volatility. The regressions with fixed effects suggest that a one-percent increase in the multiplier based on addresses holding at least 0.1% of the coins is associated with a 1.2 basis point increase in the standard deviation of returns over the next two quarters (column IV), while a one-percent increase in the multiplier based on the top-100 addresses is associated with a 0.6 basis point increase in the standard deviation of returns over the next two quarters (column V). The estimated coefficient for the reconstructed principal component (column VI) implies that an increase in its value from its 10th percentile to its 90th percentile is associated with an expected increase in the daily volatility during the next two quarters of approximately 3 percentage points.[23] This is quantitatively comparable to the relationship observed for the principal component constructed from the speculative shares in the baseline regressions.

6. Implications for evaluating large block holdings

Our results highlight the need for market participants to be vigilant when accepting large amounts of a cryptocurrency as collateral or as compensation for seed funding. The crypto multiplier predicts that winding down a large speculative position is likely to have a significant price impact unless the position is absorbed by other speculators.

An illustration is the scenario that ensued after one of Ripple's founders publicly preannounced his intention to sell-off all his holdings of the Ripple-issued cryptocurrency XRP in May 2014. The co-founder, who no longer worked for the company at that time, indicated he made this public preannouncement out of a commitment to transparency and "immense respect for the community members" (McCaleb, 2014). At that time, the co-founder held at most 9 percent of the coins (Cawrey, 2014), so the sale would increase the coin supply from the perspective of all other coin holders by at most 10 percent. Despite the maximum 10-percent increase in the coin supply for other coin holders, the exchange rate of Ripple's cryptocurrency plummeted more than 40 percent

[22] To illustrate, the maximum values of the multiplier based on addresses with at least 0.1% of the coins and the multiplier based on the top-100 addresses are, respectively, 138.7 and 859.4 before winsorizing, against median values of, respectively, 2.1 and 2.0. After winsorizing, the maximum values are, respectively, 22.7 and 39.1. This distribution remains highly skewed after winsorizing (proxy-based multipliers cannot take values smaller than one), and taking logs helps to further reduce the skewness.

[23] This is calculated as $[2.849-(-1.596)]\times 0.575$ where -1.596 and 2.849 correspond to the 10th and 90th percentiles of the principal component constructed from the log of proxy-based multipliers and where 0.575 corresponds to the coefficient in column (VI) of Table 5.

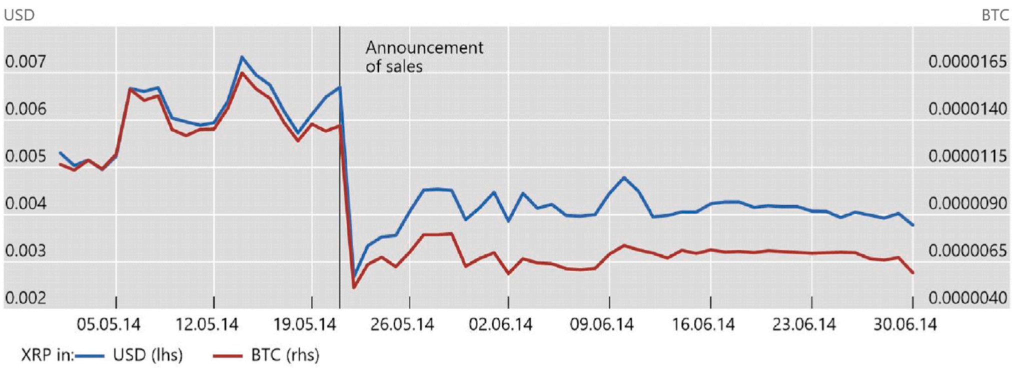

Fig. 3. The price change following ripple co-founder's sell-off announcement. Note: Exchange rate of XRP in USD (lhs) and in BTC (rhs). *Source:* coingecko.com.

following just the announcement (Fig. 3). Ripple, which relied on the sale of coins as a source of revenue, appeared to be concerned about the price impact of winding down such a large position. The company entered into a legal agreement with the co-founder that required him to spread out the sales of the coins over an extended period exceeding seven years (Long, 2014). The co-founder completed the sale of his remaining coins in 2022 (Ripple, 2022).

7. Concluding remarks

We provide a tractable indicator of volatility that relates to a cryptocurrency's use as a store of value by crypto investors (i.e., speculators). The indicator, which we call the crypto multiplier, provides the theoretical relationship between the share of a cryptocurrency that is used for payments and the response of the equilibrium market capitalization to aggregate investor flows.

The crypto multiplier predicts an amplified impact of aggregate investment flows on the market capitalization of cryptocurrencies. This amplification effect is particularly strong for cryptocurrencies that face little transactional demand, which helps us to understand why the exchange rate of a cryptocurrency like Dogecoin would increase by 50 percent around Elon Musk's tweet that Dogecoin "might be my fav cryptocurrency" in April 2019 (Dale, 2019). Celebrity endorsements of small cryptocurrencies with little transactional demand, such as the promotion of EthereumMax by Kim Kardashian in June 2021, were also followed by significant price moves (Securities Exchange Commission, 2022). Such endorsements are likely to have attracted individuals who were looking for investment opportunities rather than a new way of making payments. The approval of spot Bitcoin exchange-traded products by the Securities Exchange Commission (2024) can be seen as another event that advances cryptocurrency as an investment vehicle, given the substantial inflow of funds into spot Bitcoin ETFs and the upward pressure on the Bitcoin exchange rate in the subsequent months.[24]

Changes in investor flows occur for a multitude of reasons, some of which may be grounded in fundamentals and others which arise from the whims of influencers. The point is that if these flows are constantly changing, and the multiplier is large, then we will see high volatility, particularly when transactional demand is relatively low. The theoretical positive relationship between the crypto multiplier and exchange rate volatility also finds empirical support in predictive regressions between proxies of speculative holdings and future exchange rate volatility. A key lesson is that the volatility of cryptocurrency exchange rates is likely to remain unless the primary use case of a cryptocurrency shifts from being an investment vehicle to a means of payment.

CRediT authorship contribution statement

Rodney J. Garratt: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Maarten R.C. van Oordt:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization.

Appendix A. Proofs

This appendix provides the formal derivations of the exchange rate equation in (4), derived under Assumptions 1–2, and of the crypto multiplier equation in (5), derived under Assumptions 1–4.

[24] A simple direct comparison of the net inflows into US spot Bitcoin ETFs and the market capitalization of Bitcoin would suggest a high crypto multiplier: The market capitalization of Bitcoin increased by about USD 412 billion from the end of December 2023 to the end of June 2024, while the net inflows into US spot Bitcoin ETFs over this period totaled about USD 14.5 billion. This suggests a multiplier of more than 20. The net increase in assets under management during this period was approximately USD 25.0 billion, although this figure also reflects appreciation in the exchange rate (sources: coinmetrics.io and farside.co.uk). However, it is not advisable to draw strong conclusions from such a simple comparison, as it overlooks other investment flows, changes in transactional demand, and investor anticipation of the approval.

A.1. Derivation of the exchange rate equation in (4)

Define the average velocity of all cryptocurrency units as the total value paid in a period divided by the number of cryptocurrency units that exists, i.e.,

$$V = \frac{PT}{M}.$$

Multiplying both sides by M gives the quantity equation in (2). Plugging the equality from (3) into (2) gives

$$PT = (M - Z)V^*.$$

From Assumption 1, we have $P = P^{\$}/S$.[25] Using this assumption to replace P in (2) gives

$$\frac{P^{\$}T}{S} = (M - Z)V^*. \tag{A.1}$$

From Assumption 2, we have $MV \neq 0$, implying $(M - Z)V^* \neq 0$. Using this assumption allows us to divide both sides of (A.1) by $(M - Z)V^*$. After multiplying both sides by S, one obtains

$$S = \frac{P^{\$}T/V^*}{M - Z}.$$

Finally, using the definition $T^{\$} = P^{\$}T$ gives the exchange rate equation in (4).

A.2. Derivation of the crypto multiplier in (5)

This appendix formally demonstrates that the expression in Eq. (5) measures the dollar change in the equilibrium market capitalization of a cryptocurrency in response to a single dollar of aggregate inflows or outflows of investors' funds.

Let $\Delta > 0$ denote the net investment inflow amount in terms of dollars that aggregate investors spend on buying coins. To derive the crypto multiplier, we need to compute how the market capitalization, $S(Z) \cdot M$, changes with respect to Δ, evaluated at $\Delta = 0$. We calculate the slope of the market capitalization for both the maximum and minimum change in Z when the net amount of the aggregate spending on coins by investors equals Δ dollars. We show that both levels converge to Eq. (5) for infinitesimal values of Δ.

First, we consider the change in the exchange rate based on the maximum possible change in Z, which is the change in Z if investors can buy coins at the old (lower) price, $S(Z)$. In this case, investors could buy $\Delta/S(Z)$ coins when spending Δ dollars. Assumptions 3 and 4 imply that changes in Z do not affect the equilibrium values of M and $T^{\$}/V^*$, respectively. Hence, from the exchange rate equation (4), we have that the exchange rate as a function of the new level of Z, $Z_{max} = Z + \Delta/S(Z)$, would be

$$\begin{aligned}
S(Z_{max}) &= \frac{T^{\$}/V^*}{M - Z_{max}} \Leftrightarrow \\
S(Z + \Delta/S(Z)) &= \frac{T^{\$}/V^*}{M - Z - \Delta/S(Z)} \Leftrightarrow \\
(M - Z) \cdot S(Z + \Delta/S(Z)) - \Delta \cdot \frac{S(Z + \Delta/S(Z))}{S(Z)} &= T^{\$}/V^* \Leftrightarrow \\
S(Z + \Delta/S(Z)) &= \frac{T^{\$}/V^* + \Delta \cdot \frac{S(Z+\Delta/S(Z))}{S(Z)}}{M - Z}.
\end{aligned}$$

Using this expression, we can express the derivative of $S(Z_{max})$ with respect to Δ as

$$\begin{aligned}
\lim_{\Delta \to 0} \frac{S(Z + \Delta/S(Z)) - S(Z)}{\Delta} &= \lim_{\Delta \to 0} \frac{\frac{T^{\$}/V^* + \Delta \cdot \frac{S(Z+\Delta/S(Z))}{S(Z)}}{M-Z} - \frac{T^{\$}/V^*}{M-Z}}{\Delta}, \\
&= \lim_{\Delta \to 0} \frac{\frac{S(Z+\Delta/S(Z))}{S(Z)}}{M - Z}, \\
&= \frac{1}{M - Z},
\end{aligned} \tag{A.2}$$

where the last equality holds true because $S(Z + \Delta/S(Z)) \to S(Z)$ as $\Delta \to 0$.

Second, we consider the change in the exchange rate based on the minimum possible change in Z, which is the change in Z if investors have to buy the coins based on the new (higher) price. In this case, the new level of Z is implicitly defined as

$$Z_{min} = Z + \frac{\Delta}{S(Z_{min})}.$$

[25] For brevity, we suppress the \$/coin-superscript of $S^{\$/\text{coin}}$ in the appendices.

We again use Assumptions 3 and 4, which imply that changes in Z do not affect the equilibrium values of M and $T^{\$}/V^{*}$, respectively. Plugging the equation for the equilibrium exchange rate in (4) into the expression for Z_{min}, we can rewrite Z_{min} as

$$Z_{min} = Z + \frac{\Delta(M - Z_{min})}{T^{\$}/V^{*}},$$

which can be rewritten as

$$Z_{min} = \frac{Z + \frac{\Delta M}{T^{\$}/V^{*}}}{1 + \frac{\Delta}{T^{\$}/V^{*}}} = Z + \frac{\Delta\frac{M-Z}{T^{\$}/V^{*}}}{1 + \frac{\Delta}{T^{\$}/V^{*}}} = Z + \Delta\frac{(M - Z)}{T^{\$}/V^{*} + \Delta}.$$

Using the expression for Z_{min} in the equation for the equilibrium exchange rate gives

$$S(Z_{min}) = \frac{T^{\$}/V^{*}}{M - Z - \frac{\Delta}{S(Z)+\frac{\Delta}{M-Z}}} \Leftrightarrow$$

$$S(Z_{min})(M - Z) - \Delta \cdot \frac{S(Z_{min})}{S(Z) + \frac{\Delta}{M-Z}} = T^{\$}/V^{*} \Leftrightarrow$$

$$S(Z_{min}) = \frac{T^{\$}/V^{*} + \Delta \cdot \frac{S(Z_{min})}{S(Z)+\frac{\Delta}{M-Z}}}{M - Z}.$$

Using this expression, we can express the derivative of $S(Z_{min})$ with respect to Δ as

$$\begin{aligned}
\lim_{\Delta\to 0} \frac{S\left(Z_{min}\right) - S(Z)}{\Delta} &= \lim_{\Delta\to 0} \frac{\frac{T^{\$}/V^{*}+\Delta\cdot\frac{S(Z_{min})}{S(Z)+\frac{\Delta}{M-Z}}}{M-Z} - \frac{T^{\$}/V^{*}}{M-Z}}{\Delta}, \\
&= \lim_{\Delta\to 0} \frac{\frac{S(Z_{min})}{S(Z)+\frac{\Delta}{M-Z}}}{M - Z}, \\
&= \frac{1}{M - Z},
\end{aligned} \tag{A.3}$$

where the last equality holds true because $S(Z) + \Delta/(M - Z) \to S(Z)$ and $S(Z_{min})/S(Z) \to 1$ as $\Delta \to 0$.

The limits derived in (A.2) and (A.3) establish that the change in S with respect to an infinitesimal investment of Δ dollar equals $1/(M-Z)$, which equals $\frac{\partial S(Z)}{\partial Z} \cdot \frac{1}{S(Z)}$. To obtain the equilibrium change in the market capitalization of the cryptocurrency in response to an aggregate investor inflow, we multiply the expression with M, which gives the equation for the crypto multiplier in (5).

Appendix B. Predictive return regressions

The regressions in columns (I)-(III) of Table B.1 assess whether the proxies for the speculative position in Table 2 are positively correlated with cryptocurrency returns over the next two quarters. This is the same prediction horizon as the baseline regressions for future risk in Table 2. None of the coefficients on the proxies is statistically significant in Table B.1. We also assess whether the proxies are positively correlated with the return over the next quarter rather than the next two quarters. The results in columns (IV)-(VI) of Table B.1 show that the statistical insignificance of the results is maintained for this shorter prediction horizon.

Appendix C. The crypto multiplier and future return volatility

This appendix shows that future return volatility is positively related to the crypto multiplier, provided that shocks to the transactional demand and speculative position are not too negatively correlated.

Consider M to be approximately constant (daily changes in M are small). Define $z_{t+1} = Z_{t+1}/M$. Then, the exchange rate at $t+1$ is

$$S_{t+1} = \frac{T^{\$}_{t+1}/V^{*}_{t+1}}{M - Z_{t+1}} = \frac{T^{\$}_{t+1}/V^{*}_{t+1}}{(1 - z_{t+1})M},$$

and the gross return is

$$\frac{S_{t+1}}{S_t} = \frac{T^{\$}_{t+1}}{T_t} \cdot \frac{V^{*}_t}{V^{*}_{t+1}} \cdot \frac{(1 - z_t)M}{(1 - z_{t+1})M}.$$

This implies that the log return is

$$r_{t+1} = \log\frac{S_{t+1}}{S_t} = \log\frac{T^{\$}_{t+1}}{T_t} - \log\frac{V^{*}_{t+1}}{V^{*}_t} - \log\left(\frac{1 - z_{t+1}}{1 - z_t}\right).$$

Table B.1
Speculation and future returns.

Variables	(I) Future return (two quarters)	(II) Future return (two quarters)	(III) Future return (two quarters)	(IV) Future return (one quarter)	(V) Future return (one quarter)	(VI) Future return (one quarter)
Share of coins in addresses with at least 0.1%	0.136			0.059		
	(0.182)			(0.088)		
Share of coins in the top-100 addresses		0.112			0.042	
		(0.196)			(0.097)	
Principal component for speculative share			0.000			−0.001
			(0.029)			(0.015)
Constant	0.015	0.030	0.089*	0.022	0.032	0.054**
	(0.098)	(0.103)	(0.047)	(0.047)	(0.050)	(0.022)
Observations (cryptos)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)	544 (24)
R-squared	0.001	0.001	0.000	0.000	0.000	0.000

Note: The dependent variable in models (I)-(III) is the return on holding the cryptocurrency over the next two quarters. The dependent variable in models (IV)-(VI) is the return over the next quarter. All independent variables are measured on the last day of the preceding quarter. All models are estimated with least squares. Standard errors clustered at the cryptocurrency level are reported in parentheses. Statistical significance at the 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Table C.1
Correlation of changes in proxies for speculation and transactional demand.

	Changes in transactions per second (log)	Changes in mean amount per transaction in USD (log)
Changes in share of coins in addresses with at least 0.1%	−0.0611	0.0678
	(0.155)	(0.115)
Changes in share of coins in the top-100 addresses	−0.0473	0.069
	(0.271)	(0.108)
Changes in principal component for speculative share	0.0616	0.232
	(0.151)	(0.000)

Note: The table reports the pairwise correlations between the changes in our proxies for speculative demand and changes in two control variables that are conceptually close to transactional demand. The numbers in parenthesis report the p-values against the null hypothesis that the correlation equals zero.

Define the random variables $\widetilde{T}^{\$}_{t+1} = \log(T^{\$}_{t+1}/T_t)$, $\widetilde{V}^{*}_{t+1} = \log(V^{*}_{t+1}/V^{*}_t)$ and $\Delta\widetilde{z}_{t+1} = z_{t+1} - z_t$. Using the definitions of these random variables, which measure shocks in these quantities, we can rewrite the log return as

$$\begin{aligned} r_{t+1} &= \widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1} - \log\left(1 - \Delta\widetilde{z}_{t+1} \cdot \frac{1}{1 - z_t}\right), \\ &= \widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1} - \log\left(1 - \Delta\widetilde{z}_{t+1} \cdot \frac{M}{M - Z_t}\right). \end{aligned}$$

Using a linear approximation around one for the log-transformation yields the expression

$$r_{t+1} \approx \widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1} + \Delta\widetilde{z}_{t+1} \cdot \frac{M}{M - Z_t}.$$

The volatility of r_{t+1} is

$$\sigma^2(r_{t+1}) \approx \sigma^2\left((\widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1}) + \Delta\widetilde{z}_{t+1} \cdot \frac{M}{M - Z_t}\right).$$

If shocks to the transactional demand, $\widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1}$, and shocks to the speculative position, $\widetilde{z}_{t+1}$, are not too negatively correlated, then this expression for the volatility implies that the level of volatility at time $t+1$ increases in the crypto multiplier at time t. For example, if $\widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1}$ and $\Delta\widetilde{z}_{t+1}$ are uncorrelated, then

$$\sigma^2(r_{t+1}) \approx \sigma^2\left(\widetilde{T}^{\$}_{t+1} - \widetilde{V}^{*}_{t+1}\right) + \sigma^2\left(\Delta\widetilde{z}_{t+1}\right) \cdot \left(\frac{M}{M - Z_t}\right)^2,$$

which increases in the level of the crypto multiplier.

We do not directly observe the extent to which shocks to the transactional demand and shocks to the speculative position are negatively correlated. Two control variables in our regressions that are conceptually close to measuring the transactional demand are the number of transactions on the blockchain per second and the mean amount per blockchain transaction in USD. Table C.1 reports the pairwise correlations between changes in those variables (columns) and changes in our proxies for the speculative position (rows). The correlations range from −0.0611 to 0.232. One correlation coefficient is statistically significantly greater than zero, but none is statistically significantly below zero, lending support to the idea that shocks to the transactional demand and shocks to the speculative position are not too negatively correlated.

Table D.1
Data definitions.

Variables	Description	Source
Standard deviation of daily returns (180 days)	The standard deviation of the natural log of daily gross returns over the past 180 days, measured on the last day of the quarter [VtyDayRet180d]	coinmetrics.io
Mean absolute deviation of daily returns (180 days)	The mean absolute deviation of the natural log of daily gross returns over the past 180 days, measured on the last day of the quarter.	authors' calculations; coinmetrics.io
1-day Value-at-Risk with 95 confidence level (180 days)	The 5th percentile of the natural log of daily gross returns over the past 180 days, measured on the last day of the quarter, multiplied by minus one.	authors' calculations; coinmetrics.io
Standard deviation of daily returns (90 days)	The standard deviation of the natural log of daily gross returns over the past 90 days, measured on the last day of the quarter.	authors' calculations; coinmetrics.io
Standard deviation of weekly returns (26 weeks)	The standard deviation of the natural log of weekly gross returns over the past 26 weeks, measured on the last day of the quarter.	authors' calculations; coinmetrics.io
Share of coins in addresses with at least 0.1%	The sum of all native units held in addresses that have a balance of at least 0.1% of the current supply of native units, divided by the current supply of native units, measured on the last day of the quarter [SplyAdrBal1in1K/SplyCur].	coinmetrics.io
Share of coins in the top-100 addresses	The sum of all native units held by the 100 addresses that hold most native units, divided by the current supply of native units, measured on the last day of the quarter [SplyAdrTop100/SplyCur].	coinmetrics.io
Share of coins in addresses ≥ 1,000,000 USD	The sum of all native units held in addresses holding native units with a value of at least 1,000,000 USD, divided by the current supply of native units, measured on the last day of the quarter [SplyAdrBalUSD1M/SplyCur].	coinmetrics.io
Number of addresses with less than 100 USD	The number of unique addresses holding any amount of native units minus the number of unique addresses holding native units with a value of at least USD 100 on the last day of the quarter [AdrBalCnt - AdrBalUSD100Cnt].	coinmetrics.io
Principal component for speculative share	The first principal component extracted from the share of coins in addresses with at least 0.1%, the share of coins in the top-100 addresses, the share of coins in addresses with at least 1,000,000 USD, and the log number of addresses with less than 100 USD.	authors' calculations; coinmetrics.io
Transactions per second	The number of transactions on the last day of the quarter divided by the number of seconds, measured on the last day of the quarter [TxCntSec].	coinmetrics.io
Estimated market capitalization in billion USD	The total value of the current supply of native units in billion USD, measured on the last day of the quarter [CapMrktCurUSD].	coinmetrics.io
Mean amount per transaction in USD	The sum of the value of native units transferred, measured in USD, divided by the number of transfers between distinct addresses on the last day of the quarter [TxTfrValMeanUSD].	coinmetrics.io
Google Trend for cryptocurrency	The global trend in web searches for "cryptocurreny" on Google, measured during the last month of the quarter.	trends.google.com

Note: Descriptions are largely copied from the definitions of the relevant data items on coinmetrics.io. The terms in brackets report, if applicable, the identifiers of the data items on coinmetrics.io and the calculations based on those identifiers.

Appendix D. Data definitions

Table D.1 reports the definitions of all variables and data sources.

Data availability

Data will be made available on request.

References

Abadi, J., Brunnermeier, M., 2018. Blockchain economics. NBER Working Paper 25407.

Akana, T., Li, G., 2022. Cryptocurrency ownership: Insights from the CFI COVID-19 survey of consumers. Consumer Finance Institute Survey Brief (December), Federal Reserve Bank of Philadelphia.

Ambros, M., 2022. A digital services approach to PPP: The netflix index. Singap. Econ. Rev. 1–14.

Athey, S., Parashkevov, I., Sarukkai, V., Xia, J., 2016. Bitcoin pricing, adoption, and usage: Theory and evidence. Work. Pap..

Bakos, Y., Hałaburda, H., 2022. The role of cryptographic tokens and ICOs in fostering platform adoption. Inf. Syst. Res. 33 (2), 1368–1385.

BCBS, 2022. Prudential treatment of cryptoasset exposures. Standards, URL https://www.bis.org/bcbs/publ/d545.htm.

Benigno, P., Schilling, L., Uhlig, H., 2022. Cryptocurrencies, currency competition, and the impossible trinity. J. Int. Econ. 136, 103601.

Biais, B., Bisière, C., Bouvard, M., Casamatta, C., 2019. The blockchain folk theorem. Rev. Financ. Stud. 32 (5), 1662–1715.

Biais, B., Bisière, C., Bouvard, M., Casamatta, C., Menkveld, A., 2023. Equilibrium bitcoin pricing. J. Financ. 78 (2), 967–1014.

Bolt, W., Van Oordt, M., 2020. On the value of virtual currencies. J. Money, Credit. Bank. 52 (2), 835–862.
Budish, E., 2018. The economic limits of bitcoin and the blockchain. NBER Working Paper 24717.
Catania, L., Grassi, S., 2022. Forecasting cryptocurrency volatility. Int. J. Forecast. 38 (3), 878–894.
Cawrey, D., 2014. Price of ripple plummets as co-founder plans 9 billion XRP selloff. News report at coindesk.com (May 22).
Chaudhary, M., Fu, Z., Li, J., 2023. Corporate bond multipliers: Substitutes matter. Working Paper.
Chiu, J., Koeppl, T., 2019. Blockchain-based settlement for asset trading. Rev. Financ. Stud. 32 (5), 1716–1753.
Chiu, J., Koeppl, T., 2022. The economics of cryptocurrencies: Bitcoin and beyond. Can. J. Econ. 55 (4), 1762–1798.
Chiu, J., Wong, T.-N., 2022. Payments on digital platforms: Resiliency, interoperability and welfare. J. Econom. Dynam. Control 142, 104173.
Chod, J., Lyandres, E., 2023. Product market competition with crypto tokens and smart contracts. J. Financ. Econ. 149 (1), 73–91.
Claeys, G., Demertzis, M., Efstathiou, K., 2018. Cryptocurrencies and monetary policy. Monetary Dialogue, Requested by the Economic and Monetary Affairs Committee, European Parliament.
Cong, L., Li, Y., Wang, N., 2021. Tokenomics: Dynamic adoption and valuation. Rev. Financ. Stud. 34 (3), 1105–1155.
Cong, L., Li, Y., Wang, N., 2022. Token-based platform finance. J. Financ. Econ. 144 (3), 972–991.
Dale, B., 2019. Elon musk calls dogecoin ‘my fav cryptocurrency’. News report at coindesk.com (April 3).
Divakaruni, A., Zimmerman, P., 2024. Uncovering retail trading in bitcoin: The impact of COVID-19 stimulus checks. Manag. Sci. 70 (4), 2066–2085.
Dwyer, G., 2015. The economics of bitcoin and similar private digital currencies. J. Financ. Stab. 17, 81–91.
Fisher, I., 1911. The Purchasing Power of Money: Its Determination and Relation to Credit, Interest and Crises. Macmillan, New York.
Forsberg, L., Ghysels, E., 2007. Why do absolute returns predict volatility so well? J. Financ. Econ. 5 (1), 31–67.
Gabaix, X., Koijen, R., 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. NBER Working Paper 28, 967.
Garratt, R., Van Oordt, M., 2022. Entrepreneurial incentives and the role of initial coin offerings. J. Econom. Dynam. Control 142, 104171.
Garratt, R., Van Oordt, M., 2023. Why fixed costs matter for proof-of-work based cryptocurrencies. Manag. Sci. 69 (11), 6482–6507.
Garratt, R., Van Oordt, M., 2024. Buyback programs for platform tokens. Working Paper.
Garratt, R., Wallace, N., 2018. Bitcoin 1, bitcoin 2, ... : An experiment on privately issued outside monies. Econ. Inq. 56 (3), 1887–1897.
Gryglewicz, S., Mayer, S., Morellec, E., 2021. Optimal financing with tokens. J. Financ. Econ. 142 (3), 1038–1067.
Hałaburda, H., Haeringer, G., Gans, J., Gandal, N., 2022. The microeconomics of cryptocurrencies. J. Econ. Lit. 60 (3), 971–1013.
Hałaburda, H., He, Z., Li, J., 2021. An economic model of consensus on distributed ledgers. NBER Working Paper 29515.
Hausman, J., 2001. Mismeasured variables in econometric analysis: Problems from the right and problems from the left. J. Econ. Perspect. 15 (4), 57–67.
Hu, A., Parlour, C., Rajan, U., 2019. Cryptocurrencies: Stylized facts on a new investible instrument. Financ. Manag. 48 (4), 1049–1068.
Karau, S., Mönch, E., 2023. Is it really mine? Mining shocks and their effects on bitcoin valuations. Working Paper.
Keynes, J., 1936. The General Theory of Employment, Interest and Money. Palgrave Macmillan, London.
Koijen, R., Yogo, M., 2019. A demand system approach to asset pricing. J. Political Econ. 127 (4), 1475–1515.
Lee, J., Parlour, C., 2022. Consumers as financiers: Consumer surplus, crowdfunding, and initial coin offerings. Rev. Financ. Stud. 35 (3), 1105–1140.
Lee, J., Parlour, C., Rajan, U., 2021. An introduction to cryptocurrencies. In: Rau, R., Wardrop, R., Zingales, L. (Eds.), the Palgrave Handbook of Technological Finance. Palgrave Macmillan.
Li, J., Mann, W., 2025. Initial coin offering and platform building. Rev. Financ. Stud. 38 (7), 1921–1954.
Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Rev. Financ. Stud. 34 (6), 2689–2727.
Long, M., 2014. Settlement of Jed’s XRP. Blog Post Forum.Ripple.Com (August 14).
Makarov, I., Schoar, A., 2019. Trading and arbitrage in cryptocurrency markets. J. Financ. Econ. 135 (2), 293–319.
Malinova, K., Park, A., 2023. Tokenomics: When tokens beat equity. Manag. Sci. 69 (11), 6568–6583.
McCaleb, J., 2014. Selling my XRP. Blog Post Xrptalk.Org (May 22).
Pagnotta, E., 2022. Decentralizing money: Bitcoin prices and blockchain security. Rev. Financ. Stud. 35 (2), 866–907.
Pessa, A., Perc, M., Ribeiro, H., 2023. Age and market capitalization drive large price variations of cryptocurrencies. Sci. Rep. 13, 3351.
Petajisto, A., 2009. Why do demand curves for stocks slope down? J. Financ. Quant. Anal. 44 (5), 1013–1044.
Poon, J., Dryja, T., 2016. The bitcoin lightning network: Scalable off-chain instant payments. White Paper Version 0.5.9.2.
Prat, J., Danos, V., Marcassa, S., 2025. Fundamental pricing of utility tokens. Manag. Sci. (forthcoming).
Prat, J., Walter, B., 2021. An equilibrium model of the market for bitcoin mining. J. Political Econ. 129 (8), 2415–2452.
Ripple, 2022. The stand is finally out of tacos. Insights Post Ripple.Com (July 18).
Rogoff, K., You, Y., 2023. Redeemable platform currencies. Rev. Econ. Stud. 90 (2), 975–1008.
Schilling, L., Uhlig, H., 2019. Some simple bitcoin economics. J. Monet. Econ. 106, 16–26.
Securities Exchange Commission, 2022. SEC charges Kim Kardashian for unlawfully touting crypto security. Press Release 2022–138.
Securities Exchange Commission, 2024. Statement on the approval of spot bitcoin exchange-traded products. Statement By Gary Gensler (January 10).
Sgard, J., 2003. Hyperinflation and the reconstruction of a national money: Argentina and Brazil, 1990–2002. Working Paper.
Shen, D., Urquhart, A., Wang, P., 2020. Forecasting the volatility of bitcoin: The importance of jumps and structural breaks. Eur. Financ. Manag. 26 (5), 1294–1323.
Sockin, M., Xiong, W., 2023a. A model of cryptocurrencies. Manag. Sci. 69 (11), 6684–6707.
Sockin, M., Xiong, W., 2023b. Decentralization through tokenization. J. Financ. 78 (1), 247–299.
Stolborg, C., 2023. Demand based bitcoin pricing. Working Paper.
Van Oordt, M., Zhou, C., 2019. Systemic risk and bank business models. J. Appl. Econometrics 34 (3), 365–384.
Yermack, D., 2015. Is bitcoin a real currency? An economic appraisal. In: Chuen, D. (Ed.), Handbook of Digital Currency. Elsevier, pp. 31–43.
Zhu, Y., Hendry, S., 2019. A framework for analyzing monetary policy in an economy with E-money. Bank of Canada Staff Working Paper, 2019–1.
Zimmerman, P., 2020. Blockchain structure and cryptocurrency prices. Bank of England Staff Working Paper, 855.