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Excess liquidity, cryptocurrency returns, and the moderating role of economic policy uncertainty

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A B S T R A C T

This study extends Acharya and Naqvi's (2012) theory of liquidity-driven risk-taking to digital asset markets by examining the relationship between U.S. and Chinese excess-liquidity conditions and cryptocurrency returns. Using monthly panel data for ten major cryptocurrencies from 2019 to 2024, and defining excess liquidity and economic policy uncertainty (EPU) as binary state indicators, the baseline results show that periods of U.S. excess liquidity are associated with a 12.1 percentage-point increase in average monthly cryptocurrency returns. This liquidity-return premium is reduced by approximately 54% during episodes of rising U.S. EPU. Chinese excess-liquidity regimes are associated with a 9.3 percentage-point increase in monthly returns, but this positive association is more than offset under rising Chinese policy uncertainty, as indicated by a −13.8 percentage-point interaction effect. These findings are consistent with the interpretation that surplus-liquidity conditions coincide with stronger cryptocurrency returns, in line with risk-taking and stablecoin-based arbitrage channels, whereas rising-EPU regimes weaken the liquidity-return relationship by increasing risk aversion and reducing arbitrage efficiency. The results highlight a macro-financial channel through which liquidity conditions are linked to digital asset markets and suggest that regulators should monitor stablecoin issuance, leverage, funding conditions, and liquidity-driven speculative pressure in the crypto market.

1. Introduction

The aftermath of the 2008 Global Financial Crisis (GFC) marked a profound shift in global monetary policy. To counteract economic contraction, central banks unleashed expansive monetary programs that flooded the financial system with liquidity (Brana et al., 2012; Meegan et al., 2018). A similar surge recurred during the COVID-19 pandemic when large-scale fiscal and monetary interventions, most prominently in the United States (U.S.) and China, fueled the conditions of *excess* liquidity (Farzami et al., 2021; Gofran et al., 2022). Such liquidity, extending beyond the level warranted by macroeconomic fundamentals, has long been recognized as a double-edged sword. While stabilizing credit flows in the short run, excess liquidity can distort investors' risk perceptions and encourage speculative behavior (Acharya and Naqvi, 2012; Calcagnini et al., 2022). The resulting mispricing of risk, as shown in recent evidence (Hasan et al., 2023; Delis et al., 2023), inflates asset bubbles and amplifies systemic fragility. Yet, despite the centrality of liquidity in shaping modern financial cycles, its spillover into the digital asset domain, particularly cryptocurrencies, remains insufficiently examined.

Cryptocurrencies, characterized by high volatility, limited regulation, and speculative participation, are inherently sensitive to liquidity dynamics. While general liquidity tends to enhance market depth and reduce volatility (Leirvik, 2022; Nekhili et al., 2023), excess liquidity, which surpasses the needs of the real economy, can trigger distinct behavioral and pricing effects. Our study argues that excess-liquidity conditions are associated with stronger speculative activity in cryptocurrency markets, consistent with the view that abundant liquidity may relax risk constraints and lower perceived downside risks. According to Acharya and Naqvi's (2012) excess liquidity theory, abundant liquidity encourages investors to climb the risk ladder, reallocating capital toward higher-yielding and more speculative assets. In the context of

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digital assets, this dynamic is magnified by the entry of institutional investors who have become major conduits[1] through which macro-liquidity shocks transmit into cryptocurrency valuations (Sun et al., 2021; Huang et al., 2022).

Empirical work provides further support for this mechanism. Bouri et al. (2019) and Wang et al. (2019) observe that cryptocurrencies experience heightened speculative activity during liquidity-rich periods as investors' tolerance for risk and market exposure increases. Behavioral finance perspectives also support this linkage, showing that under abundant liquidity conditions, investors exhibit lower loss aversion and greater confidence in speculative trades (Nguyen et al., 2024; Chen et al., 2022). Consequently, cryptocurrency prices are shaped not only by technological innovation and adoption trends but also by broader macro-financial liquidity cycles. In this study, we argue that excess liquidity is expected to be positively associated with cryptocurrency returns through two reinforcing channels: (1) risk-taking and (2) arbitrage.

The first mechanism operates through the behavioral and financial channels described above. Specifically, when liquidity is abundant, capital becomes cheaper; margin constraints loosen, and speculative incentives intensify. Investors, perceiving a safety net of central bank support, are inclined to chase yield in volatile digital assets, leading to inflated valuations and amplified returns (Nguyen et al., 2024). The second mechanism relates to the growing role of stablecoins as liquidity bridges within the cryptocurrency ecosystem. Stablecoins such as Tether (USDT) and USD Coin (USDC), pegged to fiat currencies, serve as transactional and arbitrage tools that channel liquidity from the traditional financial system into digital markets. Lyons and Viswanath-Natraj (2023) demonstrate that stablecoin issuance enhances price stability by reducing peg deviations and improving market efficiency. In parallel, Ante et al. (2021) find that episodes of stablecoin issuance consistently coincide with positive abnormal returns in major cryptocurrencies. These findings imply that during periods of excess liquidity, expanded issuance of stablecoins facilitates arbitrage opportunities that elevate cryptocurrency prices. In this sense, the cryptocurrency market mirrors the liquidity-induced exuberance observed in traditional asset markets through decentralized and algorithmic conduits.

While excess-liquidity conditions may be associated with higher returns through these two mechanisms, this relationship is not unconditional. The strength of this relationship depends critically on the prevailing macro-financial environment, particularly whether economic policy uncertainty (EPU) is rising. EPU encapsulates investors' perceptions of unpredictability in fiscal, monetary, and regulatory policies (Baker et al., 2016; Altig et al., 2020). The COVID-19 pandemic, for instance, witnessed unprecedented spikes in EPU, surpassing even those observed during the GFC (Choi, 2020; Jiang and Cheng, 2021). Under such uncertainty, economic agents tend to exhibit heightened caution, delaying investment and reducing exposure to risky assets (Wen et al., 2021).

From a behavioral standpoint, prospect theory offers a compelling lens for understanding how elevated uncertainty moderates risk-taking. When policy outcomes become more uncertain, investors' risk perceptions may shift asymmetrically: they become more sensitive to potential losses and less responsive to upside opportunities, even under liquidity-rich conditions (Wang et al., 2019; Chen et al., 2022). This shift implies that the speculative channel through which excess liquidity fuels cryptocurrency returns weakens when EPU rises. Supporting this view, studies such as Wang et al. (2019), Luo et al. (2022) and Han and Wang (2023) show that firms and investors alike adopt more conservative financial strategies under policy uncertainty, dampening the transmission of liquidity shocks. Similarly, Lyons and Viswanath-Natraj (2023) document that arbitrage efficiency, which is vital for stablecoin-based liquidity flows, also declines significantly during high EPU periods as uncertainty increases the compensation demanded by arbitrageurs and reduces market-making activity.

As a result, heightened EPU can disrupt both the risk-taking and arbitrage channels through which liquidity influences cryptocurrency prices. During tranquil policy periods, excess liquidity stimulates speculative inflows and arbitrage capital, elevating cryptocurrency valuations. In contrast, under high uncertainty, these mechanisms falter, implying that investors' behavioral biases such as loss aversion and herding intensify, arbitrage opportunities diminish, and liquidity's stimulative power erodes. Empirical evidence by Duan and Urquhart (2023) and Bai et al. (2025) confirms that stablecoin effectiveness in stabilizing or supporting crypto valuations deteriorates remarkably under uncertain conditions.

By integrating these insights, our research provides two central propositions. First, consistent with liquidity-based asset pricing and behavioral risk-taking theories, excess-liquidity regimes are expected to be positively associated with cryptocurrency returns, as abundant liquidity encourages speculative behavior and facilitates arbitrage flows. Second, this positive relationship weakens substantially when EPU rises as uncertainty heightens investor caution and impairs liquidity transmission mechanisms.

This study examines the association between excess-liquidity conditions and cryptocurrency returns in the world's two largest economies, the U.S. and China,[2] while considering whether this relationship varies across EPU regimes. We employ the panel dataset comprising monthly returns of ten major cryptocurrencies including five traditional cryptocurrencies and five stablecoins, from 2019 to 2024. Excess liquidity for the U.S. and China is measured using macroeconomic deviations from equilibrium liquidity levels, employing Taylor rule residuals and Hodrick–Prescott (HP-filtered) trends. EPU indices for the U.S. and China are obtained from the news-based measures developed by Baker

[1] Fidelity's reports show that the share of U.S. institutions with digital-asset exposure rose from 22% in 2019–27% in 2020 and then 33% in 2021 (Fidelity Digital Assets, 2020; 2021). By the first half of 2022, 42% of U.S. institutional respondents reported holding digital assets, while globally 58% of surveyed institutions held digital assets, a six-percentage-point increase year-over-year, which is consistent with continued professional participation through the market downturn (Fidelity Digital Assets, 2022). On the product side, CoinShares' annual fund-flow survey reports that digital-asset investment-product AUM ended 2021 at a record USD 62.5 billion with full-year inflows of USD 9.3 billion, a 36% increase from 2020 (CoinShares, 2022). The AUM peak coincides with the peak of the crypto bull market, reinforcing the view that institutional capital allocation drove price dynamics during our examined period. Moreover, EY-Parthenon's 2023 survey of 256 global institutional decision-makers finds that 60% of respondents allocated more than 1% of their portfolio to digital assets, 69% expected to increase allocations over the following two to three years, and 93% affirmed long-term belief in the value of blockchain and crypto assets despite the preceding market turbulence (EY-Parthenon, 2023). By 2024, EY-Parthenon's follow-on survey of 277 institutions confirms that 42% of respondents increased digital-asset allocations in 2023, 67% had already invested in digital assets or related funds, and 94% believed in the long-term value of the asset class (EY-Parthenon, 2024). As a result, such evidence establishes that institutional investors were actively and increasingly present in the cryptocurrency market throughout our sample.

[2] We focus on the U.S. and China because both are the two dominant macro-liquidity sources in the global economy. The World Bank's data (data.worldbank.org) in 2024 identified the U.S. and China as the two largest economies with the U.S. recorded at about $28.75 trillion and China at about $18.74 trillion in current GDP. This scale is central to our empirical design because the theory concerns system-wide liquidity shocks rather than local equity-market conditions. Moreover, Acharya and Naqvi (2012) predict that excess liquidity matters most when it originates from monetary systems large enough to alter global risk appetite and funding conditions. Literature on cryptocurrencies also shows that crypto returns are exposed to market-specific and speculative factors, while stablecoin flows can transmit fiat liquidity into crypto prices through trading and settlement channels (Griffin and Shams, 2020; Liu and Tsyvinski, 2021).

et al. (2016). Empirically, our design is regime-based: rather than estimating the effect of continuous liquidity or EPU levels, we classify each month into binary liquidity and EPU states and examine whether cryptocurrency returns differ across these conditional regimes.

The estimated results indicate that cryptocurrency returns are higher during excess-liquidity regimes, consistent with the spillover of liquidity-driven risk-taking from traditional financial systems to digital asset markets. In the baseline estimates, U.S. excess-liquidity regimes are associated with a 12.1 percentage-point increase in average monthly cryptocurrency returns, while Chinese excess-liquidity periods are associated with a 9.3 percentage-point increase. However, rising EPU weakens this liquidity-return relationship: the U.S. interaction term indicates a reduction of approximately 54% in the liquidity-return premium, while the Chinese interaction term of −13.8 percentage points more than offsets the baseline Chinese liquidity association, reflecting investors' pronounced risk aversion and disrupted arbitrage efficiency during periods of policy ambiguity. These results echo Bordo et al. (2016), who show that rising EPU significantly reduces aggregate credit growth and dampens financial institutions' risk-taking.

Our findings contribute to the extant literature in several ways. First, we reinterpret Acharya and Naqvi's (2012) liquidity framework in the context of digital asset markets, illustrating how the risk-taking channel can operate beyond banks through institutional, decentralized and algorithmic conduits. Second, it integrates the behavioral dimension of EPU into the analysis of liquidity-driven cryptocurrency returns, linking macro-financial uncertainty to investor risk perception, heightened risk aversion, and weaker arbitrage activity. This perspective complements prospect-theory-based explanations of cryptocurrency investor behavior emphasized by Chen et al. (2022) and Yadav (2024). Finally, by focusing on excess liquidity originating from the U.S. and China, two dominant monetary actors, the study provides a global perspective on how macro-financial conditions are linked to digital asset markets, with implications for financial stability and policy coordination.

The remainder of the paper is structured as follows. Section 2 describes the data and variables and outlines the empirical methodology. Section 3 presents the empirical results and discusses their implications. Section 4 concludes the paper and offers suggestions for future research on excess liquidity and cryptocurrency markets.

2. Data and methodology

2.1. Data collection

The data consists of monthly observations from January 2019 to December 2024. The dependent variable covers a selection of the top five traditional cryptocurrencies and stablecoins by market capitalization. Traditional coins include Bitcoin (BTC), Ethereum (ETH), XRP, Binance Coin (BNB), and Solana (SOL), while stablecoins comprise Tether (USDT), USD Coin (USDC), DAI, TrueUSD (TUSD), and Stasis EURO (EURS).[3] These cryptocurrencies were selected based on two criteria: (1) sustained top market capitalization rankings and (2) the availability of uninterrupted historical data over the full sample period. Although other tokens may currently have higher market capitalizations, they were excluded due to insufficient historical coverage. Daily open price data for all selected cryptocurrencies were collected from CoinMarketCap (www.coinmarketcap.com) and aggregated into a monthly frequency.

To construct excess liquidity measures for both the U.S. and China, monthly data from January 2019 to December 2024 are collected for broad money (M2), nominal GDP (NGDP), real interest rates (RIR), inflation (INF), and real GDP per capita for both economies. All relevant macro-financial variables are sourced from the Federal Reserve Economic Data (FRED) database, the National Bureau of Statistics of China, and Chinese National Interbank Funding Center. Similarly, data from different frequencies are converted to monthly observations using standard interpolation techniques to ensure temporal consistency across variables. EPU was measured using the established indices from Economic Policy Uncertainty (www.policyuncertainty.com). Monthly EPU data for the U.S. and China were retrieved for the full sample period from January 2019 to December 2024. These indices, constructed based on newspaper coverage frequency, are widely used in the literature as a proxy for policy-related macroeconomic uncertainty and are particularly suitable for cross-country financial market studies.

To control for broader macro-financial influences, we include several control variables, particularly the bilateral exchange rate (USD/CNY), the federal funds rate representing U.S. monetary policy stance, and the Shanghai Interbank Offered Rate (SHIBOR) as China's short-term interest rate benchmark. Additionally, global commodity prices were accounted for using daily gold and crude oil prices (West Texas Intermediate), which were then aggregated to a monthly frequency. Equity market conditions were captured using the S&P 500 Index for the U.S. and the Shanghai Composite Index for China. All control variable data were sourced from FRED and Bloomberg and harmonized into monthly observations (See Appendix A1 for detailed definitions of all variables in the main regression).

The final dataset consists of a balanced panel of 10 cryptocurrencies observed over 72 months from January 2019 to December 2024, generating a maximum of 720 coin-month observations.

2.2. Regression models and techniques

To examine whether cryptocurrency returns differ across excess-liquidity regimes, this study specifies a panel regression model that captures both direct and interaction effects across time and asset classes. Following empirical strategies adopted in recent macro-financial studies of Nguyen et al. (2024) and Yen and Cheng (2021), the baseline specification is as follows:

$$Return_{it} = \alpha_0 + \alpha_1 EL_t^{US} + \alpha_2 EL_t^{US} \times EPU_t^{US} + \alpha_3 EL_t^{CN} + \alpha_4 EL_t^{CN} \times EPU_t^{CN} + \alpha_j X_{jt} + \varepsilon_{it} \quad (1)$$

In Eq. (1), the dependent variable ($Return_{it}$) is the monthly return of cryptocurrency i at time t, calculated as the percentage change in the daily open prices and aggregated at the monthly frequency. This method matches literature examining cryptocurrency behaviors under macro-financial shocks (Sharma, 2023; Beavers and Godek, 2024) and reduces noise, compared to daily or weekly returns, to be consistent with other monthly macroeconomic variables (Umar et al., 2023; Wang et al., 2019).

Excess liquidity in the U.S. and China is captured using a Taylor-based residual ,[4] which has gained popularity in recent financial

[3] At the time of selection, the market capitalizations of the traditional coins were as follows: Bitcoin (2.178 trillion USD), Ethereum (328.12 billion USD), XRP (134.88 billion USD), BNB (94.39 billion USD), and Solana (87.61 billion USD). Regarding stablecoins, the respective market caps were USDT (155.18 billion USD), USDC (60.94 billion USD), DAI (5.36 billion USD), TUSD (492.52 million USD), and EURS (140.93 million USD).

[4] The Taylor-rule sub-equation comprises real interest rates, inflation, and real GDP per capita growth to predict the equilibrium level of M2/NGDP. When actual liquidity exceeds the predicted benchmark, positive residuals are taken as proxies for excess liquidity. To align with best practices in liquidity research and avoid winsorizing a large amount of data, we apply a dummy variable equal to 1 if the residual minus 0.5 times the standard deviation of the residual remains positive, and 0 otherwise (Jiang, 2014; Bauer and Neuenkirch, 2017). This definition addresses whether cryptocurrency returns differ when the macro-financial system is a surplus-liquidity state.

Table 1
Main regressions for both traditional cryptocurrencies and stablecoins.

Return	Taylor rule		HP filter	
All	Model 1	Model 2	Model 3	Model 4
$ER^{USD/CNY}$	8.161	4.526	6.812	-2.359
	(0.87)	(0.48)	(0.70)	(-0.24)
MP^{US}	0.966	1.168	1.033	0.980
	(0.82)	(0.99)	(0.85)	(0.83)
MP^{CN}	1.399	0.386	4.595	2.050
	(0.39)	(0.11)	(1.30)	(0.58)
Gold Price	-0.005	-0.004	-0.010	-0.008
	(-0.59)	(-0.44)	(-1.16)	(-0.89)
Oil Price	-0.330***	-0.315***	-0.242***	-0.268***
	(-4.30)	(-4.13)	(-3.30)	(-3.61)
S&P500	0.007*	0.004	0.005	0.006
	(1.94)	(1.21)	(1.50)	(1.60)
Shanghai Index	0.026***	0.028***	0.022***	0.015**
	(3.98)	(4.28)	(3.31)	(2.26)
EL^{US}	12.100***	9.318**	6.511*	3.083
	(3.20)	(2.14)	(1.93)	(0.67)
EL^{US} × traditional coins		0.581		7.524**
		(0.14)		(2.42)
EL^{US} × EPU^{US}	-6.505**	-2.321	-4.876**	-0.942
	(-2.46)	(-0.66)	(-1.97)	(-0.30)
EL^{US} × EPU^{US} × traditional coins		-9.392**		-6.283*
		(-1.98)		(-1.77)
EL^{CN}	9.330**	11.110***	16.530***	15.780***
	(2.33)	(2.76)	(3.30)	(3.21)
EL^{CN} × traditional coins		27.300***		10.570***
		(2.98)		(2.66)
EL^{CN} × EPU^{CN}	-13.790***	-11.970**	-11.640**	-8.934*
	(-3.26)	(-2.31)	(-2.24)	(-1.71)
EL^{CN} × EPU^{CN} × traditional coins		-12.150*		-38.040***
		(-1.84)		(-3.21)
Constant	-131.300*	-105.700	-116.500	-32.010
	(-1.66)	(-1.34)	(-1.42)	(-0.39)
Traditional coins	No	Yes	No	Yes
Observations	720	720	720	720
R^2 within	0.110	0.128	0.098	0.127
R^2 between	0.767	0.767	0.767	0.767
R^2 overall	0.106	0.107	0.094	0.140
R^2 adjusted	0.081	0.094	0.068	0.093
Model fit test				
F-statistics	6.159	5.619	5.391	5.597
P-value	0.000	0.000	0.000	0.000
Homogeneous among coins test				
F-statistics	3.335	2.317	3.289	1.314
P-value	0.001	0.014	0.001	0.226

This table presents the main regression results examining the excess liquidity-regime effect on the returns of both traditional and stable cryptocurrencies from January 2019 to December 2024. Models 1 and 2 report estimates using excess liquidity derived from Taylor rule residuals, while Models 3 and 4 use excess liquidity estimated via the HP filter approach. Because excess liquidity and EPU are binary indicators, the coefficients should be interpreted as return differences across liquidity and uncertainty regimes. All models pool the full sample of 10 cryptocurrencies (five traditional coins and five stablecoins) and include a dummy variable for traditional coins, equal to 1 if the cryptocurrency is classified as traditional, and 0 otherwise. The regressions incorporate interaction terms between excess liquidity and EPU for both the U.S. and China, and further interactions with the traditional coin dummy to explore differential effects across coin types. Control variables include exchange rates, monetary policy rates, commodity prices, and equity indices as detailed in Table 2. All models include cryptocurrency and year fixed effects. *t*-statistics, based on two-way cluster-robust standard errors clustered by cryptocurrency and calendar month, are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

studies for its ability to reflect deviations from monetary policy equilibrium (Saiti et al., 2021; Nguyen et al., 2024). The baseline Taylor-rule measure is also complemented by an HP-filter liquidity measure in the robustness tests. This second practice, based on established methodologies of Nguyen and Boateng (2015) and Boateng et al. (2021), helps reduce dependence on one specific benchmark for equilibrium liquidity and follows the standard use of HP filter to separate cyclical deviations from trend components (Hodrick and Prescott, 1997; Ravn and Uhlig, 2002)[5]. Because excess liquidity is defined as a binary state variable, the specification should be interpreted as a conditional liquidity regime comparison. The liquidity coefficients, therefore, capture differences in cryptocurrency returns across liquidity states, rather than marginal effects of continuous changes in liquidity.

To capture macroeconomic ambiguity, this study also uses EPU indices[6] for the U.S. and China sourced from Baker et al. (2016). Following prior studies (Bouri et al., 2022; Wang et al., 2023), this study employs a binary indicator where EPU equals 1 if current EPU in month t exceeds the previous month $(t–1)$, and 0 otherwise. This dummy variable can be interpreted as a rising-uncertainty state. While a continuous measure only implies that every small change in EPU has the same marginal effect on crypto returns, the dummy definition hypothesizes that liquidity transmission weakens when EPU moves into a state that raises required risk compensation, delays investment, and reduces the effectiveness of arbitrage activity.[7]

The interaction terms examine whether the return premium associated with excess-liquidity regimes differs significantly between rising- and non-rising-EPU periods, following the theoretical framework that uncertainty induces risk aversion and delays in investment (Bloom, 2009; Gulen and Ion, 2016). This specification has also been employed in recent bank risk-taking studies under excess liquidity (Nguyen et al., 2024; Khan et al., 2017). X_{jt} is a vector of macro-financial controls including (1) exchange rate of USD/CNY–volatility in exchange rates affects international arbitrage opportunities and capital flows (Wang et al., 2019), (2) monetary policy rates – benchmark interest rates in the U.S. (Federal funds rates) and China (SHIBOR) reflect the cost of capital and are central to risk premium pricing (Yuan et al., 2022), (3) gold and oil prices – gold serves as a hedge asset, while oil is a proxy for global economic conditions and inflation expectations (Sharma, 2023), and (4) S&P 500 and Shanghai Composite Index – stock indices capture investor sentiment and broad market volatility, which spill over to crypto assets (Liu and Tsyvinski, 2021).

Eq. (1) uses two-way fixed effects with cryptocurrency and year fixed effects,[8] which addresses omitted variable bias and unobserved heterogeneity observed in the panel data (Wooldridge, 2025). All regressions are estimated with two-way cluster-robust standard errors by cryptocurrency and calendar month, reflecting two distinct sources of residual dependence in the panel. Excess liquidity, EPU, and control variables vary over time and take the same value across cryptocurrencies. Also, cryptocurrency-level clustering allows for residual dependence within a given cryptocurrency over time. Accounting jointly for these two dimensions is appropriate when errors may be correlated both across assets and across time (Petersen, 2008; Cameron and Miller, 2015; Abadie et al., 2023). Our study favors FE over dynamic GMM because the panel has a small cross-section of ten cryptocurrencies and a moderate monthly time dimension.[9] This structure is better suited for a parsimonious fixed-effects design than to an instrument-heavy dynamic panel estimator.

2.3. Descriptive statistics

Table 2 provides the summary statistics for all variables. The dependent variable, cryptocurrency returns, exhibits substantial variability, as expected given the high volatility of crypto markets documented in prior research (Corbet et al., 2018; Foglia and Dai, 2022). The mean return across all coins is 3.89%, with traditional coins significantly outperforming stablecoins. This aligns with the function of stablecoins as value-preserving instruments (Kristoufek, 2022; Cao et al., 2025), while traditional coins reflect higher speculative demand and risk-taking (Zhang et al., 2023; Yen et al., 2023). The distribution of returns shows considerable skewness and kurtosis, particularly for traditional coins like BTC and ETH, confirming the non-normality and fat-tailed behavior typical of crypto assets as reported by Cerqueti et al. (2020) and Bouri et al. (2021). In contrast, stablecoins display far less

[5] Besides the dummy variables for excess liquidity measures using Taylor rule and HP filter, we employ the global excess liquidity index as an external validation. This index is not used as the baseline measure because it aggregates liquidity conditions across major monetary areas including the Federal Reserve, ECB, Bank of Japan, and PBoC, and therefore cannot identify the country-specific U.S. and China channels. Nevertheless, it is useful as a validation test because it is constructed independently from our Taylor-rule residuals and captures broad global liquidity conditions. Supplementary Materials Figure S1 plots the global index against our Taylor rule excess liquidity regimes for the U. S. and China. The index rises sharply during 2020–2021 and peaks around early 2021, which coincides closely with the sustained U.S. excess liquidity regime, reflecting the Federal Reserve's large-scale balance-sheet expansion and emergency liquidity provision during COVID-19. The later decline from late 2021 through 2022 is also consistent with the withdrawal of surplus liquidity as global monetary conditions tightened. The Chinese excess liquidity episodes are shorter and more episodic, but several occur within periods when the global index is elevated. This pattern is consistent with the institutional distinction between sustained U.S. balance-sheet expansion and China's more targeted liquidity-management framework. Thus, the country-level measures capture the same broad liquidity cycle as an external global index while also preserving the national timing and intensity required by our empirical design. Furthermore, as a further robustness check, Supplementary Materials Table S7 estimates the model using the continuous global excess liquidity index. The results are directionally consistent with the main findings in Table 1, implying that global excess liquidity is positively associated with cryptocurrency returns, while EPU weakens the liquidity-return relationship, especially for traditional coins.

[6] The EPU index, constructed from newspaper-based text frequency methods, quantifies the level of policy-related economic uncertainty and has been validated extensively in cryptocurrency literature (Bouri et al., 2022).

[7] Such treatment is aligned with previous models in which uncertainty shocks generate precautionary delays (Bloom, 2009), policy uncertainty affects asset prices and risk premia (Pastor and Veronesi, 2012; 2013), and firms reduce investment when policy uncertainty increases the value of waiting (Gulen and Ion, 2016). Moreover, our practice is consistent with threshold-style empirical designs where observations are grouped into economically meaningful regimes rather than forced into a single linear slope (Hansen, 1999). To ensure our results are not an artifact of this binning choice, Supplementary Materials Table S5 reports parallel specifications using a continuous EPU measure as reference. The estimated results from Table S5 support the central liquidity channel and are consistent with our main findings in Table 1.

[8] Cryptocurrency fixed effects absorb time-invariant differences across assets, including design, market role, and average volatility, whereas year fixed effects absorb broad annual shocks common to all cryptocurrencies. Statistical inference is based on standard errors clustered by calendar month and cryptocurrency. Time clustering is important because excess liquidity, EPU, and macro-financial variables are common across cryptocurrencies over time, so unobserved time shocks may generate contemporaneous correlation across assets. Cryptocurrency clustering additionally allows regression disturbances for a given cryptocurrency to remain correlated over time. Because the empirical design relies on fixed-effects panel regressions rather than an exogenous identification strategy, the estimated coefficients should be interpreted as conditional associations and regime-based return differences, not as causal effects.

[9] Our panel data includes a relatively small number of cross-sectional units ($n = 10$) observed over a moderate time horizon ($t = 72$ months). On the other hand, dynamic panel GMM is designed for "large N, small T" contexts and can suffer from finite-sample biases or instrument proliferation when applied to a small-N panel. Indeed, difference or system GMM may become inconsistent or unstable with few cross-sectional units (Arellano and Carrasco, 2003; Roodman, 2009).

Table 2
Summary statistics.

	Return All	Return - stablecoins					Return - traditional coins				
		USDT	USDC	DAI	TUSD	EURS	BTC	ETH	XRP	BNB	SOL
Observations	720	72	72	72	72	72	72	72	72	72	72
Mean	3.89	-0.04	-0.01	0.00	-0.01	-0.05	5.83	6.21	4.21	10.78	11.99
Standard deviation	23.96	0.21	0.24	0.27	0.38	1.64	17.22	21.71	35.28	37.44	46.82
Min	-84.00	-1.08	-1.62	-1.16	-1.23	-3.47	-28.09	-36.25	-84.00	-34.61	-44.37
Max	265.54	0.40	0.80	1.12	2.43	5.86	59.83	91.58	147.02	265.54	193.66
Skewness	4.47	-3.45	-3.94	-0.35	3.24	0.60	0.55	1.00	1.60	4.48	2.12
Kurtosis	37.64	18.49	29.69	12.82	27.16	4.09	3.25	5.17	9.23	30.31	7.63
	Independent Variables										
	$ER^{USD/CNY}$	MP^{US}	MP^{CN}	Gold Price	Oil Price	S&P500	Shanghai	EL^{US}	EPU^{US}	EL^{CN}	EPU^{CN}
Observations	720	720	720	720	720	720	720	720	720	720	720
Mean	6.88	2.41	2.60	1848.90	68.87	4042.40	3171.80	0.38	0.50	0.18	0.51
Standard deviation	0.30	2.12	0.43	317.12	19.18	872.00	241.14	0.48	0.50	0.38	0.50
Min	6.34	0.05	1.68	1283.30	16.61	2386.10	2584.60	0.00	0.00	0.00	0.00
Max	7.31	5.33	3.35	2686.50	115.15	6074.10	3639.80	1.00	1.00	1.00	1.00
Skewness	-0.37	0.23	-0.34	0.62	-0.17	0.25	0.05	1.15	0.00	1.66	-0.06
Kurtosis	1.82	1.42	2.06	3.65	3.18	2.47	2.20	2.33	1.00	3.76	1.00

This table presents the summary statistics for all variables employed in the regression analyses over the sample period from January 2019 to December 2024. The dependent variable is the monthly return for traditional coins (Bitcoin, Ethereum, XRP, Binance Coin, Solana) and stablecoins (Tether, USD Coin, DAI, TrueUSD, Stasis EURO). The independent variables include U.S. and Chinese excess liquidity and EPU indices, with control variables capturing exchange rates, monetary policy rates, commodity prices, and equity market indices. The table reports the number of observations, mean, standard deviation, minimum and maximum values, skewness, and kurtosis for each variable. These statistics summarize the central tendency, dispersion, distribution shape, and the extent of extreme values in the data used for panel regressions.

dispersion and extreme values.

Regarding the main independent variables, both U.S. and Chinese excess liquidity measures have means of approximately 0.38 and 0.18 respectively. These values indicate that surplus-liquidity regimes were present in roughly 38% and 18% of our sample months.[10] Such a difference suggests that U.S. excess liquidity was more persistent during the sample period. This pattern is consistent with the large and sustained U. S. policy response during the COVID-19 crisis and with China's more targeted, multi-instrument liquidity management framework (Elsayed and Sousa, 2024; Wei and Han, 2021).

The EPU indicators reveal that China reported a slightly higher frequency of policy uncertainty shocks than the U.S. This is a notable observation, as it suggests that, despite narratives about China's strong policy coordination, external shocks (trade tensions and pandemic-related disruptions) likely drove higher instances of policy uncertainty in China during the sample period (Baker et al., 2020; Kamal and Wahlstrøm, 2023). This aligns with empirical findings that emerging economies, including China, have become increasingly exposed to global uncertainty spillovers (Yen and Cheng, 2021).

3. Results and discussion

Table 1 presents the main regression results, examining the return differences associated with excess-liquidity regimes derived from both the Taylor-rule residuals and the HP-filter measure, as well as how these differences vary across rising- and non-rising-EPU regimes in the U.S. and China. By using a dummy variable, we can explicitly examine different responses across distinct cryptocurrency types. Our chosen methodology is consistent with what has been employed by Duan and Urquhart (2023) and Griffin and Shams (2020), who indicated structural differences in how various digital assets react to macroeconomic shocks.

First, the estimated coefficients indicate that excess-liquidity regimes are positively associated with cryptocurrency returns, with the association generally stronger for Chinese excess-liquidity regimes across most specifications. In particular, the coefficients in Models 1 through 4 show that Chinese excess-liquidity regimes are consistently associated with higher cryptocurrency returns. Such results align theoretically with liquidity-driven risk-taking theory of Acharya and Naqvi (2012), who posited that when liquidity is abundant, financial institutions and investors tend to underestimate risk and engage in excess risk-taking, inflating asset prices and even sowing the seeds of future instability. We observe exactly this mechanism in the cryptocurrency market, that is, excess liquidity in major economies encourages investors to "climb the risk ladder" into speculative digital assets, echoing the behavior that Acharya and Naqvi (2012) theorized in the banking sector. Moreover, the relatively large estimated coefficients on the excess-liquidity variables, especially for traditional cryptocurrencies, suggest that abundant liquidity in the broader financial system is be associated with stronger demand for crypto assets, potentially bidding up prices beyond levels justified by fundamentals. This finding is conceptually similar to a credit-fueled asset bubble, except that in this case, the medium is liquidity, and the target assets are cryptocurrencies. Therefore, our evidence extends liquidity-based asset pricing theories to a new domain, showing that the risk-taking channel formerly identified in traditional finance is applicable to decentralized markets. Investors who become more confident due to relaxed monetary conditions appear to treat cryptocurrencies as high-yield substitutes when safer assets offer lower returns, a phenomenon aligned with the reach-for-yield behavior under low interest rates (Acharya et al., 2024).

Second, the interaction estimates indicate that the excess-liquidity return premium is weaker during rising-EPU periods. Through the lens of Prospect Theory and related behavioral paradigms (Tversky and Kahneman, 1992), when policy outcomes are unclear, investors become more sensitive to downside risks and less responsive to upside opportunities. In other words, higher uncertainty tends to amplify

[10] We plot the monthly U.S. and Chinese excess liquidity periods against average returns for stablecoins and traditional coins in Appendix Figure A1. The shaded regions are generated directly from the binary indicators used in the regressions. Panels A and B show that the U.S. liquidity indicator identifies the sustained liquidity regime around the COVID-19 policy response when the Federal Reserve cut rates, expanded repo operations, purchased treasury and agency securities, and introduced emergency facilities to support funding markets (Cachanosky et al., 2021). The Chinese indicator identifies shorter liquidity episodes, which are consistent with the PBoC's use of multiple targeted tools to maintain liquidity access and credit provision during the pandemic period (Funke and Tsang, 2020). Moreover, the contrast between two asset types supports the economic reasoning that traditional coin returns vary sharply around liquidity regimes, while stablecoin returns remain close to zero by design.

cautious behavior. Even if liquidity is ample, most investors may hesitate to allocate funds to volatile crypto assets because they are afraid of sudden adverse policy moves or market crashes. Our negative interaction terms support the findings of Pastor and Veronesi (2012), who demonstrated that higher political uncertainty increases the required return on equities as investors demand extra compensation for policy risk. Similarly, in the crypto context, rising-EPU regimes drive up the shadow cost of capital for speculative positions, lessening the price effect of any given liquidity injection. Simply put, the relationship between liquidity and EPU can be regarded as countervailing forces, liquidity-induced risk-taking versus uncertainty-induced risk aversion, which can be predicted by integrating Acharya and Naqvi's (2012) framework with Prospect Theory.

Besides, the estimates allow us to quantify how the coefficient-implied cryptocurrency return difference associated with excess liquidity changes under different EPU regimes.[11] Our results indicate that U.S. excess liquidity has a strong and economically meaningful effect on cryptocurrency returns, particularly when policy uncertainty is not elevated. In the baseline state where the U.S. monetary stance shifts from tightening to an excess-liquidity regime, we observe a sizeable positive return response for cryptocurrencies. Quantitatively, Model 1 suggests that the presence of U.S. excess liquidity is associated with an average monthly return increase of approximately 12.1% for the cryptocurrency portfolio. This magnitude is large by conventional asset-pricing standards and underscores the role of abundant liquidity in compressing funding constraints and encouraging risk-taking behavior. Importantly, this effect is not uniform across crypto assets. Extended specifications reveal that traditional cryptocurrencies benefit disproportionately relative to stablecoins, consistent with their greater exposure to speculative demand rather than transactional use.

However, the liquidity-return association for the U.S. excess liquidity is highly sensitive to the prevailing uncertainty regime. When U.S. EPU is elevated, the marginal effect of excess-liquidity conditions is significantly attenuated. The negative interaction between excess liquidity and EPU implies that the same liquidity surplus delivers substantially smaller return gains under high uncertainty. Using the estimated coefficients, the liquidity-driven return premium falls from roughly 12.1% to around 6.5% (approximately 54% reduction in magnitude) when EPU is unusually high. This finding is consistent with uncertainty acting as a constraint on the transmission of monetary accommodation into speculative asset prices. Even when liquidity conditions are supportive, elevated policy uncertainty reduces investors' willingness to take risks, thereby dampening the repricing of cryptocurrencies. From an asset-pricing perspective, this implies that U.S. monetary easing alone is insufficient to generate sustained crypto rallies unless it is accompanied by a stable and predictable policy environment.

Turning to China, the estimates indicate that Chinese excess-liquidity regimes are also positively associated with cryptocurrency returns despite the existence of formal restrictions on domestic crypto trading. In periods characterized by excess liquidity in China, cryptocurrency returns increase by approximately 9.3% per month on average, according to Model 1. This result highlights the global nature of crypto markets and suggests that Chinese liquidity conditions are transmitted through indirect channels such as offshore financial centers and stablecoin-based settlement mechanisms. As in the U.S. case, the positive effect of Chinese liquidity is significantly stronger for traditional cryptocurrencies than for stablecoins, reinforcing the view that liquidity shocks primarily fuel speculative rather than purely transactional crypto activity.

Yet, the Chinese liquidity-return association is even more state-dependent than its U.S. counterpart. The interaction between Chinese excess liquidity and Chinese EPU is strongly negative, indicating that heightened policy uncertainty can sharply weaken, or even fully offset, the positive liquidity-return association. Quantitatively, our estimates imply that under high Chinese EPU, the return gains associated with excess liquidity decline markedly and can approach zero. Moreover, when focusing on traditional cryptocurrencies, the triple-interaction terms suggest that the additional liquidity sensitivity enjoyed by these assets in low-uncertainty periods can be reduced by several tens of percentage points when uncertainty rises. This pattern underscores the importance of institutional and regulatory frictions in shaping the effectiveness of liquidity transmission from China into global crypto markets. Unlike the U.S., where easing episodes are often sustained and accompanied by clear communication, Chinese liquidity provision tends to be more episodic and policy uncertainty more consequential, making the crypto pricing response particularly fragile in high-EPU regimes.[12]

Our control variables also reveal critical macroeconomic relationships influencing cryptocurrency returns. Particularly, crude oil prices consistently exhibit significant negative relationships, reflecting cryptocurrencies' sensitivities to global commodity market volatility and associated macroeconomic risks, consistent with previous findings by Bouri et al. (2019). Conversely, the significant positive effects of the Shanghai Composite Index suggest spillover effects from Chinese equity market dynamics into cryptocurrency valuations, supporting the evidence of Wang et al. (2019) regarding interconnected investor behaviors. Stablecoins, by design, show negligible responsiveness to these macroeconomic controls, affirming their intrinsic purpose as liquidity conduits rather than speculative assets (Lyons and Viswanath-Natraj, 2023; Ante et al., 2021).

Lastly, our model diagnostics affirm the robustness and validity of our estimation approach. The fixed-effects estimations consistently yield statistically significant explanatory power across all models, supported by high F-statistics, and substantial within-group R-squared values. These diagnostic results suggest that the adopted methodology adequately captures the underlying dynamics of excess liquidity impacts, investor uncertainty moderation, and cryptocurrency-specific heterogeneity, ensuring empirical results suitable for guiding informed policy decisions aimed at financial stability.

[11] In addition to the marginal effect, Panels A and B in Appendix Table A2 present a coefficient-implied growth-of-one-dollar exercise for the U.S. and China. This exercise is a counterfactual designed to show the economic magnitude implied by the estimated coefficients. The calculations use the unconditional mean monthly return from Table 2, which is 3.89%, as the benchmark return when excess liquidity is absent. Then, the relevant Taylor-rule coefficient estimates from Table 1 are added to obtain the implied monthly return under each liquidity-EPU regime. In the counterfactual calculation, the liquidity and EPU indicators are switched on and off, while the remaining covariates and fixed effects are held constant at their baseline/reference values. The implied monthly returns are then compounded over a standardized 12-month horizon to express the economic magnitude of the estimated effects. The value of one dollar is computed as $(1+\bar{r})^{12}$, where $\bar{r}$ is the conditional average monthly return expressed in decimal form.

[12] To verify that our result for China is not a regional Asian liquidity effect, we re-estimate the model using South Korea as a regional comparator *(Supplementary Materials Table S6)*. South Korea is appropriate because it shares the Asian trading window with China, possesses a liquid equity benchmark through the KOSPI, and operates in the same broad regional time zone (9:00–15:30 local time). Compared to the estimations in Table 1, the Korean models still capture ordinary macro-financial co-movement; in particular, oil prices remain negative and significant, and the KOSPI coefficient is significantly positive in all specifications. What disappears is the excess liquidity transmission channel (Korean excess liquidity is positive but statistically insignificant across all four models, and the Korean liquidity-EPU interaction is also insignificant). In addition, adjusted R^2 values are also weaker in the Korean specifications. Therefore, the evidence supports a China-specific liquidity transmission channel rather than a generic Asia effect.

To assess the robustness of our empirical results, we conduct rigorous robustness checks including (1) two alternative measures for excess liquidity (Taylor rule and HP filter),[13] (2) two separate regressions for traditional coins and stablecoins, (3) three subsets for Top 3, 4, and 5 largest cryptocurrencies, and (4) models with and without the interaction term between excess liquidity and EPU. As demonstrated, excess liquidity coefficients remain positively significant for cryptocurrency returns, especially pronounced for traditional coins compared to stablecoins. The significant negative interaction terms between excess liquidity and EPU persist robustly across all robustness checks, strengthening our argument that heightened uncertainty curtails speculative enthusiasm spurred by abundant liquidity. Moreover, we confirm that the findings are not driven by a particular cryptocurrency or a narrow segment of the market, or the exceptional COVID-19 episode.[14]

4. Conclusion and policy implications

This study examines how excess-liquidity conditions in the U.S. and China are associated with cryptocurrency returns, and whether this relationship varies across EPU regimes. Employing a monthly panel of ten major cryptocurrencies from 2019 to 2024, we find that excess liquidity has a positive and economically meaningful association with cryptocurrency returns. Such evidence not only supports the liquidity-driven risk-taking framework by Acharya and Naqvi (2012) but also extends it beyond banks and conventional assets. Regarding digital asset markets, abundant liquidity can relax funding constraints, increase demand for high-risk assets, and support arbitrage flows through stablecoin-based trading channels. This interpretation is also consistent with evidence that stablecoin issuance and Tether-related flows can affect cryptocurrency prices and market efficiency (Ante et al., 2021; Griffin and Shams, 2020; Lyons and Viswanath-Natraj, 2023).

Furthermore, the positive association between excess-liquidity regimes and returns becomes weaker when EPU rises. High EPU increases the perceived cost of holding volatile assets, reduces investors' willingness to take speculative positions, and weakens arbitrage activities. In this sense, liquidity-induced risk-taking and uncertainty-induced caution operate in opposite directions. The result is in line with the broader literature showing that policy uncertainty affects asset prices, investment, and risk-taking through higher required compensation for policy risk (Baker et al., 2016; Pastor and Veronesi, 2012; Gulen and Ion, 2016). Noticeably, the moderation effect is especially relevant for China. Although onshore cryptocurrency trading is formally restricted,[15] Chinese liquidity and policy uncertainty can still reach the global cryptocurrency market through offshore intermediation, peer-to-peer exposure, and stablecoin-based settlement channels (e.g., Lyons and Viswanath-Natraj, 2023; Griffin and Shams, 2020; Chen and Liu, 2022). Therefore, a stronger Chinese effect suggests that the crypto market responds not only to direct trading access but also to the global liquidity and uncertainty conditions generated by major monetary economies.

Our findings have important policy implications for central banks and regulators, particularly in relation to monitoring liquidity conditions, stablecoin activity, leverage, and speculative pressure in digital asset markets. Central banks and regulators should consider digital assets as a potential component of the broader transmission channel of global liquidity. When liquidity is abundant and policy uncertainty is low, speculative pressure in traditional cryptocurrencies can rise quickly. When uncertainty is high, the same liquidity impulse has a weaker effect because investors require more compensation for risk, and arbitrage becomes less effective. Therefore, regulators should monitor indicators that capture liquidity spillovers into the crypto market, including stablecoin issuance, exchange funding conditions, leverage, cross-border settlement flows, and stress in stablecoin pegs. Stablecoins deserve particular attention because they link fiat liquidity to crypto trading and can transmit both excess liquidity and liquidity stress across markets. However, these results do not imply that monetary easing alone causes cryptocurrency booms. Instead, they clarify that liquidity conditions in major speculative coins are the main recipients of capital flows. For that reason, a macroprudential approach to the crypto market should combine liquidity monitoring, stablecoin oversight, and clear policy communication to reduce the risk that easy money turns into unstable speculative pressure.

CRediT authorship contribution statement

Binh Thanh Nguyen: Writing – review & editing, Methodology, Data curation. **Thanh Cong Nguyen:** Writing – original draft, Software, Resources, Formal analysis, Data curation. **Thach Nguyen:** Writing – review & editing, Validation, Supervision. **Thai Vu Hong Nguyen:** Writing – review & editing, Supervision, Project administration, Conceptualization.

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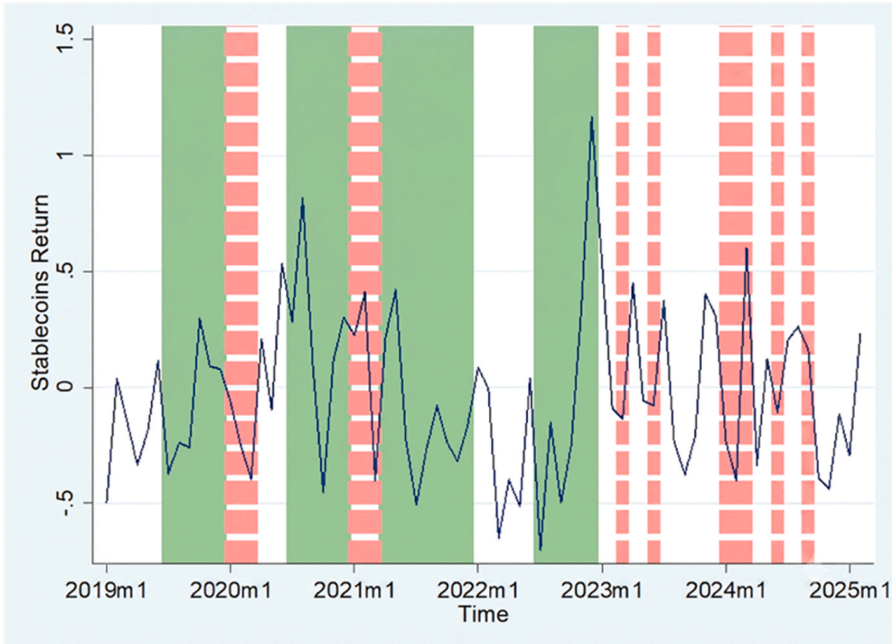
[13] We also externally validate the excess liquidity construction using the global excess liquidity index of Dark Knight Noma obtained via the website https://en.macromicro.me. This check is intentionally narrower than the baseline regressions because the global index aggregates liquidity conditions across major monetary areas and fails to isolate U.S. and China transmission separately. The consistent evidence from Supplementary Materials Figure S1 and Table S7 supports the baseline interpretation, confirming that our findings are not an artefact of a purely internal liquidity construction.

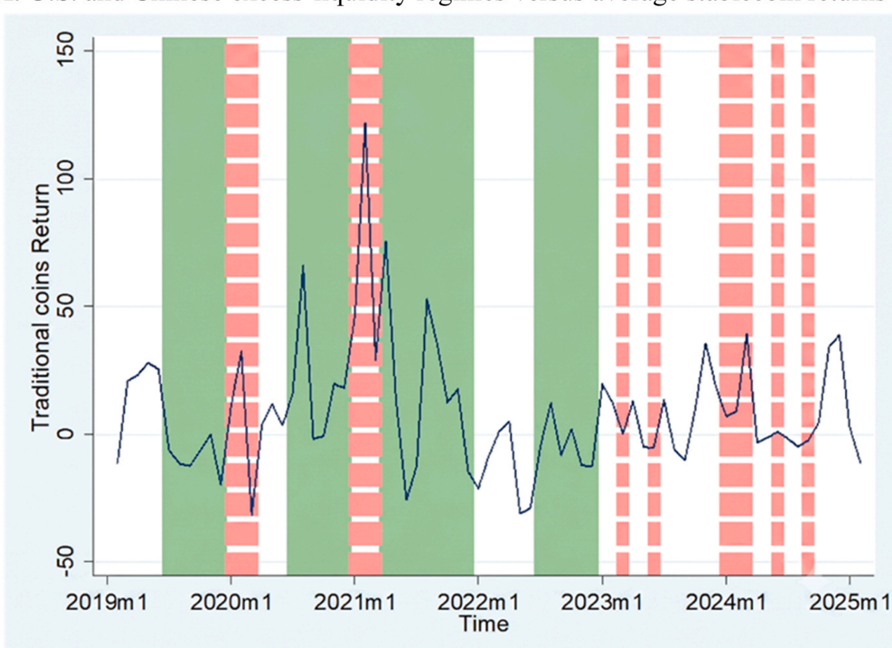
[14] We further examine whether the baseline estimates are mechanically driven by the COVID-19 pandemic by excluding the period from January 2020 to December 2021 and re-estimating the fixed effects models. This exclusion window follows the global pandemic measurement period used in the excess-mortality literature where COVID-19 impacts are measured monthly over 2020–2021 and is also consistent with evidence that the pandemic resulted in unusually large uncertainty shocks and exceptional financial-market responses (Msemburi et al., 2023; Altig et al., 2020; Baker et al., 2020). The results in Supplementary Materials Table S8 remain broadly consistent with Table 1. The pandemic appears to amplify the liquidity-crypto return channel but does not generate the central finding. Excess liquidity is still positively associated with cryptocurrency returns, and EPU continues to weaken this transmission, especially for traditional coins.

[15] The PBoC has officially banned cryptocurrency trading since September 2021 by declaring all cryptocurrency transactions illegal. The ban includes buying and selling cryptos, operating exchanges, using foreign platforms inside China via VPNs, and financial services connected to cryptos. Despite the ban, some users continue accessing cryptos via VPNs, accepting the rising risks that China is increasingly tightening enforcement against platforms engaging in crypto activities.

Appendices



Panel A. U.S. and Chinese excess-liquidity regimes versus average stablecoin returns



Panel B. U.S. and Chinese excess-liquidity regimes versus average traditional coin returns

Figure A1. U.S. and Chinese excess-liquidity regimes and cryptocurrency returns

This figure plots average monthly cryptocurrency returns together with the binary excess liquidity indicators used in the baseline regressions. Panels A and B respectively report the average return of the stablecoins and traditional ones. Green bands indicate months in which the U.S. excess liquidity dummy equals one. Red ones indicate months in which the Chinese excess liquidity dummy equals one. The return scales differ across these two panels because stablecoins have much lower return volatility than traditional cryptocurrencies.

Table A1
Variable definitions

Symbol	Variable name	Definition	Data source
Dependent variable			
Return	Cryptocurrency return	Percentage changes in daily open prices of traditional cryptocurrencies and stablecoins aggregated monthly.	CoinMarketCap www.coinmarketcap.com
Independent variables			
EL^{US}	U.S. excess liquidity	A dummy variable capturing excess liquidity in the U.S. economy. The value equals 1 if the residual obtained from Taylor-rule exceeds 0.5 times its standard deviation; otherwise, 0. Alternatively, excess liquidity is derived from the Hodrick-Prescott (HP) filter.	Federal Reserve Economic Data (FRED)
EL^{CN}	Chinese excess liquidity	A dummy variable capturing excess liquidity in the Chinese economy. The value equals 1 if the residual obtained from Taylor-rule exceeds 0.5 times its standard deviation; otherwise, 0. Alternatively, excess liquidity is derived from the Hodrick-Prescott (HP) filter.	Federal Reserve Economic Data (FRED); National Bureau of Statistics of China
EPU^{US}	U.S. economic policy uncertainty	A dummy variable capturing the economic policy uncertainty monthly index of the United States. The value equals 1 if the current EPU index is higher than its previous month's value; otherwise, 0.	Economic Policy Uncertainty www.policyuncertainty.com
EPU^{CN}	Chinese economic policy uncertainty	A dummy variable capturing the economic policy uncertainty monthly index of China. The value equals 1 if the current EPU index is higher than its previous month's value; otherwise, 0.	Economic Policy Uncertainty www.policyuncertainty.com
Control variables			
$ER^{USD/CNY}$	USD/CNY exchange rate	Daily data of the bilateral exchange rate between the U.S. dollar and Chinese yuan aggregated monthly.	Federal Reserve Economic Data (FRED)
MP^{US}	U.S. monetary policy	Federal funds rate - benchmark overnight interest rate in the U.S. (monthly rate)	Federal Reserve Economic Data (FRED)
MP^{CN}	Chinese monetary policy	Shanghai interbank offered rate–benchmark overnight interest rate in China (daily rate aggregated monthly)	Chinese National Interbank Funding Center www.chinamoney.com.cn
Gold	Gold price	Market price per ounce of gold (daily price aggregated monthly)	Federal Reserve Economic Data (FRED)
Oil	Oil price	Price per barrel of West Texas Intermediate crude oil (daily price aggregated monthly)	Federal Reserve Economic Data (FRED)
SP500	S&P 500 index	S&P 500 index – benchmark U.S. equity market index (daily values aggregated monthly)	Federal Reserve Economic Data (FRED)
SHI	Shanghai index	Shanghai Composite Index–benchmark Chinese equity market index (daily values aggregated monthly)	Bloomberg Database

This table presents the definitions and data sources for all variables included in the main regression models, covering the period from January 2019 to December 2024. The dependent variable is the cryptocurrency return of the top five traditional coins (Bitcoin, Ethereum, XRP, Binance Coin, Solana) and the top five stablecoins (Tether, USD Coin, DAI, TrueUSD, Stasis EURO). The main independent variables are excess liquidity and EPU in the U.S. and China, including their interaction terms as specified in the model. Control variables consist of the USD/CNY exchange rate, U.S. and Chinese monetary policy rates, gold price, oil price, S&P 500 index, and Shanghai Composite index. Data were primarily sourced from CoinMarketCap, FRED, Economic Policy Uncertainty, Bloomberg, and the Chinese national interbank funding center. These variables are selected to ensure consistent measurement of macro-financial conditions across both the U.S. and China in relation to cryptocurrency returns.

Table A2
Coefficient-implied twelve-month growth of one dollar under liquidity and EPU regimes

Panel A. U.S. excess liquidity and EPU regimes

U.S. excess liquidity	U.S. EPU	Coefficient-implied monthly return	12-month growth of $1
Absent	Non-Increasing	3.890%	$1.581
Absent	Increasing	3.890%	$1.581
Present	Non-Increasing	3.890 + 12.100 = 15.990%	$5.930
Present	Increasing	3.890 + 12.100 – 6.505 = 9.485%	$2.967

Panel B. Chinese excess liquidity and EPU regimes

Chinese excess liquidity	Chinese EPU	Coefficient-implied monthly return	12-month growth of $1
Absent	Non-Increasing	3.890%	$1.581
Absent	Increasing	3.890%	$1.581
Present	Non-Increasing	3.890 + 9.330 = 13.220%	$4.437
Present	Increasing	3.890 + 9.330 – 13.790 = -0.570%	$0.934

This table reports a coefficient-implied growth-of-one-dollar counterfactual based on the baseline Taylor-rule estimates for U.S. excess liquidity in Table 1. The benchmark monthly return is the unconditional sample mean return of 3.89% reported in Table 2. In the counterfactual calculation, the liquidity and EPU indicators are switched on and off, while the remaining covariates and fixed effects are held constant at their baseline/reference values. The implied monthly returns are then compounded over a standardized 12-month horizon to express the economic magnitude of the estimated effects. The value of one dollar is computed as $(1 + \bar{r})^{12}$, where $\bar{r}$ is the conditional average monthly return expressed in decimal form. When U.S. excess liquidity is absent, the coefficient-implied monthly return remains 3.89% regardless of the EPU regime because EPU enters the baseline specification through its interaction with excess liquidity rather than as a separate direct effect. When U.S. excess liquidity is present and EPU is not increasing, the implied monthly return is 15.99%, which compounds one dollar to approximately $5.93 over 12 months. When both U.S. excess liquidity and rising U.S. EPU are present, the implied monthly return is 9.485%, which compounds one dollar to approximately $2.97. The difference between $5.93 and $2.97 shows that rising U.S. EPU substantially weakens but does not fully eliminate, the liquidity-driven compounding effect.

This table reports a coefficient-implied growth-of-one-dollar counterfactual based on the baseline Taylor-rule estimates for Chinese excess liquidity in Table 1. The benchmark monthly return is the unconditional sample mean return of 3.89% reported in Table 2. In the counterfactual calculation, the liquidity and EPU indicators are switched on and off, while the remaining covariates and fixed effects are held constant at their baseline/reference values. The implied monthly returns are then compounded over a standardized 12-month horizon to express the economic magnitude of the estimated effects. The value of one dollar is computed as $(1 + \bar{r})^{12}$, where $\bar{r}$ is the conditional average monthly return expressed in decimal form. When Chinese excess liquidity is absent, the coefficient-implied monthly return remains 3.89% regardless of the EPU regime because EPU enters the baseline specification through its interaction with excess liquidity rather than as a separate direct effect. When Chinese excess liquidity is present and Chinese EPU is not increasing, the implied monthly return is 13.22%, which compounds one dollar to approximately $4.44 over 12 months. When both Chinese excess liquidity and rising Chinese EPU are present, the implied monthly return is −0.57%, which reduces one dollar to approximately $0.93 over 12 months. This contrast shows that rising Chinese EPU more than offsets the positive coefficient-implied effect of Chinese excess liquidity.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jfs.2026.101587.

Data availability

Data will be made available on request.

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