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Research

Uncertainty shocks and trading intensity of cryptocurrencies

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Abstract

This paper examines the relationship between economic policy uncertainty (EPU) and trading activity in cryptocurrency markets, focusing on Bitcoin (BTC), Ether (ETH), and Ripple (XRP) over the period 2016–2025 **AQ1** . Unlike most of the literature, which emphasizes prices and returns, we adopt a behavioural perspective by using trading volumes as a proxy for market participation. The empirical analysis relies on lag-augmented local projections (LP) to estimate the dynamic effects of persistent uncertainty shocks, using both the Global Economic Policy Uncertainty (GEPU) index and the European News-Based Uncertainty Index (ENBI). The results show a positive and statistically significant relationship between uncertainty and crypto trading volumes, particularly when accounting for structural breaks. In the period before the Market in Crypto Asset (MiCA) regulation has been adopted, a one standard deviation increase in uncertainty leads to substantial increases in trading activity across cryptocurrencies, with especially strong effects for Ripple. Additional evidence based on returns suggests that this pattern reflects speculative behaviour rather than panic-driven selling **AQ2** . The findings contrast with traditional financial markets and indicate that economic policy uncertainty acts as a catalyst for trading intensity in cryptocurrency markets.

Keywords

Cryptocurrency
Economic policy uncertainty
Financial stability
Lag model

JEL Classification

C22
E6
G18
O38

1. Introduction

Economic policy uncertainty (EPU) refers to the uncertainty surrounding governmental policies and their potential implications for the economy, especially financial markets (Pástor & Veronesi, 2012). It encompasses a broad range of issues, including fiscal policy, monetary policy, geopolitical and pandemic risks (Al-Thaqeb & Algharabali, 2019). Economic policy uncertainty is a critical factor that exacerbates risk across financial markets and the broader economy, influencing decision-making and stability. In the global financial system, digital finance has grown rapidly, and the decentralized segment (DeFi) represents a significant share of this market. DeFi is characterized by risks connected to the technology (e.g., the cyber risk) and to the absence of regulation, monitoring, and supervision.

The digital financial system was hit by the bankruptcy of large intermediaries in 2022 and 2023; these crashes impacted financial markets as a whole and their stability, given the interconnectedness among financial operators, traditional and digital. Following these crashes and given the potential to disrupt market equilibrium, it is crucial for investors and policymakers to understand the impact of persistent uncertainty shocks on digital financial markets. To fill this gap, this paper investigates whether uncertainty increases speculative trading intensity in crypto markets at the global level. We focus on trading intensity of cryptocurrencies as a behavioural measure of market participation under uncertainty over the period 2016–2025.

We look at the most recent evolution of digital financial markets, where the most popular and fastest-growing digital financial asset class is that of cryptocurrencies; its market capitalization exceeded $4 trillion in 2025 according to Binance. The cryptocurrency market is young, if compared with traditional financial segments, and trades take place in decentralized ledgers (i.e., blockchains) that can be accessed by digital investors. Blockchains developed to guarantee the privacy of data on the internet and the digital freedom of individuals, in the absence of any state control (Hughes, 1993). Decentralized trading systems guarantee anonymity of trades and security via encryption (Allen & Bambara, 2018). This also constitutes a perverse incentive for speculators and even criminals in the digital sphere (Dyson et al., 2018; Magnuson, 2020). To overcome the technological barrier of blockchains (i.e., encryption), digital financial intermediaries developed in most geographical areas, attracting also unsophisticated investors. These special intermediaries do not comply with the regulation and controls of traditional financial ones, and their disclosure of information is very limited. In most jurisdictions, institutional investors face certain limits when investing in the digital financial system because it is not supervised and monitored; the gradual increase in regulatory clarity will probably ease their access.

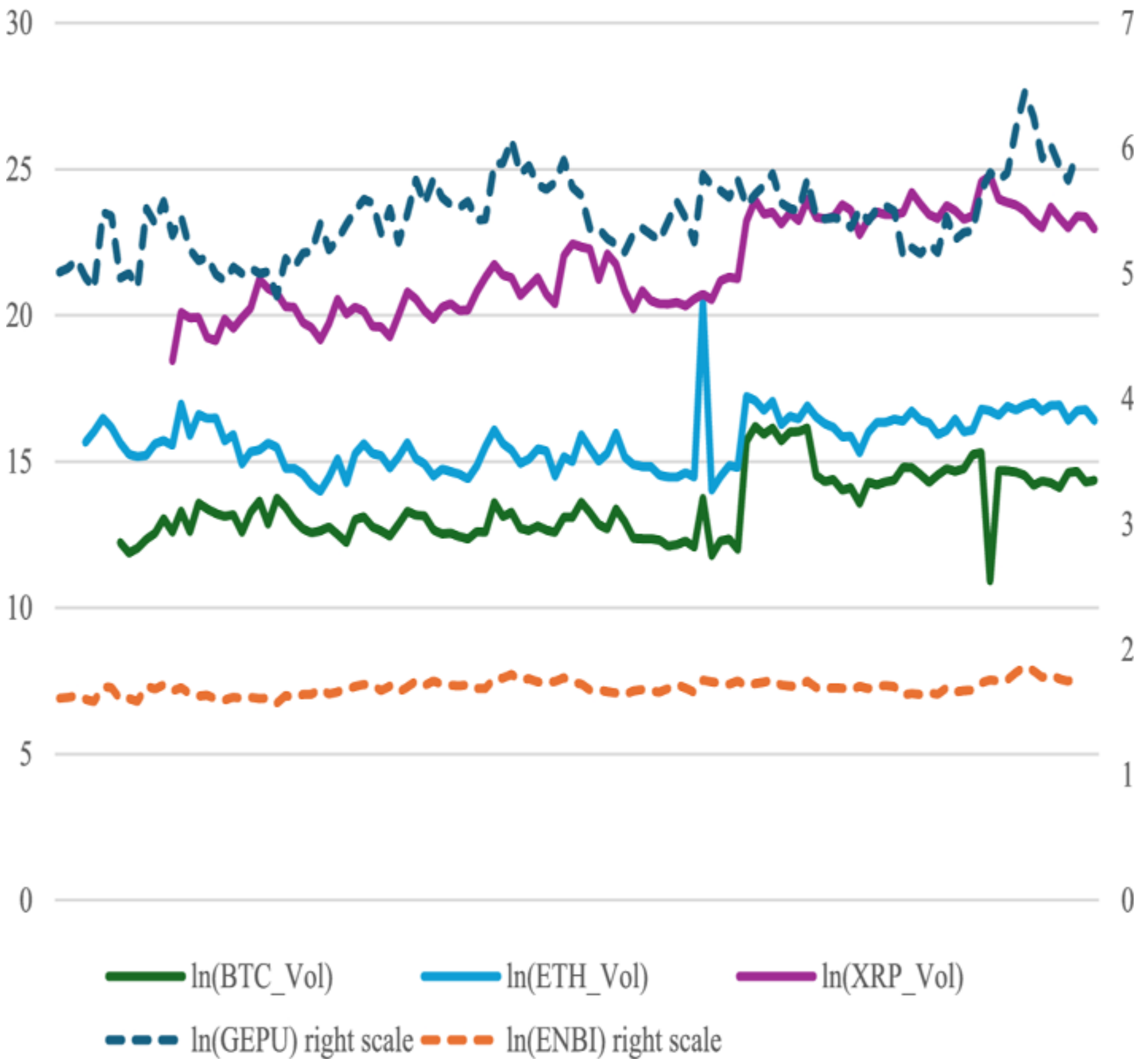
Retail investors constitute a significant portion of digital asset holders; these individuals range from early adopters of cryptocurrencies to those seeking portfolio diversification or speculative gains. According to the literature (Hackethal et al., 2022), the main characteristics of retail investors are the young age, typically within 18–34, with growing participation from older cohorts, and the motivations, i.e., interest in decentralization, financial inclusion, or the pursuit of high returns. Investors with risk-loving preferences are more likely to invest in the digital financial system (Hayashi & Routh, 2025). Risk-seeking individuals are also more likely to accept cryptocurrency as a means of payment (Sridharan et al., 2023), but the digital asset investors' base is broad and continually evolving, reflecting the diverse applications and appeal of the blockchain technology across global financial ecosystems.

Given the absence of geographical roots of digital systems, the paper investigates the relationship between economic policy uncertainty (EPU) shocks and the global trades of the most capitalized cryptocurrencies (Bitcoin, Ether, and Ripple) over the period 2016–2025 by using a robust method of estimation and inference: the lag-augmented local projections (LP). This econometric method provides reliable results in small samples, is robust to dynamic misspecification and does not need any delta method for cumulative multipliers; therefore it provides superior results if compared with GARCH, VAR/BVAR methods used in the literature. The volume of trades of cryptocurrencies has steadily increased over the period under observation, with Ripple taking the lead, followed by Ether and Bitcoin. The use of volumes instead of prices (or returns) allows us to capture the market depth and the investor behaviour.

The period under analysis (2016–2025) is relevant because it encompasses the development of cryptocurrencies from the beginning of their trades. The period includes significant shocks that hit the global economy, like the pandemic crisis of 2020, and the Russian invasion of Ukraine in February 2022. In 2022, there has been the crash of Terra-Luna stablecoins and of large digital intermediaries, like FTX, with significant effects on economic policy uncertainty (Fig. 1). The regulatory approach towards cryptocurrencies and digital assets has evolved during the last two years; in 2024, the European Union introduced the Market in Crypto Asset Regulation (MiCA, 2023) on issuers of digital assets to enhance transparency, improve disclosure and supervise their transactions, following the Financial Stability Board recommendations (Financial Stability Board, 2023). On the contrary, after 2025, the US Congress adopted a very relaxed approach towards digital trades and regulated only stablecoins (Genius Act, 2025).

Fig. 1

Economic Policy Uncertainty indices and crypto volumes, 2016–2025, monthly



The next sections review the literature and set the research question; describe the method employed to analyze the relationship between crypto volumes and EPU indices; present the data; discuss the econometric results; and provide policy implications and conclusions.

2. Literature review

Economic policy uncertainty can drive risk in various ways: by increasing market volatility, investments' and credit risks. While investments and credit risks can adjust with a certain delay to EPU shocks, financial markets react instantly, making them a suitable area to investigate the effects of shocks and reactions. The literature investigated how economic policy uncertainty (EPU) impacted traditional financial markets (Al-Thaqeb & Algharabali, 2019). Policy changes make stock returns more volatile (Pástor & Veronesi, 2012), and economic policy uncertainty (EPU) can predict future stock market volatility (Liu & Zhang, 2015). Following the literature, the fundamental relationship between economic policy uncertainty and financial markets can be represented as follows: **AQ3**

$$f_t = \sum_{s=1}^{p} \gamma_s f_{t-s} + \sum_{s=0}^{q} \beta_s EPU_{t-s} + \lambda' w_t + \varepsilon_t \tag{1}$$

where *f* is the financial asset price (or return), *EPU* is the economic policy uncertainty index, and *w* is a vector of control variables. Economic policy uncertainty can be measured by two different indices, both widely used in economic research. The first is the Global Economic Policy Uncertainty (GEPU) index, computed by the US Federal Reserve Bank; it is a GDP-weighted average of national Economic Policy Uncertainty (EPU) indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. The other EPU index is the European News-Based Uncertainty Index (ENBI), a news-based index of uncertainty computed from news related to policy-related economic uncertainty (Baker et al., 2016).

The literature showed evidence of a negative relationship in Eq. 1, i.e., when uncertainty increases, investors sell risky assets, exhibiting higher volatility, and prefer safer securities; this means that the coefficient β should be negative (Al-Thaqeb & Algharabali, 2019). A rising global political uncertainty leads to a reduction in equity returns in fifty non-U.S. countries (Brogaard et al., 2020) and an increase in households' savings (Xu, 2023).

The impact of economic policy uncertainty shocks can be viewed with respect to market volatility and investment behavior. The investment behavior is influenced by subjective preferences and cognitive factors, especially when risky payments are involved (Dominiak & Duersch, 2024). The characteristics of investors in the crypto markets are difficult to map because of the blockchain encryption and anonymity of trades. The literature has analyzed the characteristics of crypto investors; there is evidence that the crypto market is populated by irrational investors who base their investment decisions on market sentiment (Almeida & Gonçalves, 2023; Ben Osman et al., 2025). The representative crypto investor is mainly male, born between 1989 and 2000, interested in information technology, has a mid-to-low degree of financial literacy, and looks for high risk and high returns in his or her investment decisions (Auer & Tercero-Lucas, 2022; Hackethal et al., 2022; Hayashi & Routh, 2025; Xi et al., 2020).

The risk preference of investors cannot be directly observed, and some authors inferred the risk preferences from market data (Fong, 2013). Barber and Odean (2001) observed that investors, having access to a relevant amount of information, can suffer of illusion of knowledge and become overconfident in their trading choices. This bias can lead to speculative trading and bubbles, also in the digital financial system. Information can be processes by investors in different ways, leading to opposite investments choices following the same news. The different opinion of investors can reflect on prices (and returns) volatility, and volumes of trade (Harris & Raviv, 1993). Distortions can be due to risk seeking behavior and /or limited rationality of investors. Risk seeking investor react to the same information in different ways, and look for an uncertainty premium (G. Liu & Sun, 2016).

The literature also confirmed that growing uncertainty encourages a flight to safety behaviour among investors, leading to increased demand for low-risk assets, such as government bonds, and a reduction in investment in riskier assets. There is a significantly negative relationship between stock returns and EPU indices over the period 1900–2014 in the U.S. (Arouri et al., 2016). The literature considered the relationship between EPU indices and returns of financial assets and with the growth rates of relevant assets in the economy (e.g., bank credit) (Bordo et al., 2016). The EPU index of China can predict the Bitcoin monthly returns (Cheng & Yen, 2020), but the Bitcoin cannot serve as a strong hedge or safe-haven for economic policy uncertainty (Wu et al., 2019). We want to contribute to this literature, and specifically look at the relationship between crypto market (BTC, ETH and XRP) and EPU over a long period of time (2016–2025) that includes crises and witnesses the maturity of cryptos.

The financial economic literature recently paid attention to cryptocurrencies. Prices of cryptocurrencies traded on decentralized ledger (i.e., blockchains) are not free to adjust, following market's pressures, because the algorithm of the respective blockchain sets the supply of digital tokens (Allen & Bambara, 2018; Parkin, 2019). The most traded cryptocurrencies are Bitcoin (BTC), Ether (ETH) and Ripple (XRP). The Bitcoin (BTC) has a hard-cap of 21 million tokens that can be mined, with roughly 20 million already mined in 2026 and a few million lost due to hacking of wallets. The mining process of BTC is quite slow, if compared with that of ETH and XRP. Scarcity is a relevant characteristics of BTC and explains its growing prices. Ether's supply is not hard-capped and dynamically adjusts to market's demand; ETHs are traded on the Ethereum blockchain, that is faster than the Bitcoin. Ripple (XRP) has a predefined supply of 100 billion tokens, with 61billion already in circulation and is traded on a ledger with a consensus algorithm that is faster than the proof of work (BTC) and the proof of stake (ETH) (Allen & Bambara, 2018). XRP is more energy efficient than BTC and ETH and cheaper to trade.

Given the distinctive structural and institutional features of the cryptocurrency market, this paper focuses on the impact of persistent uncertainty shocks on trading volumes rather than on prices or returns. This choice is motivated by the view that, in the crypto-asset environment, prices may not yet fully or efficiently incorporate available information (Fantini et al., 2025; Tran & Leirvik, 2020; Urquhart, 2016). Consequently, volumes may provide a more informative and immediate measure of market participants' reactions to uncertainty.

The cryptocurrency market differs from traditional financial markets along several important dimensions. First, many crypto-assets lack clearly defined fundamental cash flows or intrinsic valuation benchmarks (Jarrow, 2025). Unlike equities, which can be valued through discounted cash flow models, or bonds, which promise contractual payments, cryptocurrencies often derive their value from network adoption, technological expectations, or speculative narratives. This absence of well-established valuation anchors complicates the process through which information is translated into prices. As a result, price dynamics may be driven as much by sentiment, coordination beliefs, and speculative demand as by fundamentals.

Second, the market microstructure of crypto trading platforms remains fragmented and relatively less regulated compared to traditional exchanges. Heterogeneous investor bases—ranging from retail traders to algorithmic participants—interact across multiple venues with varying levels of transparency and liquidity. In such an environment, informational frictions and limits to arbitrage may prevent prices from adjusting efficiently to new information. Persistent uncertainty shocks, whether related to macroeconomic conditions, regulatory developments, or technological risks, may therefore not be immediately or accurately reflected in price levels or returns.

From a theoretical perspective, if markets are not fully efficient in the semi-strong sense, prices may underreact, overreact, or adjust only gradually to publicly available information. In contrast, trading volume can respond more directly to shifts in beliefs, disagreement, and risk perception. Models of heterogeneous beliefs (Harris & Raviv, 1993) suggest that increases in uncertainty amplify differences of opinion among investors, leading to higher trading activity even in the absence of clear directional price changes. Similarly, in the presence of risk-seeking behaviour or bounded rationality, uncertainty may stimulate speculative trading as investors attempt to exploit perceived opportunities, further increasing volumes.

By concentrating on persistent uncertainty shocks rather than transitory fluctuations, the analysis aims to capture structural shifts in the informational and risk environment of the crypto market. Persistent shocks may alter investors' expectations, risk tolerance, and portfolio rebalancing strategies over a longer horizon, generating sustained effects on market participation and liquidity. In this framework, trading volume becomes a proxy for the intensity of belief updating, disagreement, and speculative engagement.

Therefore, the decision to abstract from prices (or returns) reflects both methodological and conceptual considerations.

Methodologically, volumes may exhibit more robust and interpretable responses to uncertainty in markets characterized by high volatility and weak valuation anchors. Conceptually, if crypto-asset prices are not yet fully efficient or informationally complete, focusing on returns may obscure the underlying behavioural and informational mechanisms at play. By examining volumes instead, the paper seeks to shed light on how persistent uncertainty reshapes trading behaviour and market dynamics in an evolving and structurally distinct financial ecosystem.

We want to investigate whether uncertainty increases speculative trading intensity in crypto markets. In particular, are crypto investors more likely to increase their trading of cryptos, following a shock?

Based on characteristics of the crypto market, we want to test the following research hypothesis:

H1: There is a statistically significant relationship between economic policy uncertainty (EPU) shocks and crypto volumes.

We investigate the crypto-uncertainty relationship with the lag-augmented local projections (LP) (Jordà, 2005; Montiel Olea & Plagborg-Møller, 2021), which has gained popularity recently as a simple, intuitive, and robust econometric method to estimate impulse response functions and dynamic multipliers (DMs) in small samples, like in this case. The robustness of this method can provide researchers with reliable results; in fact, the previous literature gave contrasting evidence. The findings of the Auto Regressive Distributed Lag (ARDL) literature showed a positive relationship between EPU and cryptocurrency returns (Cheng & Yen, 2020); Oldani et al., 2024). Others find that Bitcoin volatility is negatively related to U.S. economic policy uncertainty using the VIX and the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)-based framework (Bouri et al., 2017). The findings of the Bayesian Vector Auto Regressive (BVAR) literature show that uncertainty shocks in the US economic policies are associated with a decrease in volatility in the Bitcoin markets (Matkovskyy et al., 2020). We contribute to this literature and apply the lag-augmented local projections (LP) method of estimates; following the previous literature and as a robustness check, we have also implemented the ARDL models.

3. Method

Bitcoin (BTC), Ether (ETH) and Ripple (XRP) are the most capitalized and popular cryptos AQ4 . The relationship between the Economic Policy Uncertainty (*EPU*) index and volumes of trades (*y*) of cryptocurrencies can be described as follows:

$$y_t = \sum_{s=1}^{p} \gamma_s y_{t-s} + \sum_{s=0}^{q} \beta_s EPU_{t-s} + \varepsilon_t \qquad (2)$$

where *y* denotes the (log of) traded volumes of cryptocurrencies and *EPU* stands for the uncertainty measure of choice (as described in the following paragraph). To test the research hypothesis, we use as regression coefficients lag-augmented local-projection (LP) estimates of dynamic multipliers (DMs); differently from vector autoregressive (VAR) or autoregressive distributed lag (ARDL) models, the standard errors do not necessitate delta-method approximations to be computed. This merit of local-projection DMs carries over to cumulative DMs (CDMs), as these are the sum of the DMs over the time horizon of choice. In addition, lag augmentation accommodates autocorrelation in errors in the local approximation regressions, so that robust standard errors would require just a plain heteroscedasticity correction (Montiel Olea & Plagborg-Møller, 2021), permitting the dispensing with heteroscedasticity autocorrelation consistent (HAC) standard errors, which prove to be rather inaccurate in small samples. Finally, DMs and CDMs are identified by local projections, even if the outcome variables are non-stationary.

For each cryptocurrency *y*, namely Bitcoin (BTC), Ether (ETH) and Ripple (XRP), and economic policy index, ENBI and GEPU, we estimate LPs augmented with 11 lags of the log-volume, beyond y_{t-1}, and 11 lags of EPU, beyond its current value EPU_t, across three maximum time horizons that are H = *4, 8, and 12* months. Each LP also accommodates a set of exogenous controls c_t containing the constant term, 11-month dummies, 7 event dummies and linear and quadratic trends. Event dummies are related to the Covid pandemic (from March 2020 to January 2023), the Ukraine invasion (February 2022), the Terra-Luna stablecoin crash (May 2022), the FTX crisis (November 2022), the change in the European regulatory approach on digital assets (more rigid) (January 2024), the change in the US regulatory approach on cryptos (very relaxed) (January 2025) and the Genius Act in the US (July 2025).

In practice, this boils down to estimating for each H = 4, 8, 12, the seemingly unrelated regression estimator (SURE) based on the system of *H* equations:

$$y_{t+h-1} = X_t' \beta_{h-1}^H + \epsilon_{h-1,t} \qquad (3)$$

$$h = 1 \ldots H, X_t' = (EPU_t \ldots EPU_{t-11}\ y_{t-1} \ldots y_{t-12}\ c_t'), t = 13, \ldots T - H + 1.$$

The control vector c_t from the baseline specification is included in each horizon-specific regression. As a robustness check, it is expanded to include lagged returns, defined as log differences of prices, to control for recent price dynamic. A second robustness check replaces the linear and quadratic trend components in c_t with low-frequency Fourier terms ($k = 1$). Finally, a more parsimonious selection of lags ($EPU_t \ldots EPU_{t-7}\ y_{t-1} \ldots y_{t-8}$) will be considered in a small subsample, as indicated in the robustness-check section.

So, each SURE system yields H = *4, 8, 12* coefficient estimates on EPU_t : DM_0^H, … DM_{H-1}^H. We focus on their sum, CDM^H, measuring the total change in the crypto log-volume after *H-1* months following a persistent one-standard deviation shock to the uncertainty index:

$$CDM^H = \sum_{h=0}^{H-1} DM_h^H, H = 4, 8, 12 \qquad (4)$$

Notice that the SURE approach (implemented through the Stata command), over independent estimation of the *H* equations in (3), permits a common sample and a common covariance matrix for the DMs and so a proper evaluation of the CDM^H standard error, along with the construction of cross-equation restriction tests.

Given evidence of potential regime changes over the sample period, we assess parameter stability by allowing for differential responses across regimes and then testing homogeneity of the differential cumulated responses. Specifically, let E denote an event with known initial and final dates, and $I_E(t)$ denote the corresponding indicator function so that

$$I_E(t) = 1 \; if \; t \in E$$

and

$$I_E(t) = 0 \; if \; t \notin E$$

The stability test is implemented by replacing EPU_t in X_t of Eq. (3) with the two interaction variables $EPU_{E,t} \equiv I_E(t) \times EPU_t$ and $EPU_{\overline{E},t} \equiv [1 - I_E(t)] \times EPU_t$ where $\overline{E}$ denotes the event complementary to E. With this modification each SURE system H produces DMs that are differentiated between E and $\overline{E}$ with the resulting differentiated CDMs: $CDM_E^H = \sum_{h=0}^{H-1} DM_{E,h}^H$ and $CDM_{\overline{E}}^H = \sum_{h=0}^{H-1} DM_{\overline{E},h}^H$. Given our focus on CDMs, we construct the stability test as an F-test on linear restrictions for the null hypothesis that CDMs are equal across regimes at each horizon, i.e. H_0: $CDM_E^H = CDM_{\overline{E}}^H$. Rejection of the null hypothesis indicates that the cumulative response to uncertainty shocks differs across regimes.

Following the previous literature and as a further robustness check, an autoregressive distributed lag (ARDL) (12,11) model is estimated. The ARDL model can be defined as follows:

$$y_t = X_t' \beta + \epsilon_t, t = 13, \ldots, T \tag{5}$$

with X_t' defined as in Eq. (3). For comparability with the LP framework, we focus on CDMs rather than on the lagged coefficients themselves.

4. Data and results

4.1. Data

The empirical analysis considers the three most capitalized cryptos: Bitcoin (BTC), Ether (ETH) and Ripple (XRP); monthly data come from Investing.com (Fig. 1) and volumes refer to the number of contracts, not USD equivalent value. Global Economic Policy Uncertainty index (GEPU) data come from the US Federal Reserve Bank; data on the European News-Based Uncertainty Index (ENBI) come from Baker et al., (2016). The period under analysis goes from 4/2016 to 12/2025 (Fig. 1). The use of monthly data is conditioned on the availability of economic uncertainty indices (GEPU and ENBI), but also smooths the econometric concerns related to the excessive volatility of daily and weekly financial data. The mean value and the standard deviation of EPUs are similar in the two indices. The volume of BTC trading is conditioned by the slow speed of transactions, and the trades of ETH are ten times bigger than those of BTC (Table 1). XRP has a very fast and technologically efficient trading system; its volumes of trades are thousands of times larger than those of ETH and BTC.

Table 1

Descriptive statistics, monthly data (up to December 2025)

Series Name	Start date	Mean	SD
Global Economic Policy Uncertainty Index (GEPU)	JAN 2016	245.26	82.35
European News Based Index (ENBI)	JAN 2016	286.61	105.28
Bitcoin (BTC) volume	AUG 2016	1,460,018.32	2,262,744.60
Ether (ETH) volume	APR 2016	15,173,418.80	69,449,481.41
Ripple (XRP) volume	FEB 2017	7,626,465,794.39	10,076,768,946.09
Bitcoin (BTC) returns	SEPT 2016	0.045	0.201
Ether (ETH) returns	MAY 2016	0.051	0.299
Ripple (XRP) returns	MAR 2017	0.049	0.423
Returns are first-differenced natural-log-prices: R~~t~~$_t$ = ln(p~~t~~$_t$)-ln(p~~t − 1~~$_{t-1}$)			

4.2. Results

The natural logarithms of volumes for BTC, ETH, and XRP and two alternative measures of global uncertainty, GEPU and ENBI, are both treated as exogenous variables in the LP specifications. EPU indices, GEPU and ENBI, are standardized to ease the interpretation of results. According to results reported in Table 2, we find that the CDMs estimates are always positive and statistically significant for XRP. Following a persistent 1 standard deviation increase of uncertainty measured by ENBI the trading of XRP grows of 60.9% after 4 months. BTC and ETH shows limited or statistically insignificant response to EPU shocks at most horizons. According to our results, when uncertainty increases persistently, the trading volumes of XRP increases as well, while BTC and ETH do not seem to be affected.

Table 2

Cumulative dynamic multipliers – ~~fullsample~~full sample ~~Local~~ local projections estimates

Crypto	EPU	H = 4	H = 8	H = 12

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	– 0.5436	− 0.599	− 0.365
		(0.475)	(0.610)	(0.714)
	ENBI	− 0.619	− 0.375	0.830
		(0.533)	(0.617)	(0.804)
ETH	GEPU	0.216	0.091	0.544
		(0.183)	(0.274)	(0.491)
	ENBI	0.137	0.169	0.518
		(0.242)	(0.327)	(0.580)
XRP	GEPU	0.295	0.228	1.002
		(0.272)	(0.500)	(0.866)
	ENBI	0.609**	1.151**	2.263**
		(0.258)	(0.514)	(1.060)

Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t−1~~$_{t-1}$−y~~t−12~~$_{t-12}$, EPU~~t~~$_{t}$−EPU~~t−11~~$_{t-11}$

The many insignificant CDM values in Table 2 raise concerns about parameter instability over the full sample period, given the occurrence of major shocks, such as the pandemic crisis and the 2022 crash of digital intermediaries. To formally assess, this issue, we implement the stability test described above around the FTX breakpoint (November 2022). The results, reported in Table 3, show that parameter constancy is consistently rejected across cryptocurrencies, EPU measures, and horizons. This provides strong evidence of instability in the full sample. Therefore, we focus on a more homogeneous subsample up to December 2023, just before the implementation of the MiCA regulation. Results for this subsample (Table 4) show significantly positive effects across cryptocurrencies, EPU measures, and horizons. Following a pesistent 1 standard deviation increase of uncertainty measured by ENBI, the trading of BTC grows of 113.6% after 8 months. The DMs estimates producing the CDMs in the pre-MiCA subsample of Table 4 are portrayed in Figs 2, 3, 4, 5, 6 and 7. We notice in all cases a positive instantaneous effect, $\boxed{DM_0^H}$, followed by DMs oscillating across predominantly positive values.

Table 3

Volumes—Cumulative dynamic multipliers and stability tests – Full-sample ~~Localprojections~~local projections~~Localprojections~~ estimates on FTX-interacted EPU: EPU*I(t < Nov 2022) and EPU*I(t ≥ Nov 2022)

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU*I <	0.226	0.372	1.221*
		(0.496)	(0.360)	(0.694)
	GEPU* I ≥	− 1.834***	− 2.784***	− 4.687***
		(0.609)	(0.807)	(0.807)
	Stability F-test	9.885***	12.360***	12.360***
	ENBI*I <	0.818	1.863**	3.815***
		(0.662)	(0.724)	(0.690)
	ENBI* I ≥	− 2.313***	− 3.194***	− 4.548***
		(0.609)	(0.635)	(0.808)
	Stability F-test	16.512***	33.322***	65.323***
ETH	GEPU*I <	1.517**	0.924***	1.182**
		(0.216)	(0.297)	(0.481)
	GEPU* I ≥	− 0.099	− 0.740***	− 1.079
		(0.227)	(0.226)	(0.845)
	Stability F-test	4.684**	28.272***	5.997**
	ENBI*I <	1.123***	1.703***	1.805***
		(0.328)	(0.351)	(0.574)
	ENBI* I ≥	− 0.482	− 0.964***	− 1.909***
	Stability F-test	20.332***	88.094***	88.094***
XRP	GEPU*I <	0.736**	1.999***	2.588***
		(0.291)	(0.428)	(0.740)

~~h~~Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t−1~~$_{t-1}$– y~~t−12~~$_{t-12}$, EPU~~t−1~~$_{t-1}$– EPU~~t−11~~$_{t-11}$, EPU~~t~~$_{t}$ interacted with **I** < and **I** ≥

Crypto	EPU	H□=□4	H□=□8	H□=□12
	GEPU* I□≥□	− 0.232	− 2.204***	− 5.424***
		(0.328)	(0.487)	(1.295)
	Stability F-test	7.262***	61.946***	23.253***
	ENBI*I□<□	1.244***	3.535***	5.254***
		(0.409)	(0.667)	(0.819)
	ENBI* I□≥□	0.183	− 0.878*	− 4.382***
		(0.262)	(0.499)	(1.184)
	Stability F-test	5.062**	29.961***	61.687***
~~h~~Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t−1~~$_{t-1}$− y~~t−12~~$_{t-12}$, EPU~~t−1~~$_{t-1}$− EPU~~t−11~~$_{t-11}$, EPU~~t~~$_{t}$ interacted with **I**□<□and **I**□≥□				

Table 4

Volumes—Cumulative dynamic multipliers – pre-MICA subsample (t□<□Gen 2024) Local projections estimates

Crypto	EPU	H□=□4	H□=□8	H□=□12
BTC	GEPU	0.415	1.136	2.207***
		(0.584)	(0.728)	(0.624)
	ENBI	0.562	1.227*	3.909***
		(0.574)	(0.682)	(0.619)
ETH	GEPU	0.583*	0.808**	1.594***
		(0.293)	(0.351)	(0.512)
	ENBI	0.766**	0.977***	1.855***
		(0.319)	(0.351)	(0.624)
XRP	GEPU	0.333	1.585***	2.819***
		(0.317)	(0.347)	(0.618)
	ENBI	1.021**	3.284***	5.253***
		(0.394)	(0.595)	(0.842
Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively				
Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t~~$_{t}$-EPU~~t-11~~$_{t-11}$				

Fig. 2

YYYYYYYYYYYY Local projections of dynamic multipliers of log volumes to ENBI shocks (pre-MiCA, H=4 months)

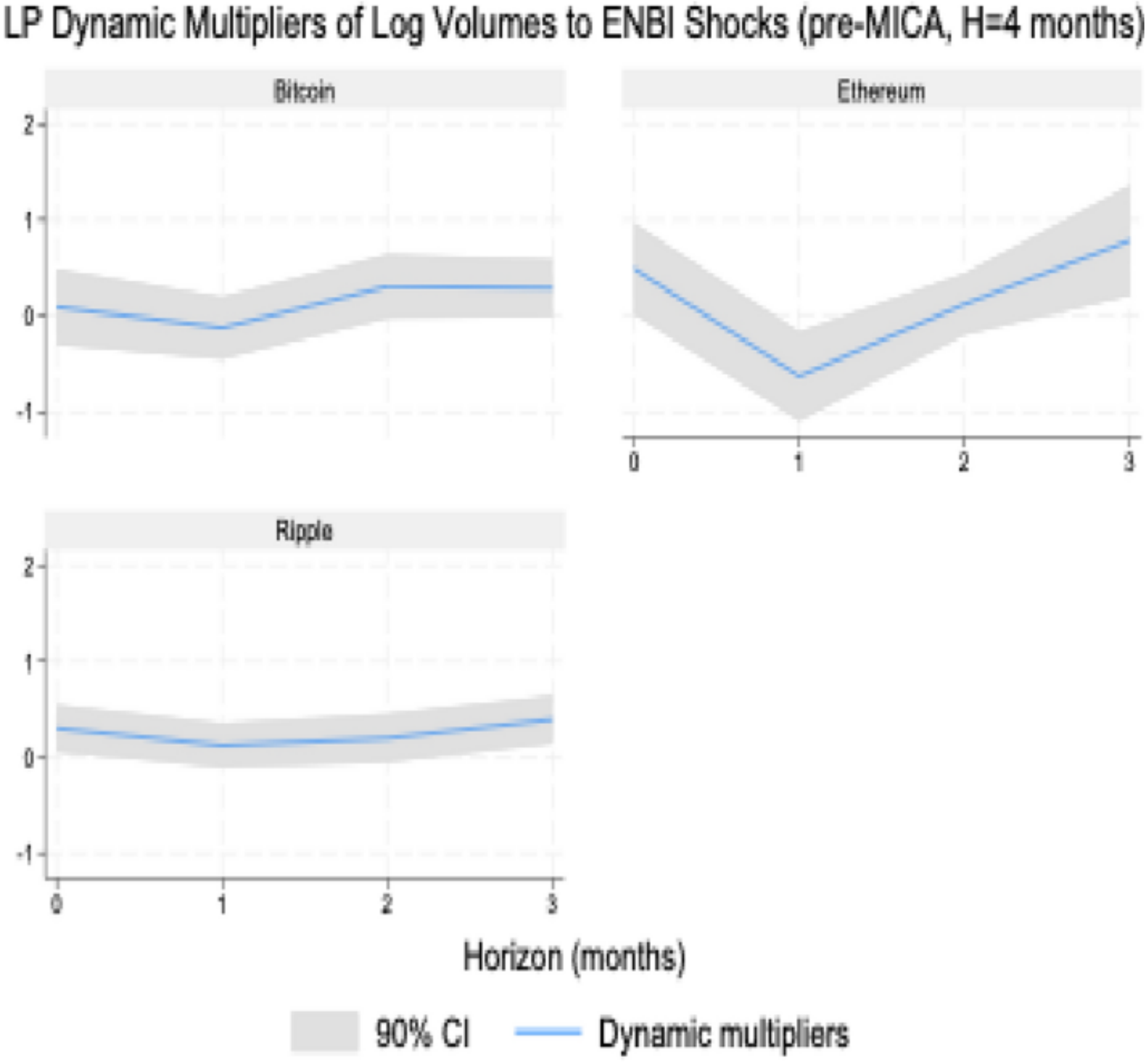


Fig. 3

YYYLocal projections of dynamic multipliers of log volumes to GEPU shocks (pre-MiCA, H=4 months)

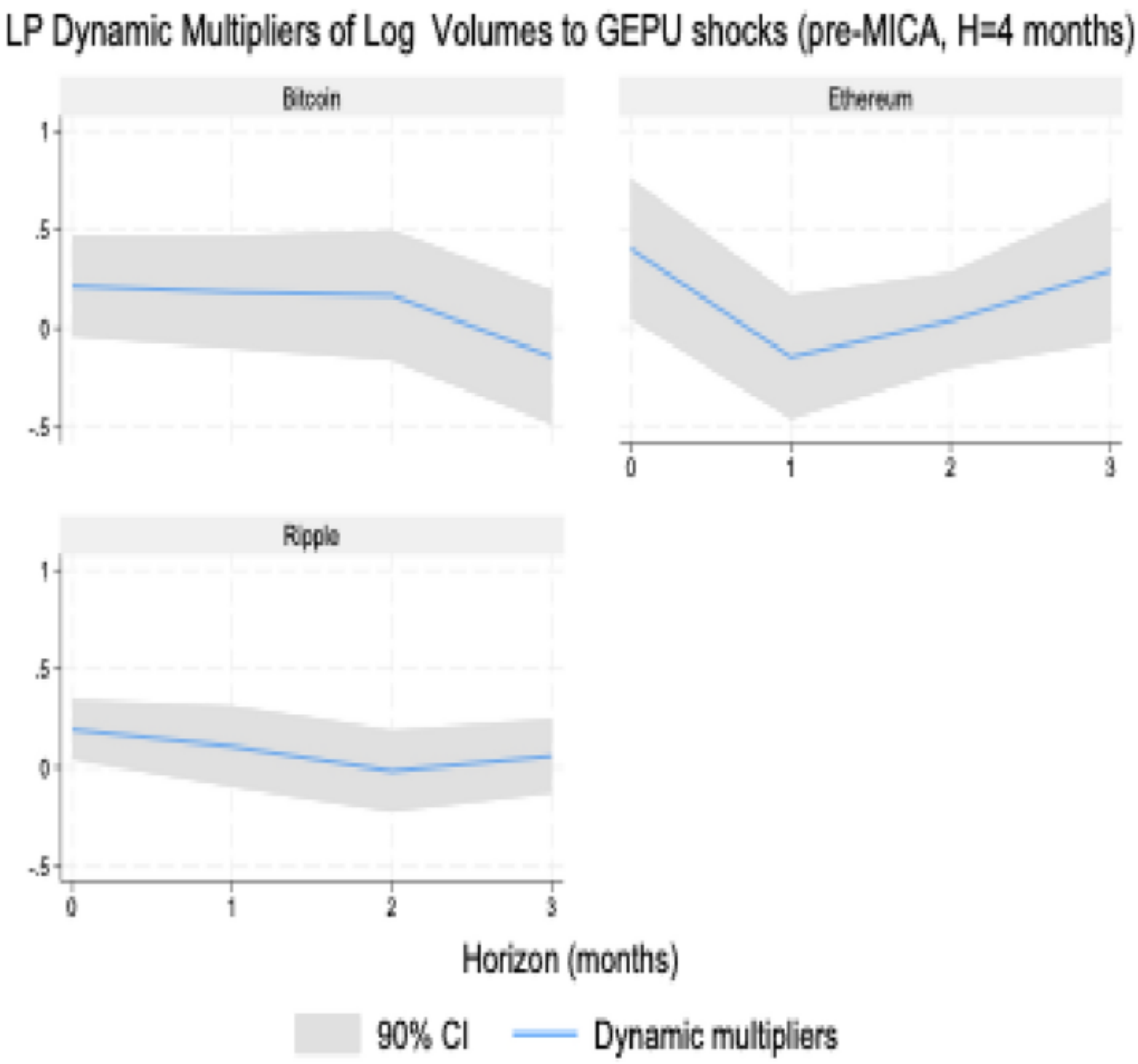


Fig. 4

YYY Local projections of dynamic multipliers of log volumes to ENBI shocks (pre-MiCA, H=8 months)

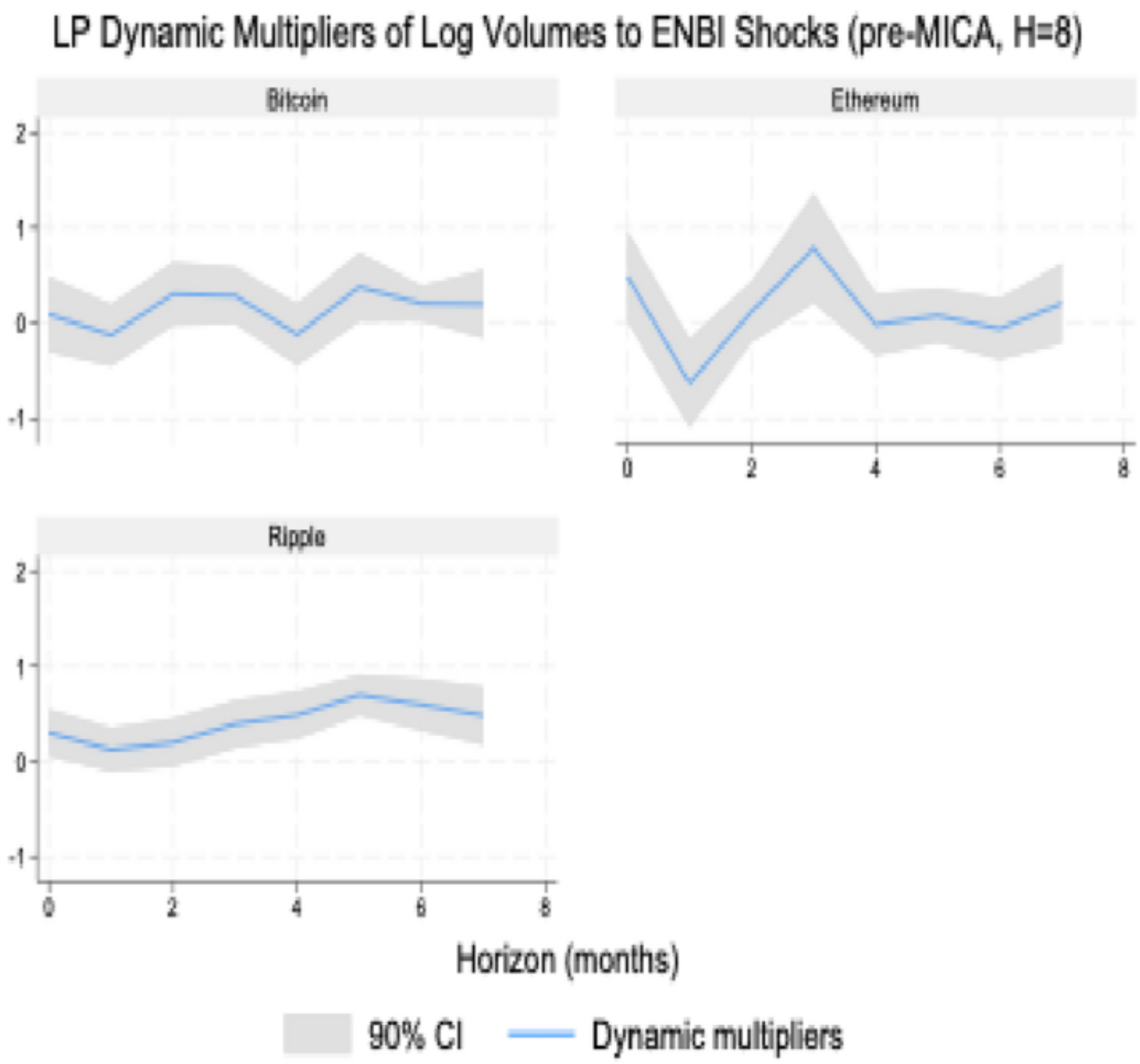


Fig. 5

Local projections of dynamic multipliers of log volumes to GEPU shocks (pre-MiCA, H=8 months) YYY

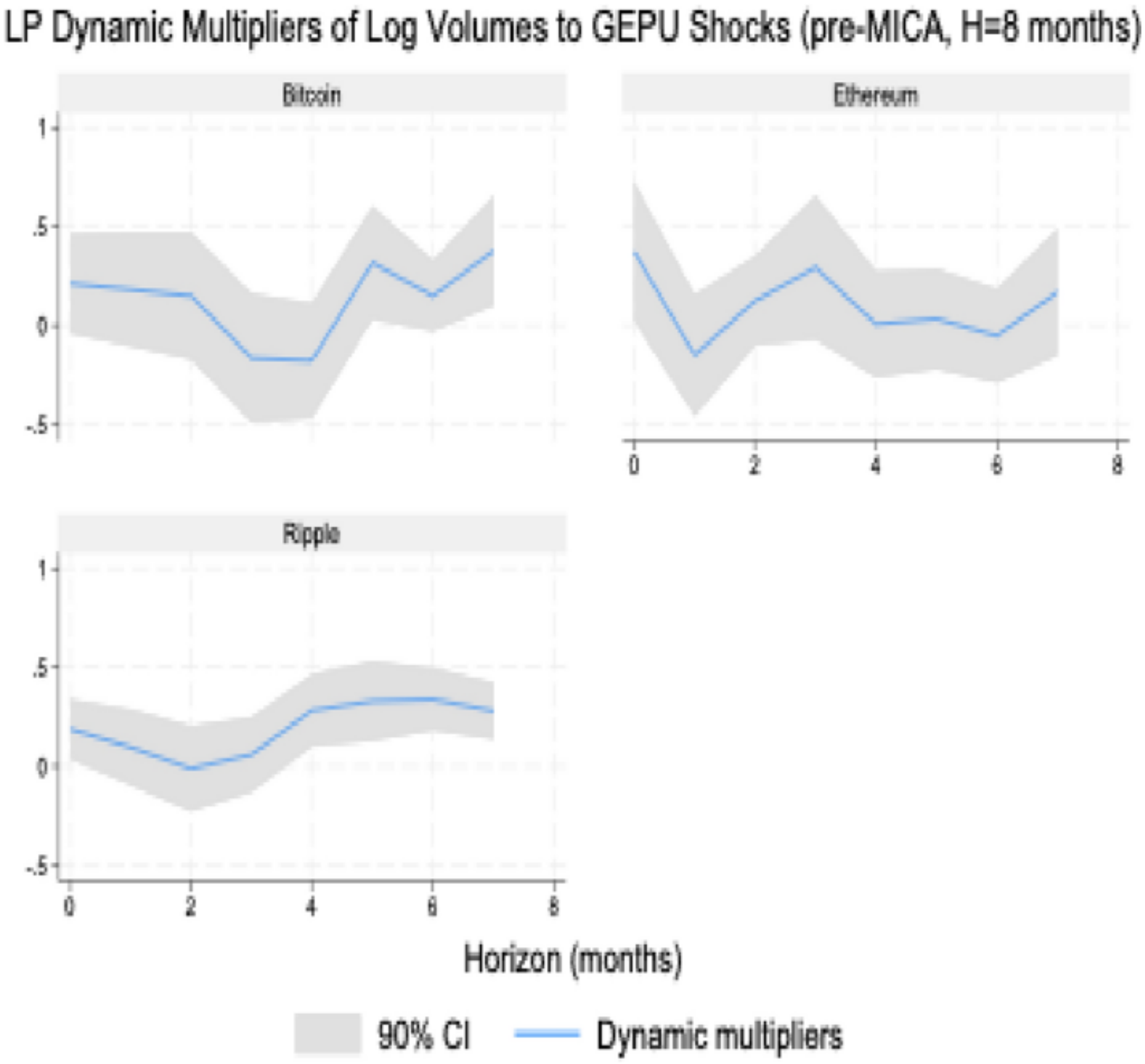


Fig. 6

YYY Local projection of dynamic multipliers of log volumes to ENBI shocks (pre-MiCA, H=12 months)

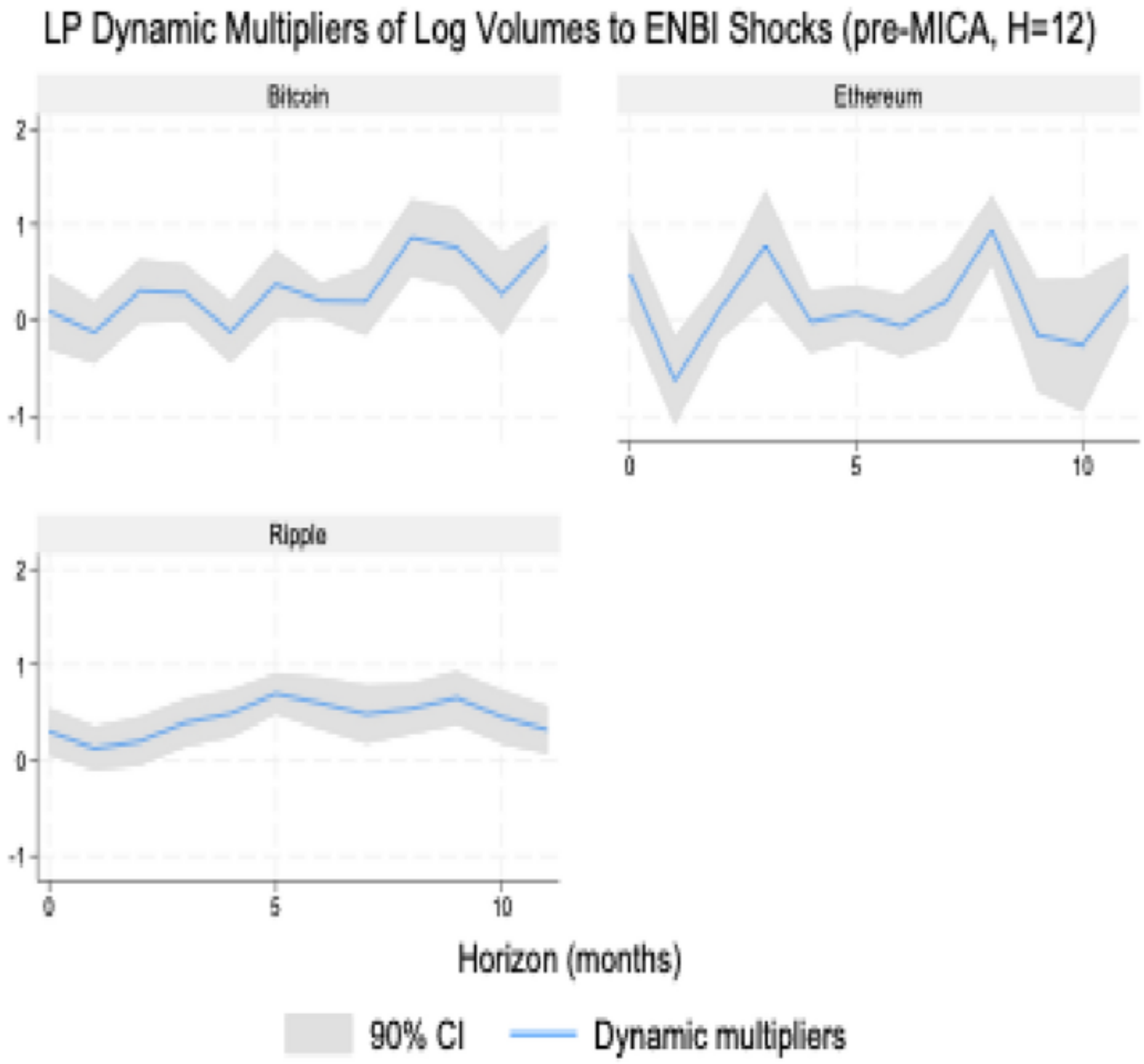
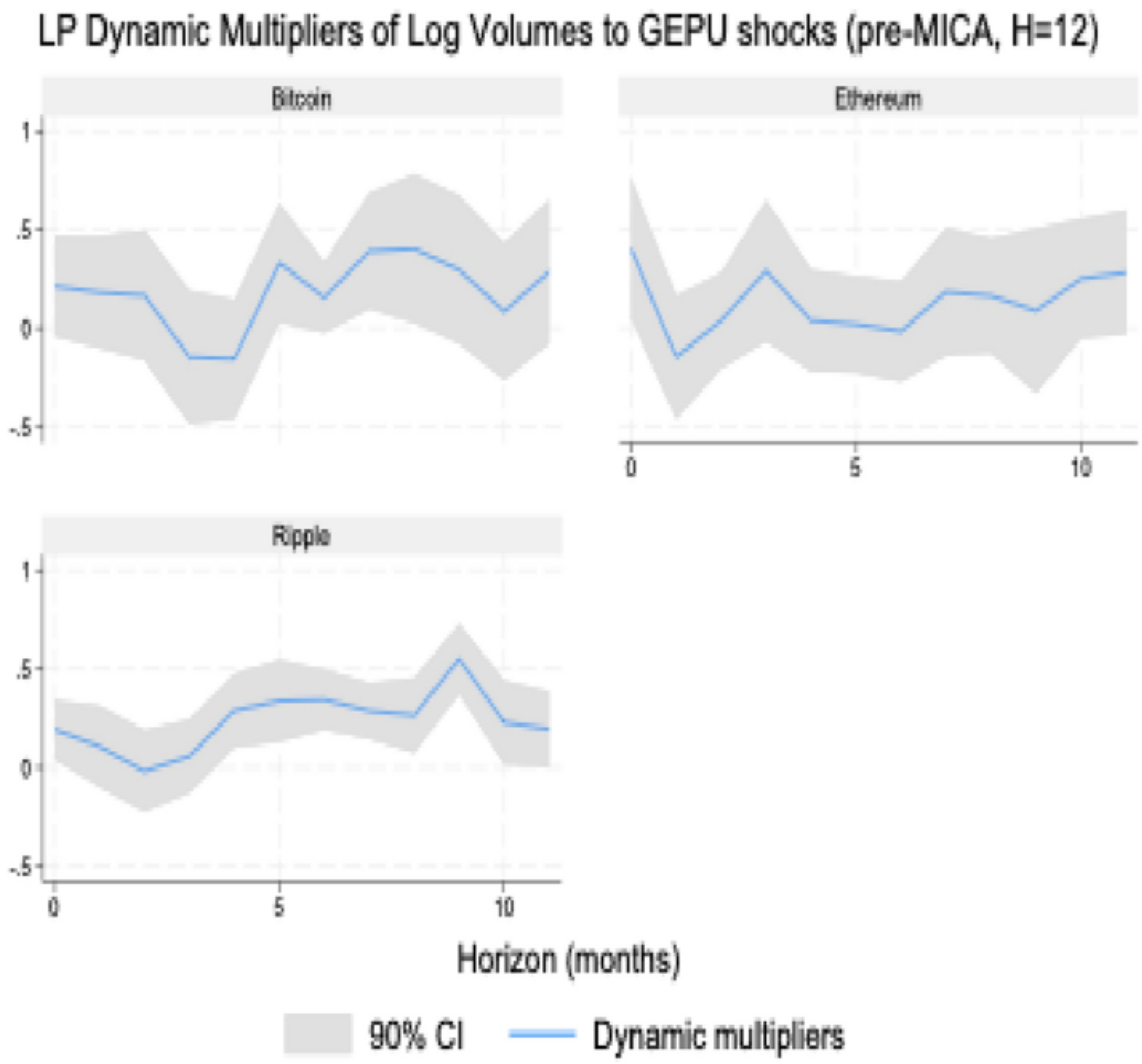


Fig. 7

YYYLocal projections of dynamic multipliers of log volumes to GEPU shocks (pre-MiCA, H=12 months)



We further investigate whether the FTX collapse represents a structural break within the pre-MiCA subsample (the sample sizes of different subsamples are reported in Table ~~@~~13 in the Appendix). The results (Table 5) confirm that before the FTX breakpoint CDMs (EPU*$I_{<}$) are always positive and, in most cases, significantly so. For BTC and ETH this is true also after the crash of FTX (EPU*$I_{>}$). The only one rejection of the stability tests across the FTX breakpoint for these two cryptos regards ETH with respect to GEPU at H = 4 and, notably, is due to a discrepancy in size between significantly positive pre- and post-FTX CDMs. This suggests that the instability, with the sign changes, observed in the full sample for BTC and ETH is primarily driven by the most recent period under observation, rather than by the FTX event itself. For XRP instead the FTX break seems relevant at H = 8, 12.

Table 5

Volumes—Cumulative dynamic multipliers and stability tests – Pre-MICA Local-projections estimates on FTX-interacted EPU: EPU*I(t < Nov 2022) and EPU*I(t ≥ Nov 2022)

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU*I <	0.753	1.745*	3.670***
		(0.607)	(0.783)	(0.639)
	GEPU* I ≥	1.842	4.401**	0.197
~~BTC~~		(2.051)	(2.460)	(2.686)
	Stability F-test	0.326	1.322	1.824
	ENBI*I <	0.554	1.168	3.647***
		(0.597)	(0.687)	(0.682)
	ENBI* I ≥	1.586	4.356*	0.104
		(2.273)	(2.538)	(3.283)
	Stability F-test	0.270	2.158	1.357
ETH	GEPU*I <	0.609**	1.385***	2.157***
		(0.297)	(0.357)	(0.488)
	GEPU* I ≥	2.320**	1.572	3.046
		(0.864)	(1.160)	(4.547)
	Stability F-test	4.201**	0.027	0.039
~~ETHETH~~	ENBI*I <	0.688**	1.082**	2.215***
		(0.304)	(0.407)	(0.607)
	ENBI* I ≥	1.920**	− 0.745	0.538
		(0.824)	(1.371)	(5.260)
	Stability F-test	2.485	1.983	0.111
XRP	GEPU*I <	0.467	1.267***	0.861
		(0.315)	(0.310)	(0.744)
~~XRP~~	GEPU* I ≥	− 0.124	− 0.911	− 7.405*
		(0.796)	(0.960)	(3.600)
	Stability F-test	0.572	5.633**	6.635**
	ENBI*I <	1.115***	2.084***	0.570
		(0.373)	(0.525)	(0.607)
	ENBI* I ≥	3.398**	− 2.988*	− 7.747**
		(1.300)	(2.345)	(3.286)
	Stability F-test	3.730*	5.492**	7.239**

Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t-1~~$_{t-1}$- EPU~~t-11~~$_{t-11}$, EPU$_{t}$ interacted with **I < **and **I ≥ **

We investigate whether the positive CDMs in the pre-MiCA period is driven by momentum in price dynamic by including the first lag of the returns (i.e., the first difference of log crypto prices) as controls. Results (Table 6) are virtually unchanged after including lagged returns as additional controls, indicating that the positive response of trading volumes to uncertainty shocks is not driven by recent price dynamics, but reflects the direct impact of uncertainty shocks.

Table 6

Volumes—Cumulative dynamic multipliers – pre-MICA subsample (t < Gen 2024) Local-projections estimates with lagged returns

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	0.376 (0.576)	1.039 (0.677)	2.171*** (0.616)

Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU$_{t}$-EPU~~t-11~~$_{t-11}$, lagged returns = ln(P~~t-1~~$_{t-1}$)-ln(P~~t-2~~$_{t-2}$)

Crypto	EPU	H = 4	H = 8	H = 12
	ENBI	0.449 (0.528)	1.046 (0.647)	3.813*** (0.582)
ETH	GEPU	0.638** (0.275)	0.791** (0.346)	1.566*** (0.501)
	ENBI	0.825** (0.319)	0.950*** (0.344)	1.854*** (0.635)
XRP	GEPU	0.327 (0.313)	1.553*** (0.318)	2.744*** (0.561)
	ENBI	0.971** (0.394)	3.104*** (0.633)	4.998*** (0.863)

Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t~~$_{t}$-EPU~~t-11~~$_{t-11}$, lagged returns = ln(P~~t-1~~$_{t-1}$)-ln(P~~t-2~~$_{t-2}$)

Since trading volume is direction-neutral, an increase in trading activity may reflect either risk-taking or panic-driven behaviour in a market driven by heterogenous believes. To shed light on, this issue, we estimate the LP model using returns as the response variable. Significantly large negative CDMs would be indicative of panic-driven selling following uncertainty shocks. Results over the pre-MiCA (Table 7) subsample tell the opposite, showing in almost all cases positive CDM's, that become always significantly positive over the longest horizon of 12 months (Table 7). This picture is largely consistent with investors repositioning towards riskier assets under heightened uncertainty.

Table 7

Returns—Cumulative dynamic multipliers – pre-MICA subsample (t < Gen 2024) Local-projections estimates

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	0.052 (0.090)	0.118 (0.082)	0.393*** (0.073)
	ENBI	0.225* (0.130)	0.283 (0.197)	0.633*** (0.207)
ETH	GEPU	0.066 (0.104)	0.186 (0.127)	0.547*** (0.154)
	ENBI	0.085 (0.143)	0.258 (0.257)	0.645** (0.282)
XRP	GEPU	− 0.066 (0.073)	− 0.058 (0.065)	0.384*** (0.096)
	ENBI	0.018 (0.113)	− 0.013 (0.212)	0.483* (0.260)

Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Returns = ln(P~~t)~~$_{t)}$-ln(P~~t-1~~$_{t-1}$). Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t−1~~$_{t-1}$− y~~t−12~~$_{t-12}$, EPU~~t~~$_{t}$− EPU~~t−11~~$_{t-11}$

The joint evidence from volumes and returns allows us to answer the research question and confirm that there exists a significantly positive relationship between economic policy shocks and crypto volumes in the pre- MiCA period, which can be interpreted as a race to risk of investors. This result is a departure from what the finance literature observed for traditional financial assets, like shares or bonds, whose demand is often reduced following growing uncertainty, but are in line with what found by other authors over shorter periods of time on the returns of BTC (Cheng & Yen, 2020; Matkovskyy et al., 2020).

4.3. Robustness check

We perform additional robustness checks to assess the sensitivity of our results to alternative sample definitions and break specifications.

As a first robustness check, we re-estimate the model on the pre-FTX subsample (Table 8). The results are qualitatively consistent with those obtained for the pre-MiCA sample, showing positive and statistically significant effects for BTC and ETH, particularly at longer horizons, while weaker and less significant responses are observed for XRP. This suggests that the positive relationship between uncertainty and crypto trading activity is not driven by the choice of the MiCA cutoff and is already present in the pre-FTX period.

Table 8

Volumes—Cumulative dynamic multipliers – pre-FTX subsample (t < Nov 2022) Local-projections estimates

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	1.838** (0.880)	3.435*** (1.078)	3.637*** (0.681)
	ENBI	1.716*** (0.605)	2.549*** (0.556)	2.367*** (0.444)
ETH	GEPU	0.743** (0.342)	1.647*** (0.327)	2.159*** (0.483)

Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$− y~~t−12~~$_{t-12}$, EPU~~t~~$_{t}$− EPU~~t−11~~$_{t-11}$

Crypto	EPU	H□=□4	H□=□8	H□=□12
	ENBI	0.479 (0.369)	1.269*** (0.438)	2.237*** (0.607)
XRP	GEPU	− 0.310 (0.505)	0.010 (0.497)	0.097 (0.887)
	ENBI	0.295 (0.366)	0.509 (0.536)	0.548 (0.642)

Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$− y~~t− 12~~$_{t-12}$, EPU~~t~~$_{t}$− EPU~~t− 11~~$_{t-11}$

As an additional robustness check we split the pre-MiCA sample in February 2020, which we take as the onset of the COVID-19 shock (Table 9). The results provide mixed evidence: parameter constancy is rejected in most specifications, though less systematically than in the full sample. However, a clear pattern emerges: CDMs estimated over the post-February 2020 period (EPU*$I_{>}$, i.e. from March 2020 onwards) are always significantly positive across all cryptocurrencies, horizons and EPU measures, while CDMs estimated over the pre-February 2020 period (EPU*$I_{\leq}$) are predominantly negative and insignificant. This asymmetry suggests that the positive response of trading volumes to uncertainty shocks in the pre-MiCA period is a phenomenon that mostly emerged following the onset of the pandemic.

Table 9

Volumes—Cumulative dynamic multipliers and stability tests – pre-MICA subsample Local-projections estimates on (t□≤□Feb-2020) interacted EPU: EPU*I(t□≤□Feb 2020) and EPU*I(t□>□Feb 2020)

Crypto	EPU	H□=□4	H□=□8	H□=□12
BTC	GEPU*I□>□	1.813**	3.938***	4.445***
		(0.691)	(0.828)	(0.776)
	GEPU*I□≤□	− 1.172*	− 1.712**	2.194*
		(0.590)	(0.685)	(1.059)
	~~StabilityStability~~			
	Stability F-test	12.255***	28.113***	2.775
~~BTC~~				
	ENBI*I□>□	1.154*	2.094***	4.678***
		(0.609)	(0.689)	(0.700)
	ENBI*I□≤□	− 1.357*	− 2.145**	0.607
		(0.770)	(0.891)	(1.305)
	~~StabilityStability~~			
	Stability F-test	8.562***	20.886***	8.239***
ETH	GEPU*I□>□	0.979***	2.390***	2.937***
		(0.280)	(0.360)	(0.625)
	GEPU*I□≤□	− 0.206	− 0.331	0.635
		(0.440)	(0.367)	(0.645)
	~~Stability~~			
	Stability F-test	6.132**	29.851***	5.830**
	ENBI*I□>□	0.938**	1.531***	2.851***
		(0.380)	(0.391)	(0.714)
	ENBI*I□≤□	0.157	− 0.138	0.859
		(0.367)	(0.600)	(0.830)
	~~Stability~~			
	Stability F-test	2.375	7.025**	3.260*
XRP	GEPU*I□>□	0.804**	2.228***	2.295**
		(0.290)	(0.442)	(0.958)
	GEPU*I□≤□	− 0.959*	− 0.259	− 0.233
		(0.487)	(0.721)	(1.300)
	~~Stability~~			
	Stability F-test	10.334***	5.896**	1.942
~~XRP~~				
	ENBI*I□>□	2.039***	4.775***	4.138***
		(0.412)	(0.853)	(1.139)

Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t-1~~$_{t-1}$-EPU~~t-11~~$_{t-11}$, EPU~~t~~$_{t}$ interacted with **I**□>□and **I**□≤□

Crypto	EPU	H = 4	H = 8	H = 12
	ENBI*I ≤	− 2.035**	− 2.329	− 3.720**
		(0.810)	(1.421)	(1.359)
	~~Stability~~			
	Stability F-test	17.671***	12.856***	13.166***
Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t-1~~$_{t-1}$-EPU~~t-11~~$_{t-11}$, EPU~~t~~$_{t}$ interacted with **I** > and **I** ≤				

The foregoing pattern is confirmed by a further LP estimation, restricted to the post-February 2020/pre-MiCA subsample (Table 10), which shows significantly positive CDMs in almost all specifications. Notice that due to the small sample size of this interval, a more parsimonious lag selection ($\boxed{EPU_t \ldots EPU_{t-7}\ y_{t-1} \ldots y_{t-8}}$) was adopted for this analysis.

Table 10

Volumes—Cumulative dynamic multipliers – post-COVID, pre-MICA subsample (Feb 2020 < t < Gen 2024) Local-projections estimates

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	1.590 (0.884)	2.294** (0.934)	3.553** (1.177)
	ENBI	2.299*** (0.637)	1.830*** (0.352)	5.149*** (0.794)
ETH	GEPU	0.937* (0.457)	0.756* (0.361)	1.590*** (0.488)
	ENBI	1.660** (0.586)	0.970** (0.417)	2.276*** (0.608)
XRP	GEPU	0.746* (0.379)	1.808*** (0.239)	3.206*** (0.646)
	ENBI	-0.151 (0.439)	1.161*** (0.329)	3.253*** (0.894)
Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-8~~$_{t-8}$, EPU~~t~~$_{t}$-EPU~~t-7~~$_{t-7}$				

As a fourth check, we allow for a more flexible time trend specification by including low-frequency Fourier terms (k = 1). The results for the pre-MiCA sample (Table 11) remain qualitatively unchanged, confirming that our findings are not driven by the choice of trend functional form. We also experimented with additional Fourier frequencies (e.g., k = 2), obtaining similar results (not reported for brevity).

Table 11

Volumes—Cumulative dynamic multipliers – pre-MICA subsample (t < Gen 2024) Local-projections estimates (Fourier trend specification)

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	0.393 (0.569)	1.245* (0.722)	2.962*** (0.627)
	ENBI	0.602 (0.542)	1.250* (0.660)	4.211*** (0.562)
ETH	GEPU	0.888*** (0.309)	1.232*** (0.375)	2.110*** (0.507)
	ENBI	0.944*** (0.325)	1.205*** (0.375)	2.183*** (0.575)
XRP	GEPU	0.874** (0.364)	2.509*** (0.436)	4.689*** (0.824)
	ENBI	1.263*** (0.408)	3.502*** (0.596)	6.583*** (1.045)
Heteroscedasticity-robust SE in parentheses; *, **, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t~~$_{t}$- EPU~~t-11~~$_{t-11}$, Fourier trends (k = 1): sin(2πt/T), cos(2πt/T)				

Finally, we estimate an ARDL(12,11) specification on the pre-MiCA subsample. For consistency with the local projection framework, we focus on CDMs derived from the ARDL specification, rather than on the individual lag coefficients. The results (Table 12) are qualitatively consistent with the local projection estimates, confirming a positive relationship between uncertainty and crypto trading volumes, particularly for ETH and XRP at longer horizons.

Table 12

Volumes—Cumulative dynamic multipliers – pre-MICA subsample (t < Gen 2024) ARDL(11,12) estimates

Crypto	EPU	H = 4	H = 8	H = 12

Crypto	EPU	H = 4	H = 8	H = 12
BTC	GEPU	0.150 (0.578)	0.770 (0.854)	0.823 (1.036)
	ENBI	0.872 (0.730)	2.415* (1.258)	1.501 (1.569)
ETH	GEPU	0.060 (0.277)	0.524** (0.257)	0.404** (0.203)
	ENBI	0.129 (0.363)	1.254*** (0.335)	0.536* (0.297)
XRP	GEPU	0.387 (0.255)	1.008*** (0.261)	1.429*** (0.388)
	ENBI	1.114** (0.496)	2.726*** (0.789)	4.026*** (1.431)

Heteroscedasticity-robust SE in parentheses; *,**, *** is significant at 10%, 5% and 1% respectively. Controls: constant term, 11-month dummies, 7 event dummies, linear and quadratic trends, y~~t-1~~$_{t-1}$-y~~t-12~~$_{t-12}$, EPU~~t~~$_{t}$-EPU~~t-11~~$_{t-11}$

Taken together, the results of Tables 8, 9, 10, 11 and 12 consistently point to the period following the onset of the COVID 19 pandemic as the primary driver of the positive uncertainty-volume relationship documented in the pre-MiCA sample, and rule out that this is an artifact of sample choice, trend specification or estimation framework.

5. Policy implications

The findings of this paper carry several important implications for policymakers, regulators, and market participants and relate to the improvement of market transparency, the reduction of informational frictions, and the robustness market infrastructures. First, the evidence that economic policy uncertainty increases trading activity in cryptocurrency markets, rather than reducing it, suggests that digital assets may serve as a channel for speculative behaviour, and probably exacerbate periods of macroeconomic instability. This highlights the need for policymakers to consider crypto markets as a source of potential instability within the broader financial stability framework, especially during times of high uncertainty. Similarly to traditional financial markets, authorities should monitor real-time metrics of digital markets (e.g., volatility, volumes spikes, leverage ratio and concentration).

Second, the results point to the importance of regulatory clarity and consistency. The presence of structural breaks associated with major events and regulatory changes indicates that shifts in policy regimes can significantly alter market dynamics. Policymakers should therefore prioritize transparent, coordinated, and predictable regulatory approaches to reduce uncertainty and limit excessive speculative responses. In this direction goes the introduction of a comprehensive frameworks such as the European Union's MiCA regulation.

Third, the prevalence of retail investors and the observed tendency toward risk-seeking behaviour under uncertainty raise concerns about investor protection in the digital ecosystem. Sentiment driven investments' choices can be mitigated by strengthening the information on risks, eliminating the "high-return, low-risk" myth. It is necessary to enhance disclosure requirements, and improve market surveillance to strengthen the information available. Target financial education initiatives for crypto investors, particularly less sophisticated participants, should be offered, following the OECD guidelines (OECD, 2025).

Fourth, given the interconnectedness between digital and traditional financial systems, episodes of heightened speculative activity in crypto markets may have spillover effects. Regulators should strengthen monitoring tools and data collection on trading volumes, returns, leverage, and cross-market exposures to better assess and address systemic risks.

6. Conclusion

This paper examined the relationship between economic policy uncertainty (EPU) and trading activity in cryptocurrency markets, focusing on Bitcoin, Ether, and Ripple over the period 2016–2025. By adopting trading volumes as a proxy for investor behaviour and employing lag-augmented local projections (LPs), we provide new evidence on how persistent uncertainty shocks affect participation in digital financial markets.

The empirical findings consistently point to a positive and statistically significant relationship between uncertainty and trading volumes, particularly when accounting for structural breaks and focusing on the pre-MiCA subsample. While full-sample estimates suggest instability of coefficients, the subsample analysis reveals that increases in economic policy uncertainty systematically stimulate trading activity across all major cryptocurrencies. Ripple exhibits the strongest and most robust response, while Bitcoin and Ether show significant effects once parameter instability is addressed.

Importantly, complementary evidence from return-based specifications indicates that this increase in trading activity is not associated with panic-driven sell-offs. Instead, it reflects a pattern of speculative engagement and portfolio rebalancing towards riskier assets (i.e., race to risk). This behaviour stands in contrast to the "flight-to-safety" typically observed in traditional financial markets under heightened uncertainty.

These results highlight the specific structural and behavioural characteristics of cryptocurrency markets, where the absence of clear valuation anchors, the prevalence of retail investors, and informational frictions may amplify speculative responses to uncertainty. At the same time, the presence of structural breaks, particularly around major events such as the FTX collapse and regulatory changes, underscores the evolving nature of these markets and the importance of accounting for regime shifts.

Overall, the findings suggest that economic policy uncertainty plays a distinct and non-traditional role in digital financial ecosystems, acting as a driver of trading intensity rather than a deterrent to risk-taking. Future research could further explore cross-market linkages, investor heterogeneity, and the role of different regulatory frameworks in shaping these dynamics (e.g., in Asia). AQ5

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Data availability statement

Data on crypto come from https://www.investing.com/crypto/; GEPU data come from the St. Louis Fed https://fred.stlouisfed.org/series, and ENBI data come from Baker et al. (2016) https://www.PolicyUncertainty.com.

Declarations

Conflict of interest

The authors declare no competing interests.

Appendix

See Table

Table 13

Sample sizes across subsamples (volumes and pre-MICA returns)

~~v~~Variable	~~epu~~Economic Policy Uncertainty index	full sample	pre-FTX	pre-MICA	post-COVID
BTC (volume)	~~enbi~~ENBI	113	75	89	46
	~~gepu~~GEPU	111	75	89	46
ETH (volume)	~~enbi~~ENBI	117	79	93	46
	~~gepu~~GEPU	115	79	93	46
XRP (volume)	~~enbi~~ENBI	107	69	83	46
	~~gepu~~GEPU	105	69	83	46
BTC (returns)	~~enbi~~ENBI			88	
	~~gepu~~GEPU			88	
ETH (returns)	~~enbi~~ENBI			92	
	~~gepu~~GEPU			92	
XRP (returns)	~~enbi~~ENBI			82	
	~~gepu~~GEPU			82	

Sample sizes refer to all subsamples for trading volumes. Return-based specifications are estimated only on the pre-MICA sample. Post-COVID refers to observations from March 2020 onwards within the pre-MICA subsample.

13.

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